ESTIMATING MINIMUM THRESHOLDS OF NATURAL VEGETATION FOR THE INTEGRATED MANAGEMENT AND PROTECTION OF WATER QUALITY IN SOUTH AFRICAN CATCHMENTS

by

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Abstract

Despite multi-level commitments to Integrated Water Resources Management (IWRM), many of South Africa's water quality problems are attributable to the negative impacts of anthropogenic land use on water quality. Academics and policymakers have warned that unless action is taken to improve water resources management through the implementation of coordinated, proactive, and data-driven strategies, the country faces a water crisis that will have severe socio-ecological consequences. As natural vegetation acts as a sink, thus protecting water resources from diffuse pollution, the preservation of an adequate amount within catchment areas is important. However, among several pertinent questions, it is not clear (1) how much natural vegetation cover is required, (2) at which scale(s) this would be most effective, (3) how natural vegetation should be classified, and (4) whether the fragmentation of natural vegetation is a significant factor. To answer these questions, regression analysis was used to model relationships between water quality (measured using a composite pollution index) and metrics of natural vegetation (estimated from national land cover maps) at multiple scales across a sample of sub-catchments located within South Africa's Berg-Olifants, Breede-Gouritz, and Mzimvubu-Tsitsikamma Water Management Areas. Across this sample, a statistically significant, nonlinear, and inverse relationship was found between proportions of natural vegetation cover and pollution levels. This relationship was strongest (1) when natural vegetation was defined as an aggregation of indigenous woody vegetation, wetlands, and forestry plantations, and (2) when measured across the whole catchment and within a 200 m riparian buffer zone. At both scales, however, fragmentation was not found to be significant. The models further indicated that approximately 82 to 90% natural vegetation cover was necessary at these scales to keep pollution scores within acceptable levels. Additional nonlinear thresholds estimated using breakpoint analysis also suggested that if proportions of natural vegetation fall below 45% (across the whole catchment) and 60% (within a 200 m riparian buffer zone) a dramatic increase in pollution levels can be expected. The study has direct relevance for IWRM in so far as these results demonstrate (1) the critical importance of preserving areas of natural vegetation for water quality management and (2) the possibility of providing actors with quantifiable and context-specific management targets which can inform multistakeholder decision-making processes at appropriate spatial scales.

Keywords: land use, land cover, water quality, water quality index, thresholds, IWRM, South Africa

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Declaration

I, Kent Anson Locke, hereby declare that all work in this thesis, save for that which is properly acknowledged, is my own. Each contribution to this thesis from the work(s) of others has been duly attributed, cited, and referenced.

Signed: Signed by candidate Date: 22/01/2024

In loving memory of Audrey Catherine Locke
(1951 – 2020)

Preface

In many ways, the clock is ticking. With progress reportedly flagging, the 2030 deadline for the United Nations Sustainable Development Goals (SDGs) is rapidly approaching. Among other ambitions, this includes realising universal and equitable access to water of acceptable quality by, inter alia, reducing pollution, restoring aquatic ecosystems, and implementing Integrated Water Resources Management (IWRM). In South Africa, however, the quality and availability of the country's freshwater resources are, by all accounts, steadily deteriorating. This is attributable, at least in part, to a persistent lack of integration in the management of water and related sectors, as well as ongoing contamination from a multitude of point and non-point sources. At the global scale, the sterling work of Johan Rockström and others at the Stockholm Resilience Centre has made it abundantly clear that humanity is very close to pushing Earth's interconnected ecological systems—including its aquatic systems—past critical tipping points, with catastrophic and potentially irreversible socioeconomic and environmental consequences. If, at both local and global scales, we are to avoid these impending crises, we urgently need to generate knowledge and develop tools and strategies that will empower us to manage and protect our natural resources in an integrated, informed, and responsible manner. Against this backdrop, this doctoral thesis represents approximately two and a half years of research into the use of statistical approaches to assess and model the impacts of land use/land cover (LULC) on water quality, with particular consideration given to the relevance of this research for the implementation of IWRM. Both domestically and internationally, investigating and understanding the complex relationships between land use and water quality is an urgent imperative—especially if the research can generate quantifiable, scale-appropriate, and context-specific guidelines to inform and support the efforts of policymakers and administrators.

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List of Acronyms

ACRU	Agricultural Catchments Research Unit
AI	Aggregation Index
ANZG	Australian and New Zealand Governments *OR* Australian and New Zealand Guidelines [for Fresh and Marine Water Quality]
BASINS	Better Assessment Science Integrating Point and Nonpoint Sources
CER	Centre for Environmental Rights
CMA	Catchment Management Agency
CMF	Catchment Management Forum
CMME	Canadian Council of Ministers of the Environment
CMS	Catchment Management Strategy
CSES	Complex Social-Ecological System
CSIR	Council for Scientific and Industrial Research
CWP	Centre for Watershed Protection
DEA	Department of Environmental Affairs
DEAT	Department of Environmental Affairs and Tourism
DFFE	Department of Forestry, Fisheries and the Environment
DO	Dissolved Oxygen
DWA	Department of Water Affairs
DWAF	Department of Water Affairs and Forestry
DWS	Department of Water and Sanitation
EC	Electrical Conductivity
FAO	Food and Agriculture Organisation
GEMS	Global Environment Monitoring System
GIS	Geographical Information Systems
GWP	Global Water Partnership
HDX	Humanitarian Data Exchange
IPCC	Intergovernmental Panel on Climate Change
IWA	International Water Association
IWRM	Integrated Water Resources Management
LULC	Land Use/Land Cover
LULC-WQ	Land Use/Land Cover-Water Quality [used to describe the nexus thereof]
MAP	Mean Annual Precipitation
NCMP	National Chemical Monitoring Programme
NDVI	Normalised Difference Vegetation Index
NPI	Nemerow's Pollution Index
NPSP	Nonpoint Source Pollution
NVII	Natural Vegetation Integrity Index
NWRS	National Water Resource Strategy
OCHA	Office for the Coordination of Humanitarian Affairs
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
POP	Persistent Organic Pollutant
QR	Quantile Regression
RBZ	Riparian Buffer Zone

RQIS	Resource Quality Information Services
SANLC	South African Land Cover [map]
SANSA	South African National Space Agency
SASS	South African Scoring System
SAWQ	South African Water Quality [guidelines]
SDG	Sustainable Development Goal
SDR	Studentised Deleted Residual
SPSI	Science-Policy-Stakeholder Interface
SWAT	Soil Water Assessment Tool
SWSA	Strategic Water Source Area
TIN	Total Inorganic Nitrogen
UN	United Nations
UNDP	United Nations Development Programme
UNEP	United Nations Environmental Programme
UNESCO	United Nations Educational, Scientific and Cultural Organisation
UNICEF	United Nations Children's Fund
USAID	United States Agency for International Development
USEPA	United States Environmental Protection Agency
USGS	United States Geological Survey
WMA	Water Management Area
WMO	World Meteorological Organisation
WQI	Water Quality Index
WRC	Water Research Commission
WWC	World Water Council

CHAPTER 1: Introduction

"As humanity's most precious global common good, water unites us all. That's why water needs to be at the centre of the global political agenda."
—António Guterres (UN Secretary-General, quoted in Kőrösi, 2023, p. 2)

Water, which is vital to every aspect of life, society, and the economy, is arguably one of the most important natural resources on Earth (Rockström et al., 2014; Kőrösi, 2023; Scanlon et al., 2023; Vollmer et al., 2023; Wang et al., 2023a). Likewise, the equitable and sustainable provision of clean water is essential for promoting socioeconomic development (OECD, 2017; Winter, 2018; Biswas & Tortajada, 2019; Cheng et al., 2022; Paná et al., 2022; van Deventer et al., 2022; UNEP, 2023a). Moreover, while physical constraints on freshwater availability undoubtedly affect many regions of the world—including South Africa—it has been argued that water supply issues are often due to mismanagement rather than natural limitations (UNDP, 2013; Biswas & Tortajada, 2016; Woodhouse & Muller, 2017; de Oliveira Vieira et al., 2020; Hay, 2021; Adom & Simatele, 2022; Mugejo et al., 2022; du Plessis, 2023; Vollmer et al., 2023). This so-called "crisis of management" has long been the refrain of the World Water Council (WWC), which observed in an early position paper that:

> There is a water crisis today. But the crisis is not about having too little water to satisfy our needs. It is a crisis of managing water so badly that billions of people—and the environment—suffer badly… There is a water crisis, but it is a crisis of management. (Cosgrove & Rijsberman, 2000, pp. xix, xxvii)

Concomitantly, the availability of water is as much a function of *quality* as it is of *quantity* (McCutcheon et al., 1993; National Research Council, 2001; Tundisi et al., 2015; Deng et al., 2023; du Plessis, 2023; Gikas et al., 2023). The deterioration of water quality has thus become a global issue of almost unparalleled significance (Rockström et al., 2014; Biswas & Tortajada, 2019; Tozer, 2023). One of the major causes of water quality degradation (both locally and globally) is diffuse pollution, which is often associated with unsustainable land use/land cover (LULC) changes driven by anthropogenic activities such as urbanisation, agriculture, commercial forestry, and mining (Foley et al., 2005; Falkenmark, 2011; Falkenmark et al., 2014; Malek & Verburg, 2020; Gomes et al., 2021; Taylor & Rising, 2021; Bohenek & Sulliván, 2022; Liu et al., 2022; Xu & Xiao, 2022; Goswami et al., 2023). According to Kajitvichyanukul and D'Arcy (2022, p. xv), the problem of land-use-related diffuse pollution is "huge in scope and extent, encompassing everything from nutrients and sediment to micro- and nanoparticles, toxic metals, pesticides, faecal pathogens and even water-borne litter."[1] Szymańska-Walkiewicz et al.

[1] This quote is lifted from the preface to what is arguably one of the most current, authoritative, and comprehensive texts on the impact of land-use-related diffuse pollution on water quality, published recently by the International Water Association (IWA), UK.

(2023) have thus argued that, globally, the availability of usable freshwater is decreasing rapidly as a result of inappropriate land use in catchment areas. Moreover, the predicted impacts of climate change are expected to exacerbate many water-related problems (OECD, 2017; Woodhouse & Muller, 2017; du Plessis, 2019b; WMO, 2022; Ciampittiello et al., 2023; du Plessis, 2023; IPCC, 2023; Nath et al., 2023).

Thus, for academics, policymakers, and practitioners alike, developing informed and integrated strategies to better manage the negative impacts of LULC on water quality is an urgent imperative (Dawson & Smith, 2010). One such strategy includes the preservation and/or restoration of natural vegetation across catchments and within riparian areas. By acting as a sink, intercepting and transforming many of the contaminants contained in surface runoff, natural vegetation can assist in protecting receiving water bodies from diffuse pollution (Stutter et al., 2012; Kreye et al., 2014; de Mello et al., 2017; Open Space Institute, 2018; Cecílio et al., 2019; Fernandes et al., 2021; Piffer et al., 2021; Cheng et al., 2022; Cooke et al., 2022; Wang et al., 2023a). Kajitvichyanukul and D'Arcy (2022, pp. xv, 286), for instance, refer to “the vital importance of landscape interventions [which] reduce mobilisation and loss of potential pollutants to the water environment.”

Considered through the lens of Sustainable Development, wherein the goal is to attain a harmonious balance between socioeconomic development and environmental protection, a reasonable (if superficially simplistic) question is whether, and by what means, the minimum amount of natural vegetation necessary to protect water resources can be reliably estimated. This question, which appears in various forms in the published literature, remains largely unanswered (see, for example, Brabec et al., 2002; Death & Collier, 2010; Iñiguez-Armijos et al., 2014; Hanna et al., 2021). Moreover, as will become apparent, the question itself is far more complex than it initially appears, and answering it requires the consideration of several additional theoretical, methodological, and contextual matters. While there exists an extensive body of literature pertaining to the impacts of LULC on water quality, including publications documenting the use of statistical methods to quantify these impacts, relatively little attention has been paid to the determination of minimum thresholds of natural vegetation required for the protection and/or maintenance of water quality. In addition, notwithstanding several decades of research, several areas of uncertainty persist. These knowledge gaps relate primarily to the location, scale, and spatial configuration of LULC within catchment areas, and how these may influence the impact of the latter on water resources.

The State of Water Resources and the Impact of LULC on Water Quality in South Africa

South Africa is classified as a water-stressed country. The country receives an average of 450 mm of rainfall per annum (well below the global average of approximately 960 mm) and precipitation patterns vary substantially in time and space (Knight, 2019b; Bischoff-Mattson et al., 2020; du Preez & van Huyssteen, 2020; DWS, 2022b). In addition to these physical constraints, water availability in South Africa is further limited by persistent and, by all accounts, worsening water quality problems that are largely anthropogenic (CSIR, 2010; Nel et al., 2011a; DEA, 2012; Donnenfeld et al., 2018; DWS, 2018; du Plessis, 2019b; du Preez & van Huyssteen, 2020; DWS, 2022a). According to du Plessis (2023, p. 109), ongoing water quality degradation in South Africa has now reached “crisis levels.”

In 2010, the South African Centre for Scientific and Industrial Research (CSIR, 2010, p. 65) reported “a gradual decline in the volume of water available per person, progressive worsening of water quality, loss of biological integrity in our aquatic ecosystems, and continually rising costs associated with treating water for people to drink,” concluding that “this will prevent us from achieving social and economic growth and eliminating poverty.” According to the *2nd South Africa Environmental Outlook* report published by the Department of Environmental Affairs, many South African river systems are under stress due to pollution (DEA, 2012). The latest version of the report, published ten years later, revealed that many of the same issues persist (DFFE, 2022a). It has also been alleged that freshwater ecosystems in South Africa are among the most degraded on Earth (Farrell et al., 2015). In 2016, owing to pollution and catchment degradation, approximately 40% of water bodies in South Africa were regarded as having poor water quality and were therefore declared non-compliant according to national water quality standards (Stats SA, 2019a, p. 56; 2019b, p. 167). More recently, the United Nations Environmental Programme (UNEP), based on data gathered through its Global Environment Monitoring System (GEMS) for freshwater, reported that only 52% of South Africa’s water bodies are classified as having good ambient water quality (United Nations, 2023c). A recent national biodiversity assessment further estimated that 64% of river ecosystems are in some way threatened, and pollution is considered to be one of the major pressures that place these systems at risk (Skowno et al., 2019). The Department of Water and Sanitation (DWS) has also made the staggering admission that between 1999 and 2011, the extent of major rivers in South Africa classified as having a poor ecological condition increased by 500%, with some rivers pushed beyond the point of recovery (DWS, 2018, p. 2). While these figures may vary (being reported at different times, by different institutions, and using different metrics) they paint a deeply concerning picture of the state of water resources in South Africa. By all accounts, the quality of the country’s freshwater resources has been steadily—if not rapidly—declining for several years, without any significant sign of improvement. In perhaps the most recent assessment of the situation, du Plessis (2023, p. 47) concluded that “long-term data trends show that South Africa’s rivers and dams have significantly deteriorated over the past three decades.” Moreover, it has been acknowledged that these water quality challenges are already having significant impacts on the South African economy and the well-being of citizens (DWS, 2018). Without urgent action, the situation is likely to worsen. Indeed, du Plessis (2023, p. 50) has also reported that “water pollution levels are predicted to reach catastrophic levels in the near future.” Regrettably, poor communities, who lack the resources necessary to adapt, will be most vulnerable to—and thus worst affected by—ongoing water quality degradation and water scarcity (du Plessis, 2019b; Jones et al., 2023).

While point-source pollution is a major concern and has therefore received significant attention both domestically and internationally, there is growing recognition that diffuse pollution,[2] driven largely by land-use-related activities, contributes significantly to the contamination of surface and groundwater resources and is an issue that urgently needs to be addressed (Pegram & Görgens, 2000; Anderson & McDonnell, 2005; Griffin et al., 2014; Bosman et al., 2018; du Preez & van Huyssteen, 2020; DWS, 2021; D'Arcy et al., 2022b; DWS, 2022b). According to various reports, the most prominent water quality issues in South Africa include eutrophication, salinisation, acidification, turbidity, sedimentation, and bacteriological contamination. Other reports have noted growing concerns related to persistent organic pollutants (POPs), pesticides, and heavy metals. These problems are typically linked to urban areas and informal settlements, discharges and/or spills from wastewater treatment works and industrial sites, effluent from mining operations, and return flows from agricultural land and commercial forestry plantations (DEAT, 2006; DEA, 2012; Dabrowski et al., 2013; Griffin et al., 2014; DWS, 2018; King et al., 2018; du Preez & van Huyssteen, 2020; DWS, 2022a; Riddell et al., 2022; du Plessis, 2023).

The ongoing threat that these activities present to water quality, and therefore the pressing need to address them, was confirmed in a recent assessment which reported a significant expansion over the last two decades of urban areas, cultivated land, mines, and commercial forestry plantations in South Africa (DFFE, 2022b). Acknowledging these threats, the DWS, as part of its *National Water and Sanitation Master Plan*, has issued a "call to action" that includes tasks such as (1) developing and implementing a diffuse pollution mitigation strategy that includes the regulation of land use, (2) implementing programmes to rehabilitate catchments, and (3) continuing to conduct research on the impacts of land use on water-related ecosystems (DWS, 2018, pp. 32, 58).

The available evidence therefore makes it clear that the quality (and thus availability) of South Africa's already limited freshwater resources is rapidly deteriorating, and that the problem principally appears to be one of poor management (e.g., a failure to effectively manage the negative impacts of LULC on water quality). Furthermore, as the following paragraphs elucidate, this can be linked to difficulties and delays in implementing Integrated Water Resources Management (IWRM) in South Africa.

Integrated Water Resources Management in South Africa

The Global Water Partnership (GWP, 2000, p. 22) have defined IWRM as "a process which promotes the coordinated development and management of water, land and related resources, in order to

[2] While many texts use the term "nonpoint source pollution" (NPSP) to describe the issue, Kajitvichyanukul and D'Arcy (2022) prefer the term "diffuse pollution" for reasons of conceptual clarity and technical accuracy. The same position is adopted here, although the terms may be used interchangeably.

maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems." Notwithstanding the strong criticism that IWRM has received from some quarters, its inherent logic has nevertheless earned it wide and enthusiastic embrace, especially among the international development community (Biswas, 2004; Medema & Jeffrey, 2005; Merry, 2008; Mukhtarov, 2008; Kadi, 2014; Ibisch et al., 2016; Kumar et al., 2019; du Plessis, 2023; Grison et al., 2023). Moreover, IWRM is now considered to be the dominant paradigm in the management of water resources (Jonker, 2014; Martínez-Santos et al., 2014; Movik et al., 2016; Malaza & Mabuda, 2019; Lukat et al., 2022b). The main principles of this holistic systems-based approach are as follows:

- The sustainable management of water resources through balancing social, economic, and environmental interests.
- A coordinated, multisectoral, and transdisciplinary approach to the management of water and related resources.
- Contextual, adaptive, and participatory decision-making processes, informed by the best available knowledge.
- Devolved catchment-scale management.

As indicated by the GWP definition cited above, IWRM places particular emphasis on the need for integration in the management of land and water resources (see also Calder, 2005; Mitchell, 2005; Bandaragoda, 2006; Kasbohm et al., 2009; Calder, 2012; Falkenmark et al., 2014; Setegen, 2015; Tejada-Guibert, 2015; Borchardt et al., 2016; Duda, 2017). The GWP (2000, p. 60) go on to explain that "in the context of IWRM the management of land use is as important as managing the water resource itself since it will affect flows, patterns of demand and pollution loads" (see also GWP, 2004). UNESCO's implementation guidelines for IWRM have also noted that "cumulative land uses in a river basin, such as urban development, agriculture and forest conservation, can have profound impacts on water resources in the basin and vice versa" (UNESCO, 2009, p. 4). The South African White Paper on National Water Policy, which is essentially underpinned by the principles of IWRM, has further noted that "since many land uses have a significant impact upon the water cycle, the regulation of land use shall, where appropriate, be used as an instrument to manage water resources within the broader integrated framework of land use management" (DWAF, 1997; see also Movik et al., 2016).

South Africa, which boasts some of the world's most progressive water management legislation, has often been considered to be at the forefront of IWRM implementation (Herrfahrdt-Pähle, 2010; Claassen, 2013; Schreiner, 2013; Movik et al., 2016; Palmer & Munnik, 2018; Stuart-Hill et al., 2020; du Plessis, 2023). From a policy perspective, the management of water resources in South Africa is informed by the principles of IWRM, while the effective implementation of these principles is widely considered essential for addressing the country's complex water management challenges (Herrfahrdt-Pähle, 2010; Mauck, 2012; Armitage et al., 2014; Jonker, 2014; van Koppen & Schreiner, 2014; Movik et al., 2016; Meissner et al., 2017; Malaza & Mabuda, 2019; Stuart-Hill et al., 2020; Adom & Simatele, 2022). Recent national assessments published by the United Nations (UN) report that overall progress in the implementation of IWRM in South Africa is “high” (UNEP-DHI, 2023; United Nations, 2023c). However, not only are the UN’s national assessments based on self-reporting by the country in question, but many commentators have concluded that the implementation of IWRM in South Africa has been severely hampered, resulting in persistent fragmentation and reactive planning in the management of water, land, and related sectors (see, for example, Claassen, 2013; Schreiner, 2013; van Koppen & Schreiner, 2014; Meissner et al., 2017; Palmer & Munnik, 2018; du Plessis, 2019b; Stuart-Hill et al., 2020; Adom & Simatele, 2022; Lukat et al., 2022a; du Plessis, 2023). Moreover, many reports and commentaries have specifically highlighted South Africa’s failure to manage the impact of LULC on water quality according to the principles of IWRM (Pollard, 2002; Funke et al., 2007; Pollard & du Toit, 2008; Movik et al., 2016; DWS, 2017e; Stats SA, 2019a). Dabrowski et al. (2013, p. iii), for instance, have claimed that the lamentable state of the country’s water resources is evidence of the failure to effectively manage the link between land use and water quality in an integrated manner.

South Africa’s Impending Water Crisis and the Need for Research to Inform Improved Management Strategies

The latest draft of the South African *National Water Resources Strategy* (NWRS) states that “as water plays a central role in all sectors… its allocation, development, management and protection is an essential prerequisite for inclusive economic growth, poverty reduction and the significant reduction of inequality in South Africa” (DWS, 2021, p. 35). Furthermore, the DWS has recognised that “sustainable development in South Africa is critically dependent upon an assured supply of good quality water” (DWS, 2017e, p. 1). However, since the advent of democracy in 1994, South Africa continues to face significant hurdles with regard to inequality, poverty, and socioeconomic development (World Bank Group, 2018; Francis & Webster, 2019; Oqubay et al., 2021). Water availability, upon which socioeconomic development is dependent, is a complex national issue that remains a major impediment to meeting South Africa’s developmental goals (CSIR, 2010; Nel et al., 2011a; DWS, 2017e, 2018; Winter, 2018; Adom & Simatele, 2022; van Deventer et al., 2022; du Plessis, 2023). The *NWRS* has therefore described the sustainable management of the country’s scarce water resources as “a pressing concern” (DWS, 2021, p. 43). Moreover, among its various constitutional obligations, the State is required to take reasonable measures to (1) provide all South Africans with access to water, (2) secure their right to an environment that is not harmful to their health or wellbeing, and (3) protect the environment by, inter alia, preventing pollution and ecological degradation (see Sections 24 and 27 of the Constitution; Republic of South Africa, 1996). Finally, as a signatory to the UN Sustainable Development Goals (SDGs), South Africa is committed to ensuring the availability and sustainable management of water and sanitation for all people by 2030 (SDG 6; United Nations, 2015).

Falling under SDG 6, the following targets, which are described as being integrated, indivisible, and mutually reinforcing, are of particular relevance:

- Improve water quality by reducing pollution, eliminating dumping, and minimising the release of hazardous chemicals and materials, halving the proportion of untreated wastewater, and substantially increasing recycling and safe reuse globally (Target 6.3).
- Implement integrated water resources management at all levels, including through transboundary cooperation as appropriate (Target 6.5).
- Protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers, and lakes (Target 6.6).

Therefore, developing effective strategies to protect the integrity of what is an unquestionably valuable and increasingly scarce resource, and doing so in line with the principles of IWRM, are imperatives that South Africa is obliged to pursue under both domestic law and international agreement. However, without urgent interventions to address the underlying causes, most authors agree that the looming water crisis in South Africa is likely to have dire socioeconomic and environmental consequences (DWS, 2018; Jolk et al., 2018; Winter, 2018; du Plessis, 2019b; Hughes, 2019; du Plessis, 2021; Adom & Simatele, 2022; du Plessis, 2023). Several years ago the CSIR (2010, pp. 9, 13) claimed that a "radical improvement" in water quality management approaches was required and that "water quality will progressively deteriorate unless corrective management actions are implemented effectively and continuously." The CSIR (2010, p. 5) further noted that "the biggest threat to a sustainable water supply in South Africa is not a lack of storage, but the contamination of available water resources through pollution." A decade after these alarming warnings were published, academics and experts in the field are asserting that water management in South Africa has now reached a critical point, requiring urgent, proactive, and decisive action. In her book, *South Africa's Water Predicament*, du Plessis (2023, p. 164) has concluded that "it cannot be disputed that South Africa's water resources are under severe pressure... ultimately threatening national water security." In particular, it has been suggested that there is a lack of understanding among actors of the true nature and magnitude of the problem, as well as a failure on the part of those responsible to make proper use of the available data to plan and act strategically and proactively (du Plessis, 2019b; Hughes, 2019; du Plessis, 2021; DWS, 2021; du Plessis, 2023). According to Knight (2019b, p. 91), for example, improved water management in South Africa will require "a better and more integrated understanding of water systems in their totality." Muller (2019, p. 7) has likewise suggested that "the key to achieving water security [in South Africa] is for government and citizens to *understand* and manage the country's water resources" (emphasis added). Similarly, while arguing that "informed action as well as proactive water management practices are required," du Plessis (2023, p. 167) has also acknowledged that "this will only be possible with the use of up-to-date information and data." The DWS (2017e, p. 19) has likewise recognised that "proactive and integrated water resource planning to timeously address future water resource challenges is essential to maintaining water security.” A proactive, informed, and data-driven approach, based on an integrated understanding of the complex social-ecological systems being managed, is therefore key.

Furthermore, climate change is expected to intensify many water quality problems, including diffuse pollution associated with anthropogenic land use (OECD, 2017; Woodhouse & Muller, 2017; WWF, 2017; du Plessis, 2019b, 2021; DWS, 2022b; WMO, 2022; Montefiore et al., 2023). As early as 2008, the IPCC reported that “higher water temperatures and changes in extremes, including floods and droughts, are projected to affect water quality and exacerbate many forms of water pollution” (Bates et al., 2008, p. 3). The most recent climate science confirms that climate change will worsen existing water quality problems (Jiménez Cisneros et al., 2014; Michalak, 2016; WMO, 2021; Wade et al., 2022; Ciampittiello et al., 2023; IPCC, 2023). D'Arcy et al. (2022a, p. 15) similarly confirm that, because diffuse pollution is largely weather-driven, “the pressures of climate change are likely to exacerbate the drivers for and impacts of diffuse pollution.” Abiodun et al. (2021, p. 2), with specific reference to South Africa, have noted that “an increasing number of studies have highlighted that projected climate change may influence the hydrological cycle and water yield in South Africa’s river catchments by intensifying floods and droughts, enhancing evapotranspiration, and changing soil moisture, runoff, and water quality.” The *NWRS* has also acknowledged that “water is the primary medium through which the impact of climate change will be felt in South Africa” (DWS, 2021, p. 102; 2022a, p. 41). Du Plessis (2019b, p. 168) has further claimed that climate change has already had a “significant influence on current and future water stress and scarcity” and has contributed to the growing water crisis in the country (see also Otto et al., 2018; Ziervogel, 2019; Pascale et al., 2020; Bartlett, 2022; UNICEF, 2022; World Weather Attribution, 2022; du Plessis, 2023). While some authors have cautioned that it may be premature to link droughts and floods to global warming (e.g., Muller, 2018; Archer et al., 2022; Hughes, 2022), this position is becoming increasingly untenable, and it remains undisputed that the impacts of climate change on water quality and availability necessitate better management of what will become an increasingly scarce resource (Prosser et al., 2021; Tozer, 2023).

Recognising the manifold threats posed to water resources in South Africa, and the necessity of a coordinated approach to managing these threats, the *NWRS* has concluded that “it is thus important for South Africa to focus its water resource planning to improve IWRM to ensure water security” (DWS, 2021, p. 43). Therefore, an ongoing and urgent concern is the identification and development of tools that will not only facilitate the implementation of IWRM, but also address the complex challenges germane to the management of water resources in South Africa (including, critically, issues of water quality and the negative impacts of LULC). This task is especially pertinent in South Africa, where, despite its prominence in national policy, the implementation of IWRM is lagging.

Investigating Relationships Between LULC and Water Quality Using Statistical Approaches: Existing Research and Current Knowledge Gaps

A seminal report published by the South Africa Water Research Commission (WRC) has asserted that understanding the impacts of LULC on water quality has the potential to "soundly inform" both water quality management and land use management (Dabrowski et al., 2013, p. iii). Furthermore, it has been argued that models are one of the "most effective and widely used" methods for quantifying the impact of environmental changes on hydrology and water quality (Wang et al., 2022, p. 2). To this end, a variety of complex process-based hydrological modelling applications can be used to predict the impact of LULC, among other variables, on hydrological systems (Fatichi et al., 2016; Rodríguez-Romero et al., 2018; Malherbe et al., 2019b; Horton et al., 2022). However, these models have been criticised for their complexity and intensive data and calibration requirements (Dabrowski et al., 2013; Fatichi et al., 2016; Malherbe et al., 2019b; de Mello et al., 2020). By contrast, statistical methods such as regression analysis offer a comparatively simple, and thus widely used, approach for investigating, quantifying, and modelling the relationship between key metrics of water quality and LULC (Giri & Qiu, 2016; Slaughter & Mantel, 2017; Rodríguez-Romero et al., 2018; Ullah et al., 2018; Cheng et al., 2022; Łaszewski et al., 2022; Mashala et al., 2023). In a widely referenced publication, Sliva and Williams (2001) maintain that, when coupled with Geographic Information Systems (GIS), multivariate statistical methods can be effective for modelling the complex relationships involved in catchment management. Another oft-cited review has observed that "hundreds of studies document statistical associations between land use and measures of stream condition using multisite comparisons and empirical models, and collectively these studies provide strong evidence of the importance of surrounding landscape and human activities to a stream's ecological integrity" (Allan, 2004b, p. 263). According to Rothenberger et al. (2009, p. 521), such models provide "a simple but effective analytical approach with predictive power." With reference to South Africa, Du Plessis, et al. (2015, p. 648) have proposed that these models can "promote informed and accurate decision making within the [domestic] water management sector" and thereby improve coordination and communication between scientists and policymakers.

An extensive and methodologically diverse body of literature documents the use of such statistical approaches—including correlation analysis, various forms of regression analysis, and principal component analysis—to assess the impacts of LULC on water quality (Manfrin et al., 2016; de Oliveira et al., 2017; Martin et al., 2017; Cheng et al., 2022; Mashala et al., 2023). A review of the literature reveals several recurrent themes and findings. For example, agricultural and urban areas, which are sources of diffuse pollution, are often negatively correlated with water quality (Ullah et al., 2018; Cheng et al., 2022; D'Arcy et al., 2022a; de Mello et al., 2022; Mararakanye et al., 2022; Zhou et al., 2022). In contrast, native forests and other natural vegetation types tend to be positively associated with water quality (Ullah et al., 2018; Fernandes et al., 2021; Cheng et al., 2022; Li et al., 2022b; Caldwell et al., 2023; Qiu et al., 2023; Roldán-Arias et al., 2023; Xu et al., 2023a). However, notwithstanding these broad areas of consensus, the literature also demonstrates that there are several significant theoretical and methodological issues around which uncertainty persists, or which have not received sufficient consideration. These are outlined briefly below.

Scale-Dependency

The relationship between LULC and water quality is said to be "scale-dependent" and the location of LULC within a catchment often has a significant influence on its relationship with receiving water bodies (Allan et al., 1997; Gove et al., 2001; Buck et al., 2004; King et al., 2005; Lintern et al., 2018; Vera Mercado & Engel, 2021; Heidkamp & Christian, 2022; Zhong et al., 2022). It is commonly assumed, for example, that LULC adjacent to water bodies (i.e., riparian land use) will have the most significant impact on water quality (Osborne & Kovacic, 1993; Johnson et al., 1997; Gove et al., 2001; Tiner, 2004; Waite et al., 2010; Miller et al., 2011; Ou et al., 2016; Ramião et al., 2020). While this is a logical supposition, and notwithstanding the evidence that supports it, others have suggested that in some circumstances the cumulative effects of LULC across the whole catchment may be more influential (Brabec et al., 2002; Allan, 2004a, 2004b; Elizabeth, 2009; Tran et al., 2010; Tromboni & Dodds, 2017; de Mello et al., 2020; Ramião et al., 2020; Thomas et al., 2020). Moreover, studies which have attempted to determine the scale at which LULC is most significant, or which have compared the relative influence of LULC at different spatial scales, have reported mixed results. Most authors thus agree that the question of scale remains largely unresolved (Mwaijengo et al., 2020; Park & Lee, 2020; Song et al., 2020; Wu & Lu, 2021; Zhang et al., 2021; Cheng et al., 2022; Kuranchie et al., 2022; Zhong et al., 2022; Mashala et al., 2023; Wang et al., 2023a).

Landscape Configuration

Another commonly held belief is that as natural vegetation cover becomes more fragmented, its ability to intercept, filter, and cleanse overland flow of contaminants—i.e., to act as a sink—is reduced (Gergel et al., 2002; Lee et al., 2009; Shupe, 2013; de Mello et al., 2020; Thomas et al., 2020; de Mello et al., 2022). Several studies have tested the influence of landscape configuration on water quality and many have reported that increased fragmentation, especially of natural vegetation, is associated with poor water quality (Shen et al., 2015; Ding et al., 2016; Shi et al., 2017; Liu & Yang, 2018; Zhang et al., 2019; Liu et al., 2021; Wu & Lu, 2021; Zhong et al., 2022; Wang et al., 2023a). However, counterintuitively, depending largely on its location within a catchment area, there is some evidence to suggest that more fragmented patches of natural vegetation may just as effective (if not more so) at protecting water resources from diffuse pollution as more aggregated patches (Qiu & Turner, 2015; Clément et al., 2017; Thomas et al., 2020; Liu et al., 2021). Hence, the significance of landscape configuration—and the particular importance of the contiguity of natural vegetation with respect to its ability to protect water resources—is yet another area of uncertainty in the literature.

The Influence of Confounding Factors and Geographic Bias in the Literature

The relationship between LULC and water quality in any given region is additionally influenced by a variety of geographically specific environmental variables. These include geology, soil type, topography, and local climatic conditions (Fitzpatrick et al., 2001; Fraser, 2002; Baker, 2005; Rothwell et al., 2010; Lintern et al., 2018; Mashala et al., 2023). The significance of this finding is twofold. On the one hand, these environmental factors often have a direct impact on local water quality, which can in turn make it difficult to assign causality to LULC when conducting statistical analyses (Magierowski et al., 2012; Ramião et al., 2020; Crooks et al., 2021; Dymek et al., 2021; Wu & Lu, 2021). Consequently, several authors have emphasised the need to account for these variables in the design of studies and/or when conducting statistical analyses (King et al., 2005; Ding et al., 2015; Lintern et al., 2018; de Mello et al., 2022; Kuranchie et al., 2022; Simpson et al., 2022).

Moreover, owing to the additional influence of these local environmental factors, the relationship between water quality and LULC, as well as the existence and/or nature of any thresholds in this relationship, are likely to be particular to the region in question (Baker, 2005; Chiang et al., 2021). Due to this inherent specificity, the extrapolation of data and results from ecologically disparate regions is not an adequate substitute for local research (Dallas & Day, 2004, p. 2). It is therefore essential to conduct research at appropriate regional scales in order to understand LULC-WQ dynamics in different contexts. However, notwithstanding a relatively recent increase in the publication of such research in China and some South American countries, most of the existing research has been conducted in temperate zones in North America and Europe. Comparatively few studies have been undertaken in other climatic regions or in less developed countries (Baker, 2005; Tromboni & Dodds, 2017; Kronvang et al., 2020; Bohenek & Sulliván, 2022; Prakoso et al., 2023). In South Africa, for example, Riddell et al. (2022, p. 170) reported that there is an insufficient understanding of the processes and impacts of land-use-related diffuse pollution on water resources. Slaughter and Mantel (2017, p. 499) have also expressed the view that water quality research and modelling in South Africa are relatively undeveloped and constrained by a lack of data, funding, and technical expertise. While there have been, especially in recent years, several studies undertaken concerning impacts of LULC on water quality in South Africa (see Appendix 5), most of these have simply confirmed what now amounts to common knowledge regarding the influence of LULC on water resources (generally observing that agricultural and urban land use have a detrimental impact on water quality). Moreover, very few studies have reported specific or quantifiable targets to inform strategies for the management and protection of water resources.

Classifying Natural Vegetation

Apropos of the preceding point, one corollary of the geographical bias apparent in the existing literature is that indigenous forests are often considered to be representative of natural vegetation (a point illustrated, for instance, in a review by Morse et al., 2018). However, vegetation that might be considered “natural” in any given region will vary according to local ecology and climatic conditions (Sprugel, 1991). For example, it may be inappropriate to assume that forested land is analogous to natural vegetation in regions typified by other indigenous vegetation types. Moreover, when considering the relationship between natural vegetation and water quality, it is apparent that different classes of vegetation have varying and often inconsistent impacts (positive and negative) on water resources (Cole et al., 2020). Thus, with respect to the buffering potential of natural vegetation (i.e., its ability to protect water resources from diffuse pollution by intercepting contaminated overland flow) it may also be incorrect to assume that, for a given region, all classes of indigenous vegetation may be aggregated into a single land cover class. Therefore, when considering the impacts of LULC on water quality, and especially when using GIS and remote-sensing data to assess these impacts, it is important to determine contextually appropriate metrics for defining and classifying natural vegetation according to the aims and objectives of the study. This issue, however, has not been given due attention in the existing literature.

The Use of Composite Water Quality Indices and Site-Specific Guidelines

While most studies have investigated the impacts of LULC on individual physiochemical water quality parameters, several others have recognised that water quality can be assessed holistically using composite water quality indices (WQIs) (Wang & Zhang, 2018; Gossweiler et al., 2019; Paná et al., 2022; Pandey et al., 2023; Wang et al., 2023a). Several established WQIs have been used for this purpose, each of which has its own advantages and limitations (Abbasi & Abbasi, 2012; Uddin et al., 2021; Chidiac et al., 2023; Lukhabi et al., 2023). Despite its relative simplicity and intuitive appeal, however, none of the reviewed studies have considered Nemerow’s Pollution Index (NPI) when modelling the impacts of LULC on water quality. Originally designed for use by the United States Environmental Protection Agency (USEPA), the NPI offers a convenient and yet robust method for quantifying the aggregate impact of multiple parameters on overall water quality (Nemerow, 1991; Abbasi & Abbasi, 2012). Moreover, the notion of establishing site-specific water quality guidelines using a reference condition approach has been largely overlooked when investigating the impacts of LULC on water quality. Several environmental agencies, however, have argued that guidelines based on local reference conditions are preferable to generic water quality standards because they offer contextually appropriate criteria against which observed water quality measurements can be evaluated (e.g., DWAF, 1996; USEPA, 2000; CCME, 2016; ANZG, 2018)—(for discussions on, and examples of, the use of a reference condition approach to setting site-specific water quality guidelines see Hawkins et al., 2010; Soranno et al., 2011; Pardo et al., 2012; McDowell et al., 2013; van Dam et al., 2014; Duan et al., 2019; van Dam et al., 2019; Urbanič et al., 2021).

Thresholds and Tipping Points in the Context of LULC-WQ Studies

Ecological thresholds have become increasingly important for informing policies for the sustainable management of natural resource systems (Huggett, 2005; Foley et al., 2015; Kelly et al., 2015; Munson et al., 2018). Examples from around the world demonstrate that incorporating thresholds into conservation strategies can facilitate improved management outcomes (ibid.). As such, thresholds are now viewed as indispensable tools for ecological restoration projects and land use planning (Muradian, 2001; Zhang et al., 2018). Thresholds are particularly attractive because they provide planners and policymakers with non-arbitrary targets which can guide environmental decision-making (Foley et al., 2015; Kelly et al., 2015; Wang et al., 2023a). Johnson (2013, p. 58) has concluded that "the threshold concept has much intuitive appeal: there is a strong theoretical foundation for nonlinear dynamics, critical response points are integrated easily within regulation, and regulatory thresholds allow the consideration of both current and potential future effects of development."

In the context of water resources management, research has shown that aquatic systems may exhibit nonlinear responses to changes in LULC, particularly when a percentage of a catchment exceeds a certain amount of urban or agricultural land use (Dodds et al., 2010; Tayyebi et al., 2015; Tromboni & Dodds, 2017; Grimstead et al., 2018; D'Amario et al., 2019; Chen & Olden, 2020; Liu et al., 2021; Wang et al., 2023a). According to Wang et al. (2023a, p. 2), such thresholds can "be used as long-term goals for water quality protection." By virtue of the fact that most studies are conducted in urban settings, the majority of the LULC thresholds described in the literature relate to either urban or impervious cover (Grimstead et al., 2018; Liu et al., 2021). Such studies often have reported (with remarkable consistency) that water quality degradation typically occurs when urban/impervious cover in a catchment reaches between 10 and 15% (e.g., Schueler, 1994; Arnold & Gibbons, 1996; Paul & Meyer, 2001; Brabec et al., 2002; Groffman et al., 2006; Tayyebi et al., 2015; Medupin et al., 2020; Song et al., 2020). Accordingly, thresholds of impervious cover are "commonly used as benchmarks of water quality planning and protection in local, watershed, and regional planning efforts" (Brabec, 2009, p. 425).

A number of studies have also reported thresholds of agricultural land use, although the results of these studies have been far less consistent than those involving urban/impervious land cover (e.g., Wang et al., 1997; Fitzpatrick et al., 2001; Wang et al., 2003; Allan, 2004b; Riseng et al., 2010; Huang & Klemas, 2012; Feld, 2013; Tayyebi et al., 2015; Grimstead et al., 2018; D'Amario et al., 2019; Li et al., 2021). Logically, the impact of agricultural land on water quality depends largely on the type and/or intensity of agriculture, as well as on the particular management practices employed. This makes it difficult to determine universal and consistent thresholds. Thus, according to the review by Allan (2004b, p. 273) cited above, “the wide range of responses reported from streams draining agricultural landscapes clearly indicates that extent of agriculture is not by itself sufficient [as a land use indicator].” Similarly, in mixed land use catchments, or in landscapes dominated by other land uses, the extent of urban/impervious cover may not be the most appropriate metric on which to base thresholds for the management and protection of water quality (Klein, 1979; Brabec et al., 2002; Allan, 2004a; King et al., 2005; Zampella et al., 2007; Brabec, 2009; Schueler et al., 2009; Dabrowski & de Klerk, 2013; Shen et al., 2015). Therefore, despite their popularity, metrics of urban and agricultural land cover both have limited value when used on their own to estimate thresholds for the protection of water resources. While it is possible to construct multivariate models that simultaneously incorporate several different classes of LULC as explanatory variables, multicollinearity between these variables is a common problem (Tu, 2011a; Magierowski et al., 2012; de Oliveira et al., 2017; Helsel et al., 2020; Li et al., 2022b; Mashala et al., 2023). By contrast, natural vegetation cover, when appropriately classified for a given region, may prove to be a universally relevant metric on which to base thresholds for the protection of water quality, and which also avoids the problem of multicollinearity.

By comparison, however, relatively few studies have sought to estimate thresholds of natural vegetation cover in the context of water quality management. Moreover, when such findings have been reported, they tend to be incidental to other results. Notwithstanding this, based on the studies that have been published, it is apparent that metrics of natural vegetation may serve as useful predictors of water quality. Moreover, these studies suggest that it may be possible to estimate the minimum amount of natural vegetation cover required to protect water quality in a given region (Black et al., 2004; Death & Collier, 2010; Tran et al., 2010; Miller et al., 2011; Feld, 2013; Attua et al., 2014; Iñiguez-Armijos et al., 2014; Midway et al., 2015; Clément et al., 2017; de Mello et al., 2017; Morse et al., 2018; Zhong et al., 2022). However, as noted in the preceding paragraphs, the research conducted to date leaves several important questions largely unanswered. Given the geographical bias of the existing research, discussions on determining contextually specific metrics by which to classify and measure natural vegetation for this purpose are conspicuously absent from the literature. In addition, the significance of the location and/or configuration of natural vegetation in a landscape, in relation to its effectiveness in protecting water resources from diffuse pollution, remains a knowledge gap that has not yet been adequately addressed.

Problem Statement and Hypothesis

Acknowledging the severity and extent of the impacts of land-use-related diffuse pollution on water quality, D'Arcy et al. (2022b, p. 268) have advocated for landscape interventions that will (1) minimise the mobilisation of contaminants, (2) capture contaminants that are mobilised, and (3) enhance the self-purification of water. The preservation of naturally vegetated areas, which serve all three of these functions, is thus a critical aspect of protecting water resources from pollution derived from LULC. Furthermore, partly due to the impacts of unregulated and/or unsustainable land use practices, as well as an attendant failure to effectively address these impacts through the proper implementation of IWRM, South Africa's already stressed water resources (and thus the nation's economy and society) are under threat from diffuse pollution. Against this background, the country has both domestic and international mandates to work towards the equitable provision of clean water for all citizens through the implementation of IWRM. Riddell et al. (2022, p. 170), with reference to the stated goals of the South African *National Water and Sanitation Master Plan* (DWS, 2018, cited above), have thus described the implementation of catchment-based diffuse pollution mitigation strategies, including the regulation of land use, as an urgent issue. With a view to informing such strategies, while it has been unequivocally established in the existing literature that urban and agricultural areas are typical sources of diffuse pollution, metrics of these land use classes, on their own, cannot adequately account for the combined influence (both negative and positive) of the diverse mosaics of LULC which may be present in catchment areas. Moreover, multivariate statistical models in this context are likely to encounter difficulties associated with multicollinearity between explanatory variables. However, not only does natural vegetation have a universally ameliorative effect on water quality, but evidence has shown that the extent of natural vegetation in a catchment can, by itself, serve as a good statistical predictor of the condition of aquatic ecosystems. It is thus hypothesised that appropriate statistical modelling approaches may be used to estimate minimum thresholds of natural vegetation cover necessary for the integrated management and protection of water quality in a given region. This hypothesis presupposes that natural vegetation, when appropriately classified as a distinct class of land cover, may have superior utility as a metric for modelling and threshold estimation.

Aims and Objectives

Two main aims informed the present study: (1) To test the above hypothesis, the principal aim of this study was to develop statistical models of the relationship between water quality and natural vegetation in the chosen study area, from which thresholds of natural vegetation could be estimated for the protection and maintenance of water quality. (2) Ancillary to this, based on the knowledge gaps and methodological issues identified above, this study also sought to test and evaluate suitable methods and metrics for this purpose (including the handling of extraneous variables which might otherwise reduce the predictive power of the models). Therefore, concomitant to these two aims, this study sought to address these knowledge gaps through the following specific objectives:

i. Assessing the usefulness of Nemerow's Pollution Index (NPI), in combination with site-specific water quality guidelines derived from local reference condition data, as a tool for the evaluation of water quality and as a metric for modelling and threshold estimation.
ii. Determining and evaluating the utility of a contextually specific metric by which to classify natural vegetation for the purpose of modelling and threshold estimation, with particular reference to its ability to protect water resources from diffuse pollution.
iii. Assessing the influence and/or significance of the location and fragmentation of natural vegetation within a landscape (questions of scale and landscape configuration, respectively).
iv. Minimising the potentially confounding influence of additional variables so as to isolate the impacts of LULC on water quality.

The arguments for the proposed research, as well as the links between each of the relevant theoretical and/or contextual issues, are summarised in the conceptual framework illustrated below in Figure 1. (In the electronic version of this document, Figure 1 is included as a vector graphic, allowing the reader to zoom and pan as necessary).

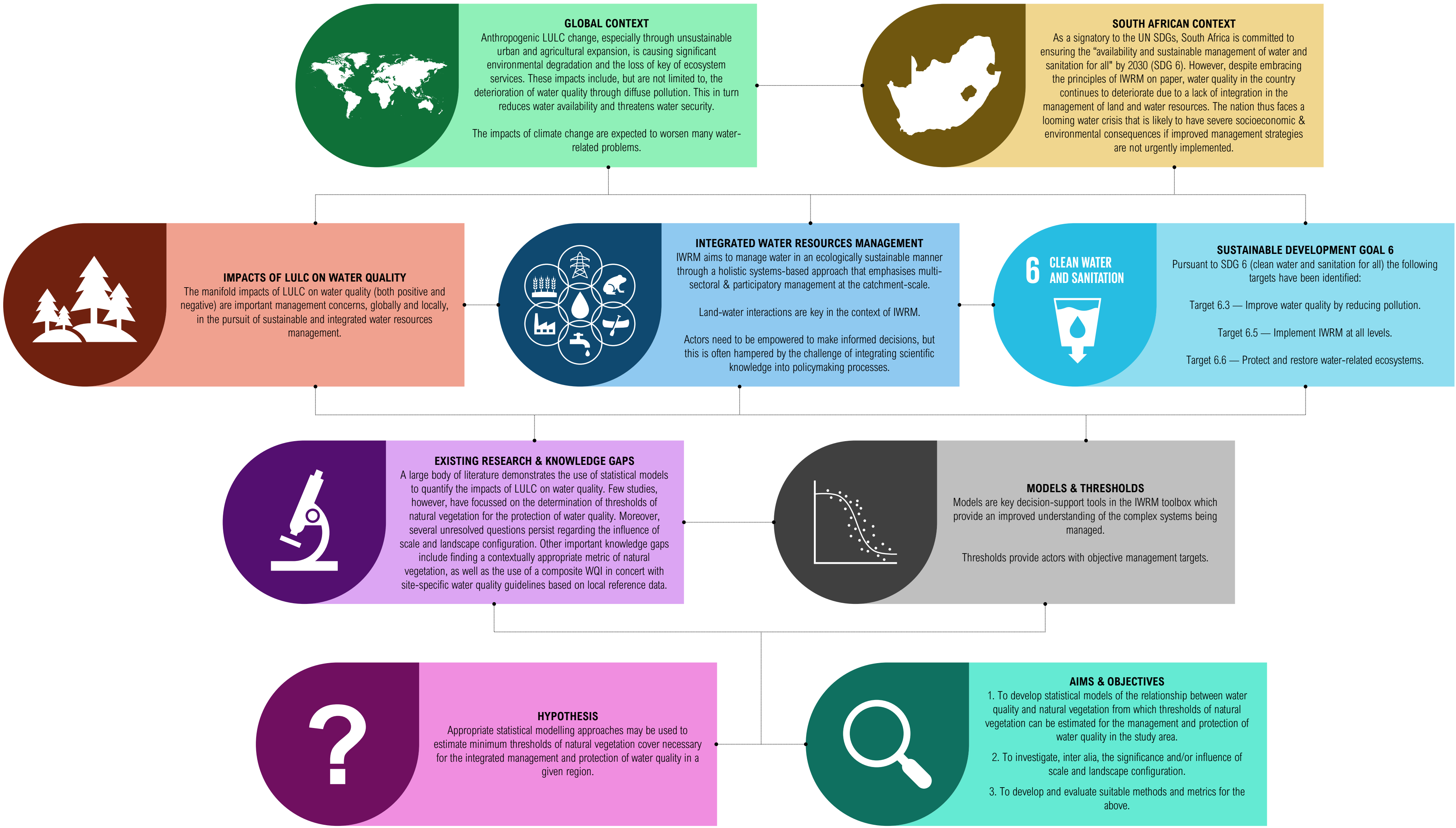

Figure 1. Conceptual framework of the current study, showing links between the theoretical and contextual issues, as well as the hypothesis, aims, and objectives.

Scope and Limitations

Geographically, this study is limited to the South African context, with models and thresholds estimated using data representative of a discrete hydrological region located in the south-western part of the country (see Chapter 5 for a description of the study area). However, there is scope to apply the methods developed in this study in other regions (both domestically and internationally) and at alternative spatial scales. In addition, modelling and threshold estimation were conducted using existing LULC and water quality data obtained from the relevant national government departments. This was partly due to time and resource constraints, but also in order to test the viability of using publicly available datasets for this purpose. Finally, simple statistical methods (such as regression analysis) were favoured over more complex process-based models (such as SWAT, BASINS, WASP, and ACRU). Not only does the existing literature demonstrate the adequacy of simple statistical methods, but the latter are also less technical and data-intensive and are thus quicker and easier to implement (an important consideration if the methods tested in this study are to be implemented by water resource managers who will only need a basic working knowledge of statistical methods).

Significance

This study makes several important theoretical and practical contributions which are relevant to the field of water resources management in both domestic and international contexts. Not only does the study address an urgent practical issue (to wit, the deterioration of water quality in South Africa due to ineffective and uncoordinated land use management), but it also speaks to some of the persistent knowledge gaps and areas of uncertainty identified in the existing academic literature.

There is, in the first instance, a pressing need to address South Africa's current water management challenges, of which diffuse pollution derived from poorly managed LULC is a key concern. These issues are directly relevant to South Africa's socioeconomic development and the achievement of the United Nations SDGs as they relate to water and sanitation. An important requirement in this regard is the determination of objective and scientifically rigorous management guidelines which, being relevant to the work of policymakers and resource managers, can facilitate coordinated and informed catchment-scale management in line with the principles of IWRM. Knowledge of minimum thresholds of natural vegetation cover necessary for the protection of water quality, if accurately estimated using appropriate statistical methods, would be of inestimable value in this regard.

This study also contributes new knowledge to an important and ongoing field of research by explicitly addressing several persistent knowledge gaps. Comparatively few studies, for example, have specifically sought to estimate thresholds of natural vegetation for the protection of water quality. Moreover, few studies, if any, have addressed the need to identify contextually appropriate metrics by which to classify natural vegetation for this purpose. In addition, as noted above, questions related to the importance of scale and landscape configuration remain largely unresolved. Finally, while composite WQIs have been successfully utilised in several of the reviewed studies, the use of Nemerow's Pollution Index—a simple and intuitive water quality assessment tool—in combination with site-specific water quality guidelines derived from local reference data, has been overlooked.

While models (in the general sense) are seen as key decision-support tools for the implementation of IWRM, very few studies have drawn explicit links between IWRM and the use of statistical approaches to model the impacts of LULC on water quality (when IWRM is referenced in these studies, it often receives only a cursory mention). None of the studies expound upon the relevance of this type of research to the implementation of IWRM, nor do they discuss in detail how this type of work can be used to address the challenge of incorporating scientific knowledge into policy and decision-making processes.

Overview

The remaining seven chapters of this study are divided into two parts. The first part provides context for the study by positioning the research within the framework of IWRM (Chapter 2), providing an overview of the impacts of land use on water quality (Chapter 3), and reviewing the existing literature as it pertains to the use of statistical approaches to assess the impacts of LULC on water quality (Chapter 4). The second part of the study describes the chosen study area (Chapter 5), outlines the methods and results (Chapter 6), and discusses these results in light of the reviewed literature, current knowledge gaps, and present aims (Chapters 7 and 8). A brief outline of each chapter is provided below.

Chapter 2 situates this study within the context of IWRM as the dominant paradigm in the field of water resources management. Reviewing the voluminous literature on the subject, the chapter identifies the principles of IWRM which might be considered essential to the framework. In doing so, the chapter also demonstrates the critical importance of the land-water nexus in the context of IWRM. The chapter goes on to note the role of models as key decision-making tools that can facilitate the integration of scientific knowledge into planning and policymaking processes, thereby supporting the implementation of IWRM. After evaluating the extent to which IWRM has been successfully implemented in South Africa, the chapter concludes by arguing that the use of models to estimate thresholds of natural vegetation for the protection of water quality is an important research endeavour that is in line with, and supportive of, many of the principles of IWRM.

Chapter 3 of this study provides an overview of the typical impacts of different classes of LULC on water quality, synthesising information from several primary studies and prominent reference texts. The chapter outlines the negative impacts of agriculture, urban areas, commercial forestry, and mining operations on water resources. It also discusses the role of natural vegetation in protecting water resources from diffuse pollution and the subsequent importance of maintaining naturally vegetated areas across catchments and within riparian areas.

Chapter 4 provides a review of the extensive body of literature as it pertains to the use of statistical methods to investigate, assess, and/or quantify the impacts of LULC on water quality. The review identifies some of the commonly used methods, data sources, and metrics, and goes on to discuss major research trends and other notable findings. Important knowledge gaps and methodological concerns (including questions related to scale, landscape configuration, and the influence of potentially confounding environmental variables) are noted. The use of statistical approaches to identify LULC thresholds, as well as the limitations of metrics of urban and/or agricultural land cover in this regard, are discussed in some detail. Finally, based on the reviewed literature, the chapter presents a case for the estimation of thresholds of natural vegetation for the protection of water resources.

Chapter 5 presents an overview of the chosen study area. The chapter focusses on the extent to which several key local environmental variables, each of which has the potential to "confound" subsequent statistical analyses, vary across the region.

Chapter 6 provides an account of the methods used and results obtained at each step of the investigation. The chapter describes (1) the procedure for selecting a cross-sectional sample of sub-catchments in the study area; (2) the evaluation of water quality across these sub-catchments using Nemerow's Pollution Index and site-specific water quality guidelines; (3) the means, metrics, and scales at or by which natural vegetation was classified across the sub-catchments; and (4) the approach to (and results of) the regression analysis and threshold estimation procedures. The chapter also demonstrates how the estimated thresholds of natural vegetation were applied in the study area to classify quaternary catchments according to the likely risk of land-use-related diffuse pollution.

Chapter 7 offers an in-depth discussion of the results, focussing on (1) the previously identified knowledge gaps and areas of uncertainty; (2) the utility of natural vegetation as a metric for modelling and threshold estimation, and how this speaks to the research hypothesis; and (3) the potential applications, recommendations, and implications of the results with respect to improving and advancing the integrated management and protection of water quality in South Africa. The limitations of the study are recognised and discussed.

Chapter 8 concludes the discourse by highlighting the key findings of the study and reviewing the significance and/or contribution of each to the existing body of research. The chapter also considers the implications of these findings for IWRM, focussing on the value of modelling and threshold estimation for the integration of scientific knowledge into multistakeholder decision-making processes. It closes by suggesting possible directions for further research.

CHAPTER 2:

Integrated Water Resources Management and the Land-Water Nexus in South Africa

"The principles of integrated water resource management (IWRM) when applied effectively can solve the water crisis in major parts of the world and help us transit toward a greener economy and environmental governance."
—Nath et al. (2023, p. 367)

Introduction

In order to effectively manage the impacts of LULC on water quality, an integrated approach is required which acknowledges that land and water resources, and the complex processes which link the two, are part of a broader social-ecological system that must be managed holistically. Integrated Water Resources Management (IWRM) has thus emerged as a fundamental governance paradigm of which the coordinated management of such systems is a cornerstone. This chapter situates the present study within the context of the IWRM framework and highlights the need for tools and strategies that support integrated land and water resources management. The aims of the chapter are to (1) distil the concept of IWRM as far as possible into its essential principles; (2) demonstrate that developing statistical models of the relationship between LULC and water quality at the catchment scale is an important pursuit that is justified by, and supportive of, many of the central principles of IWRM; and (3) argue that such models would have great value for advancing the implementation of IWRM in South Africa.

Background to IWRM

IWRM is fundamental to any discussion on water governance (Ison & Wallis, 2017; Bilalova et al., 2023) and has thus received considerable attention from academics and practitioners alike (Setegen, 2015, p. 3). In the voluminous literature that has been published to date, IWRM has been variously referred to as a "concept" (e.g., Anderson et al., 2008), a "theory" (e.g., Grigg, 2016), a "strategy" (e.g., Medema & Jeffrey, 2005), a "framework" (e.g., O'Keeffe, 2012), a "principle" (e.g., Movik et al., 2016) or "set of principles" (e.g., Lipchin, 2014), a "perspective" (e.g., Kidd & Shaw, 2007), a "paradigm" (e.g., Pahl-Wostl & Sendzimir, 2005), a "philosophy" (e.g., UNEP, 2012), a "process" (e.g., GWP, 2000), a "tool" (e.g., Setegen, 2015), an "approach" (e.g., UNEP, 2021), an "ambition" (e.g., Jeffrey & Gearey, 2006), an "ideology" (e.g., van Koppen et al., 2016), a "mantra" (e.g., Giordano & Shah, 2014), and a "buzzword" (e.g., van der Zaag, 2005). Described by some as "controversial" (Martínez-

Santos et al., 2014, p. 18), IWRM has even been likened to a religion by one author (see Merry, 2008, p. 900). Swatuk and Qader (2023, p. 2) have argued that IWRM is "partly theory, partly operational framework, and partly a practical approach toward sustainable water management." This varied list of descriptors is indicative of the diverse range of perspectives held by IWRM's various proponents and detractors. Some authors, for example, have vehemently declaimed IWRM as ambiguous, ineffective, naïve, or unrealistic (Grison et al., 2023; Swatuk & Qader, 2023) and it has subsequently attracted a long list of critics (e.g., Biswas, 2004; van der Zaag, 2005; Jeffrey & Gearey, 2006; Biswas, 2008b, 2008a; Matz, 2008; Medema et al., 2008; Merry, 2008; Molle, 2008; Giordano & Shah, 2014). Nevertheless, notwithstanding the scepticism expressed from some quarters, IWRM has experienced wide and enthusiastic embrace, especially among the international development community (Tejada-Guibert, 2015; Ibisch et al., 2016; Malaza & Mabuda, 2019; du Plessis, 2023; Grison et al., 2023; Sugam et al., 2023). Ultimately, the inherent logic of IWRM has prevailed and its "proven principles" have endured (Kadi, 2014, p. 3; Grigg, 2016, p. 3). Anderson et al. (2008, p. 668) have thus concluded that "on the basis of its ability to address the integrated nature of managing complex water resource systems, few can argue against the value of an IWRM approach" (see also Martínez-Santos et al., 2014, p. 17). As such, IWRM is now widely considered a pivotal strategy for addressing today's water-related issues (Grison et al., 2023; Nath et al., 2023).

Nevertheless, from academic, theoretical, and philosophical perspectives, there has been little success in codifying a universally agreed-upon definition of IWRM and there is no single formulation of IWRM that covers, to the satisfaction of all authors, the multiple dimensions of integration that have emerged as the concept has evolved (Jønch-Clausen & Fugl, 2001; Biswas, 2004; Anderson et al., 2008; White, 2013; Grigg, 2016; Ibisch et al., 2016; de Oliveira Vieira, 2020; Bilalova et al., 2023). It is thus not surprising that some have referred to IWRM as an "elusive and fuzzy concept" (van der Zaag, 2005, p. 865; Medema et al., 2008, p. 6). Moreover, several authors are of the view that inconsistent definitions of IWRM hamper its implementation (e.g., Jønch-Clausen & Fugl, 2001; Jonker, 2007; Medema et al., 2008; Molle, 2008; Jonker, 2014; Ibisch et al., 2016), and that progress in water resource management is thus partly dependent on developing a common understanding of the paradigm (GWP, 2000; Cardwell et al., 2006; Mukhtarov, 2008; Bilalova et al., 2023).

However, difficulties in defining IWRM do not invalidate it as a strategy for the management of water resources. This has been demonstrated by several case studies in which the successful implementation of IWRM has resulted in tangible and positive management outcomes (see, for instance, Lenton & Muller, 2009; Pahl-Wostl et al., 2011b; White, 2013; Martínez-Santos et al., 2014; Borchardt et al., 2016; Grigg, 2016; de Oliveira Vieira et al., 2020).[3] According to du Plessis (2023, p. 30), there is

[3] Despite a growing body of anecdotal evidence that attributes improvements in water governance to IWRM, Bilalova et al. (2023, p. 2) claim that "few empirical studies exist that assess how IWRM implementation

"growing evidence" that IWRM can have "considerable, long-term benefits to water security and overall water management within various contexts" (see also Pahl-Wostl et al., 2011b, p. 298). In addition, the implementation of IWRM need not follow a particular blueprint, and its essential principles can be applied in an adaptive manner according to local circumstances and needs (as called for by Vollmer et al., 2023). Furthermore, it has been argued that no alternative management framework is as effective in reconciling the complexity of water resource systems and the conflicting agendas that characterise them (GWP, 2004; Snellen & Schrevel, 2004; Kadi, 2014; Donoso & Bosch, 2015; Badham et al., 2019). Hence, IWRM is now widely recognised as "the most cost-effective, socially viable, and ecologically sound strategy for managing water" (Kumar et al., 2019, p. 300).

However, while most authors (including some of the most ardent critics) have affirmed the value and necessity of IWRM in principle, this view is held in tandem with the candid acknowledgement that implementing and operationalising IWRM in practice can be a challenging process (GWP, 2000; Jeffrey & Gearey, 2006; Funke et al., 2007; Giordano & Shah, 2014; Kadi, 2014; Ibisch et al., 2016; Jønch-Clausen, 2016; Borden & Goodwin, 2022). Consequently, the development of tools and strategies that facilitate the translation of IWRM's rhetoric into effective practice is an ongoing concern (Ibisch et al., 2016; Kumar et al., 2019). This is especially pertinent in South Africa, where the implementation of IWRM, despite its prominence in policy, is lagging.

The Emergence and Codification of IWRM: Conceptual History and Present Status

IWRM emerged in response to several perceived shortcomings in the way that the water sector has historically been managed (GWP, 2000; Lenton & Muller, 2009; Movik et al., 2016; de Oliveira Vieira, 2020; GWP, 2022a; UNEP, 2023b). Central to the development of IWRM was a growing appreciation that water governance issues are complex and multidimensional problems that require coordinated, multisectoral, and transdisciplinary solutions (GWP, 2000; Jønch-Clausen & Fugl, 2001; Biswas, 2004; Medema & Jeffrey, 2005; Xie, 2006; Pahl-Wostl et al., 2011a; Woodhouse & Muller, 2017; de Oliveira Vieira, 2020; Katusiime & Schütt, 2020). Antithetically, the water sector has historically been managed in isolation from other sectors and has been dominated by top-down, technocratic approaches to narrowly-defined problems that are, in reality, characterised by complex ecological, socioeconomic, and political dimensions (GWP, 2000; Mitchell, 2005; Xie, 2006; Molle, 2008; Mukhtarov, 2008; Pahl-Wostl et al., 2011a; Pahl-Wostl et al., 2011b; Giordano & Shah, 2014; de Oliveira Vieira, 2020; GWP, 2022a). As one author has articulated, "Agriculture people think about food; energy people think hydropower; and water people think drinking water or industrial supply" (Duda, 2017, p. 5). The situation to which IWRM thus responds has been described by Vollmer et al. (2023, p. 233) as one in

influences certain water-related sustainability issues such as water efficiency, demand management, climate change adaptation, water security and stress."

which the traditional management approach was "overly simplified and siloed… reductionist, technocratic and ill-suited to the complex realities most watersheds face." By contrast, IWRM embraces a holistic, adaptive, multisectoral, and multidisciplinary approach to the management of water and related resources (Bilalova et al., 2023; UNEP, 2023b). Snellen and Schrevel (2004, p. 23) have recorded that "from the very start, it was clear that IWRM required fundamental changes in terms of values, beliefs, perceptions and political positions." For this reason, several authors have described the emergence of IWRM as a critical "paradigm shift" in water resources management (van der Keur et al., 2008; Pahl-Wostl et al., 2011a; Malaza & Mabuda, 2019; GWP, 2022a; Lee et al., 2022b). In sum, the traditional, fragmented approach that had previously characterised water management was no longer seen as viable. Consequently, a "more holistic approach" was called for (du Plessis, 2023, p. 27).

Various texts have traced the emergence, conceptual evolution, and formalisation of IWRM (e.g., Snellen & Schrevel, 2004; Rahaman & Varis, 2005; Cardwell et al., 2006; Lenton & Muller, 2009; Mauck, 2012; Kadi, 2014; Tejada-Guibert, 2015; Borchardt et al., 2016; Grigg, 2016; Woodhouse & Muller, 2017; de Oliveira Vieira, 2020; Meran et al., 2021; Bilalova et al., 2023; Nath et al., 2023). It is apparent from these accounts that the IWRM paradigm has evolved over several decades, becoming increasingly formalised over time as a model for the management of water resources. This process has included several key intergovernmental conferences on water resources management, each of which has helped to refine and reinforce the IWRM paradigm. Snellen and Schrevel (2004, p. 23), in describing the emergence of IWRM, have recorded the following:

> Its roots can be traced to the [1977] International Conference in Mar del Plata, where the need for coordination in the water sector was stressed, and the Brundtland Commission report, which was the first call for development that would not compromise the needs of future generations. Its basic principles were largely established by 1992, the year in which the Dublin Guiding Principles were formulated and the United Nations Conference on Environment and Development was held in Rio de Janeiro.

IWRM is now universally considered to be the dominant water governance paradigm (Jonker, 2014; Martínez-Santos et al., 2014; Tejada-Guibert, 2015; Ibisch et al., 2016; Movik et al., 2016; Chikozho & Mapedza, 2017; Lukat et al., 2022b; Bilalova et al., 2023; du Plessis, 2023). It has been adopted by several key international organisations—including the Global Water Partnership (GWP), the International Water Association (IWA), the Food and Agriculture Organisation (FAO), the World Water Council (WWC), the World Bank, and the United Nations and its various subsidiaries—all of which promote IWRM (or its principles) as a means to address complex water management challenges (Bilalova et al., 2023; Grison et al., 2023; Sugam et al., 2023). The prominence of IWRM as a global water management paradigm is reflected in its inclusion in the United Nations Sustainable Development Goals (SDGs) (United Nations, 2015; Bilalova et al., 2023). Malaza and Mabuda (2019, p. 10) have thus observed that IWRM "now enjoys international endorsement at the highest level." The importance of IWRM was reaffirmed most recently at the 2023 United Nations Water Conference held in New

York (Kőrösi, 2023). Thus, IWRM is far from a fading narrative. Not only does it have prominence as a global strategy for the management of water resources, but it also remains a major research topic (Ibisch et al., 2016). This is evident from the growing output of academic publications in which IWRM is a central theme (see Figure 2 below).

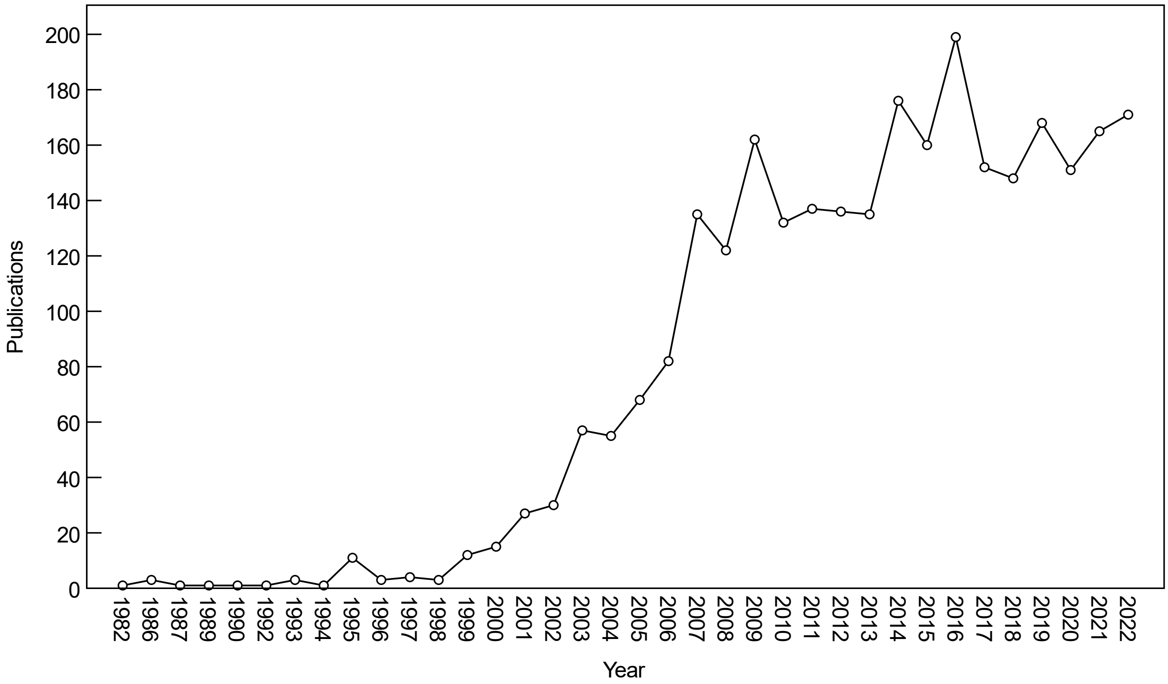

Figure 2. IWRM-related academic publications by year. Data obtained from the Scopus database, reflecting publications in which the terms “Integrated Water Resources Management" OR “IWRM” appear in the article title, abstract, or keywords.

Universal Principles of IWRM

Over time, as the IWRM paradigm has evolved, different aspects of the framework have been emphasised and different authors have offered varying interpretations of what “integration” should mean in the context of water management (Tejada-Guibert, 2015; Grigg, 2016). However, these diverse perspectives are not necessarily in conflict with one another, nor are they mutually exclusive. Instead, they reflect the broad, multidimensional nature of the IWRM framework, which is nevertheless underpinned by several essential principles upon which there is general agreement (Anderson et al., 2008; Bilalova et al., 2023). The following definitions illustrate that while different aspects of integration may be stressed at different times and in different contexts, the essential principles of IWRM remain discernible throughout.

> [IWRM] is a philosophy, a process and a management strategy to achieve sustainable use of the resources by all stakeholders at catchment, regional, national and international levels, while maintaining the characteristics and integrity of water resources at the catchment scale within agreed limits. (Görgens et al., 1998, p. 69)

IWRM is a process which promotes the co-ordinated development and management of water, land and related resources, in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems. (GWP, 2000, p. 22; UNEP, 2023b)

[IWRM] is a participatory planning and implementation process, based on sound science, that brings stakeholders together to determine how to meet society's long-term needs for water and coastal resources while maintaining essential ecological services and economic benefits. IWRM helps to protect the world's environment, foster economic growth, and sustainable agricultural development, promote democratic participation in governance, and improve human health. Worldwide, water policy and management are beginning to reflect the fundamentally interconnected nature of hydrological resources, and IWRM is emerging as an accepted alternative to the sector-by-sector, top-down management style that has dominated in the past. (USAID, quoted in Merry, 2008, p. 900)

[IWRM] is a step-by-step process of managing water resources in a harmonious and environmentally sustainable way by gradually uniting stakeholders and involving them in planning and decision making processes, while accounting for evolving social demands due to such changes as population growth, rising demand for environmental conservation, changes in perspectives of the cultural and economic value of water, and climate change. (UNESCO, 2009, p. iii)

[IWRM is] the coordinated planning, development, protection and management of water, land and related resources in a manner that fosters sustainable economic activity, improves or sustains environmental quality, ensures public health and safety, and provides for the sustainability of communities and ecosystems. (American Water Resources Association, quoted in Engberg, 2014, pp. 3–4)

[IWRM is] a process that promotes the coordinated development and management of water, land, and related resources in a drainage basin to maximise economic and social welfare equitably without compromising the sustainability of vital ecosystems. (Katusiime & Schütt, 2020, p. 1)

[IWRM] is an approach that helps to balance competing water demands from across society and the economy, without compromising the sustainability of vital ecosystems. This is achieved through coordinated policy and regulatory frameworks, management arrangements and financing. (UNEP, 2021, p. VII)

An IWRM approach is an open, flexible process, bringing together decision-makers across the various sectors that impact water resources, and bringing all stakeholders to the table to set policy and make sound, balanced decisions in response to specific water challenges faced. (IWA, 2022)

IWRM is a cross-sectoral policy approach designed to replace the traditional, fragmented sectoral approach to water resources and management that has led to poor services and unsustainable resource use. Integrated Water Resources Management is based on the understanding that water resources are an integral component of the ecosystem, a natural resource, and a social and economic good. (UNEP, 2023b)

The so-called "Dublin Principles" (UNEP, 1992; GWP, 1996), which were formulated and subsequently endorsed at the 1992 International Conference on Water and the Environment (held in Dublin, Ireland), are also frequently quoted:

1. Fresh water is a finite and vulnerable resource, essential to sustain life, development and the environment.
2. Water development and management should be based on a participatory approach, involving users, planners and policymakers at all levels.
3. Women play a central part in the provision, management and safeguarding of water.
4. Water has an economic value in all its competing uses and should be recognized as an economic good.

These four principles have remained central to the IWRM framework for more than 30 years (GWP, 2022a). Thus, while a universal blueprint for IWRM may not exist, there are several universal principles upon which the contextual implementation of IWRM is based. As per Pahl-Wostl et al. (2011b, p. 298), while the principles of IWRM may be flexibly implemented according to the contextual needs of each scenario, "the underlying paradigm remains the same." This is evident from the repeated emphasis that these principles have received throughout the published literature. A survey of this literature—which includes academic reviews, case studies, guidelines, and policy documents—reveals several common themes, which, while not exhaustive, are deemed to be essential to the IWRM framework. These are described below, organised under eight separate headings (although there is significant overlap between them). If these principles, and the objectives they reflect, appear complex, difficult to untangle, and ambitious, it is because they reflect the nature of the multidimensional, often intractable, governance issues that IWRM seeks to address. Taken together, however, they build a strong case for the use of models to inform multistakeholder planning and decision-making processes at the catchment scale.

1. Balancing Social, Economic, and Environmental Agendas for the Sustainable Management of Water Resources

A defining characteristic of IWRM is the overarching goal of managing water resources in an environmentally sustainable manner by balancing socioeconomic and ecological interests (Xie, 2006; Medema et al., 2008; Setegen, 2015; IWA, 2022; Bilalova et al., 2023; Nath et al., 2023). Although historically viewed as antagonistic, within the framework of IWRM these priorities (i.e. economic development, ecological protection, and social equity) are pursued concurrently (Tejada-Guibert et al., 2015; Ibisch et al., 2016; Meran et al., 2021; GWP, 2022a). The ultimate aim of IWRM, therefore, is to simultaneously advance these three agendas in a balanced manner through the coordinated stewardship of water and related resources, in order to meet socioeconomic needs in an equitable and ecologically sustainable manner.

2. A Holistic Approach Based on Systems Thinking

Owing to the systems approach adopted by IWRM, one of the fundamental tenets of the paradigm is that the hydrological system is viewed as part of a larger, complex social-ecological system (CSES) (Pahl-Wostl et al., 2011b; Grigg, 2016; Giupponi & Gain, 2017; Palmer & Munnik, 2018; Meran et al., 2021; GWP, 2022a; Swatuk & Qader, 2023; Vollmer et al., 2023). The various social, economic, and ecological aspects of this system (e.g., land, water, energy, and food) are all interconnected and thus require a holistic, coordinated management approach. IWRM further recognises that the hydrological system is itself complex and multidimensional, comprising several interlinked processes and subsystems, as well as a number of related management concerns (including, inter alia, surface water resources, ground water resources, overland runoff, wetlands, estuaries, supply, demand, wastewater treatment, stormwater management, pollution management and resource protection, and drought and flood management). As an integrated, systems-based management approach, IWRM considers these connected systems, their constituent parts, and the governance issues that pertain to them, holistically, being cognisant of the complex relationships, interactions, feedback loops, and uncertainty that exist within and between them (GWP, 2000; Jønch-Clausen & Fugl, 2001; Medema & Jeffrey, 2005; Mitchell, 2005; Jeffrey & Gearey, 2006; Medema et al., 2008; van der Keur et al., 2008; Giordano & Shah, 2014; Grigg, 2016; Palmer & Munnik, 2018; Katusiime & Schütt, 2020; GWP, 2022a; Kőrösi, 2023).

3. A Coordinated, Multisectoral, and Multilevel Approach to the Management of Water Resources

If, as described in the preceding section, water resources only one aspect of a larger complex social-ecological system, it follows that effectively managing this system necessitates a coordinated, multisectoral, and multilevel governance approach (Giordano & Shah, 2014; Grigg, 2016; Stuart-Hill et al., 2020; GWP, 2022a; Parween, 2022; Bilalova et al., 2023; Lukat et al., 2023). Hence, in the first instance, IWRM promotes integration *within the water sector* (GWP, 2000; Jønch-Clausen & Fugl, 2001; Anderson et al., 2008; Kasbohm et al., 2009; Lenton & Muller, 2009; Claassen, 2013; Haddad & Solomon, 2023; Sugam et al., 2023), while simultaneously requiring cross-sectoral integration *between the water sector and other related sectors* (GWP, 2000, 2004; Kasbohm et al., 2009; Lenton & Muller, 2009; Smith & Jønch-Clausen, 2015; Tejada-Guibert et al., 2015; Haddad & Solomon, 2023; Lukat et al., 2023). Moreover, IWRM also requires *integration across multiple levels*, which includes horizontal and vertical integration (1) within government, (2) between state and non-state actors, and (3) at different administrative and geographical scales (Xie, 2006; Lenton & Muller, 2009; Horlemann & Dombrowsky, 2010; Engberg, 2014; Smith & Jønch-Clausen, 2015; Grigg, 2016; Meran et al., 2021; Lukat et al., 2023). This complexity is reflected in Jønch-Clausen’s (2016, p. vi) description of integration as “a difficult combination of the horizontal integration between sectors and stakeholders at all levels, and the vertical integration from the… catchment level [to]… the national and the regional levels." Lubell and Balazs (2018, p. 572) have similarly described it as "coordinated decision making among different geographical, hydrological, and jurisdictional scales." Lukat et al. (2023, p. 50) have therefore argued that as "many [of the] decisions affecting water resources are taken outside the water sector" IWRM is contingent upon "intensive coordination, vertically across different levels of government and horizontally across policy sectors."

4. Subsidiarity and Catchment-Scale Management

IWRM advocates the devolution of administrative responsibility to the lowest appropriate level (a principle known as "subsidiarity") (GWP, 2000; Xie, 2006; Tejada-Guibert et al., 2015; Grigg, 2016; GWP, 2022a; Vollmer et al., 2023). Accordingly, while it is recognised that certain responsibilities should remain vested in authorities at a national or regional level—especially those related to oversight and policy coordination—the operational implementation of IWRM should take place at the lowest suitable level. This means that, wherever possible and appropriate, policies, plans, and decisions relating to the management of water and related resources should be developed and operationalised by stakeholders at a local level, while still being informed by national and regional policy.

A key aspect of subsidiarity is the management of water resources at the catchment scale (Molle, 2006; Cervoni et al., 2008; UNESCO, 2009; de Oliveira Vieira, 2020; GWP, 2022a; du Plessis, 2023; Kikoyo, 2023; Sugam et al., 2023). Hence, according to Martinez-Santos et al. (2014, p. 40), "the basic tenet of IWRM is that the basin is the natural management unit." Conceptually and functionally, many of the systemic complexities of water resource management occur at the catchment level. Although not closed, catchments represent discrete social-ecological systems within which water and related resources can be logically and holistically managed (GWP, 2000; Jønch-Clausen & Fugl, 2001; Cervoni et al., 2008; Lenton, 2011; Tejada-Guibert, 2015; Grigg, 2016; de Oliveira Vieira, 2020; Bilalova et al., 2023). Figure 3 below illustrates this point. The diagram shows that, through their shared dependence on the catchment's water resources, the various social, economic, and ecological parts of the system are inextricably interlinked. Hence, actions and decisions in one part of the catchment will impact other aspects of the system in other parts of the catchment. Swatuk and Qader (2023, p. 4) have therefore described catchments, from an IWRM perspective, as "the ideal organisational unit upon which to scaffold appropriate water management infrastructure." Thus, frequently echoed in the literature is the assertion that IWRM "promotes the management of water and related resources… *on a watershed basis*" (Roy et al., 2011, p. 9, emphasis added).

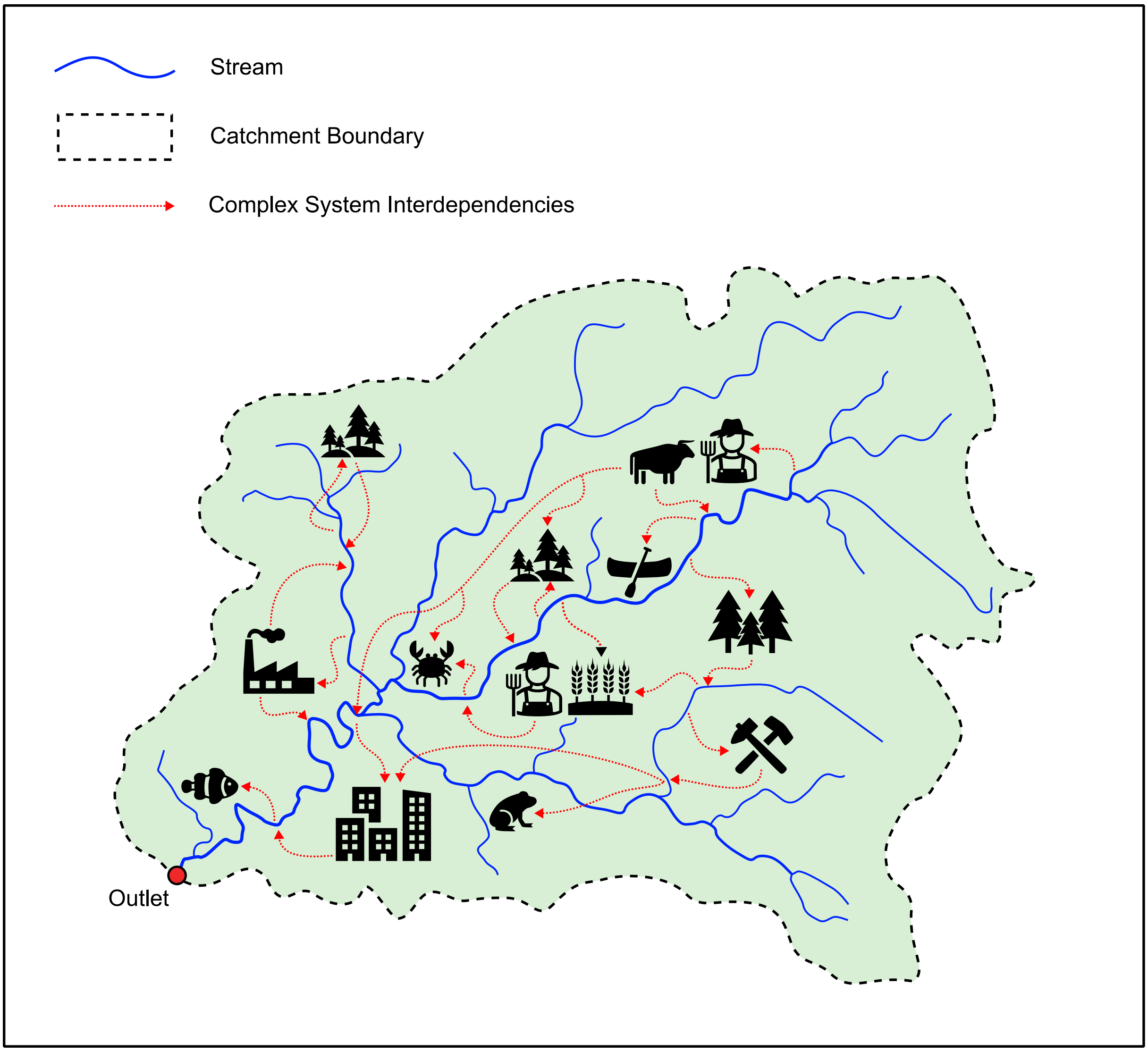

Figure 3. Illustration of a catchment as a complex system, comprising multiple social, economic, and ecological elements, all of which are inextricably linked by their mutual dependence on shared water resources.

Catchments also represent a coherent space in which a diverse network of actors—who tend to operate at disparate administrative and geographical scales—can coordinate their efforts, thus helping to overcome the typical mismatch between administrative and ecological boundaries often highlighted in the literature (GWP, 2000; Herrfahrdt-Pähle, 2010; Horlemann & Dombrowsky, 2010; Grigg, 2016). Figure 4 below shows how the boundaries of three hypothetical administrative entities (such as local governments or municipalities) may not align with those of the catchment system for which they share a management responsibility.

The principle of catchment-scale management is most often implemented through the establishment of River Basin Organisations (RBOs), which serve as arenas for participation, coordination, and trans-sectoral cooperation between stakeholders at different administrative levels (GWP, 2000; UNESCO, 2009; Horlemann & Dombrowsky, 2010; Patterson et al., 2013; UNEP, 2014; Grigg, 2016; Ibisch et al., 2016).

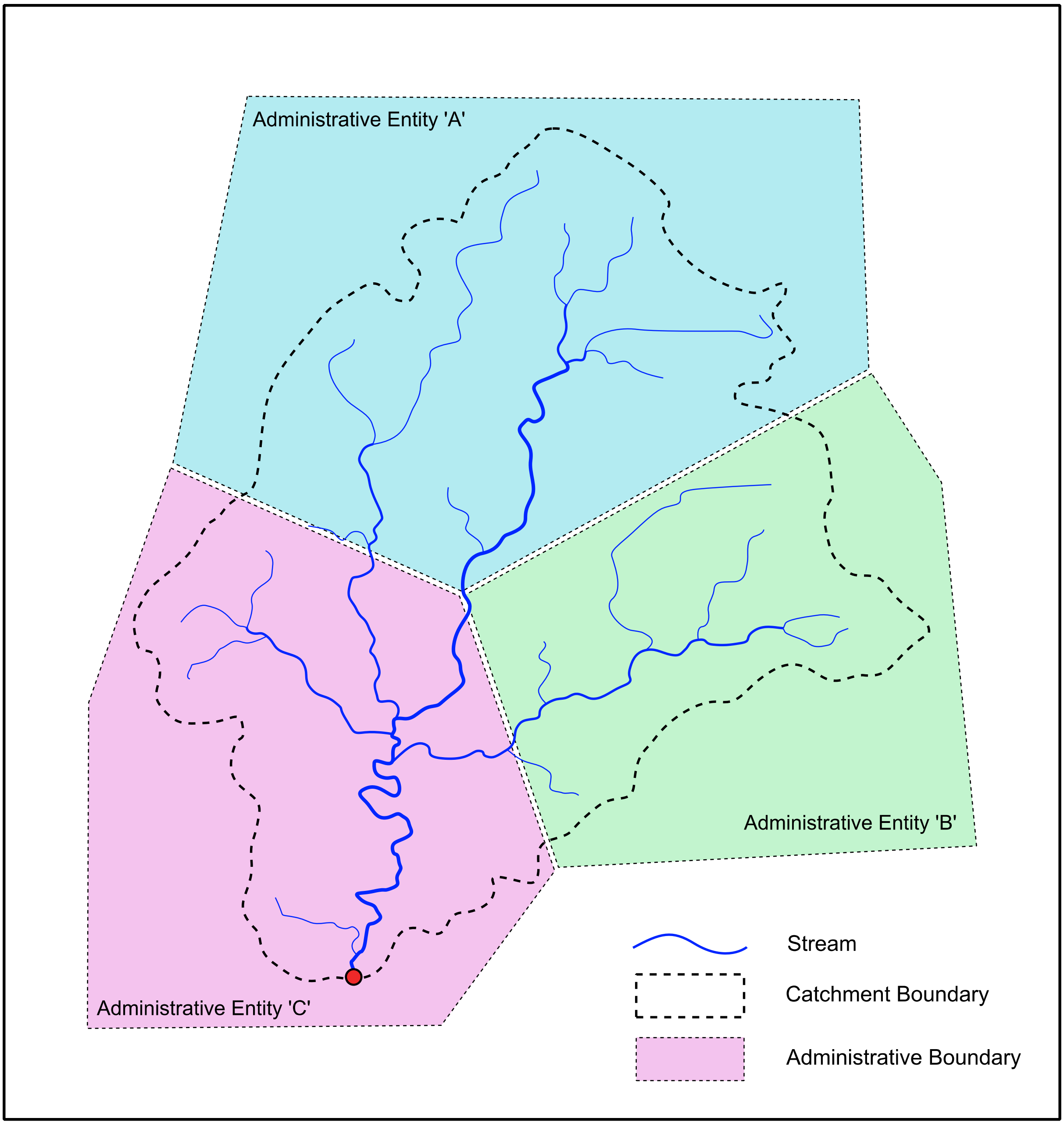

Figure 4. Illustration showing how the jurisdictional boundaries of administrative entities (such as local governments or municipalities) may not align with the geographical boundaries of the catchments for which they share an administrative responsibility. IWRM therefore advocates management of the system at the catchment scale, often through institutional structures such as River Basin Organisations (RBOs), to resolve this mismatch.

As hydrological units, however, catchments can be delineated at multiple scales (Kikoyo, 2023). The extent of a catchment will, for example, depend upon where its outlet is located, making it possible to have multiple "nested" catchments (i.e., catchments within catchments, see Figure 5). Therefore, the principle of catchment-scale management can itself be applied at different scales. On the one hand, international cooperation is frequently called for in the management of *transboundary catchments* (UNESCO, 2009; Hooper & Lloyd, 2011; Martinez-Santos et al., 2014; United Nations, 2015; Borchardt et al., 2016). In contrast, at the local end of the scale it is possible to manage river systems within smaller *sub-catchments* (also variously referred to in the literature as "sub-basins", "microbasins", or "micro-catchments") (Visscher et al., 1999; GWPSA, 2009; Hernández, 2013; Lardizabal, 2015; Breulmann et al., 2022; Tinoco et al., 2022; Kikoyo, 2023). Between these two extremes, IWRM can also be implemented within *sub-national regional catchment areas* (Hooper, 2006; Denby et al., 2016; Kikoyo, 2023).

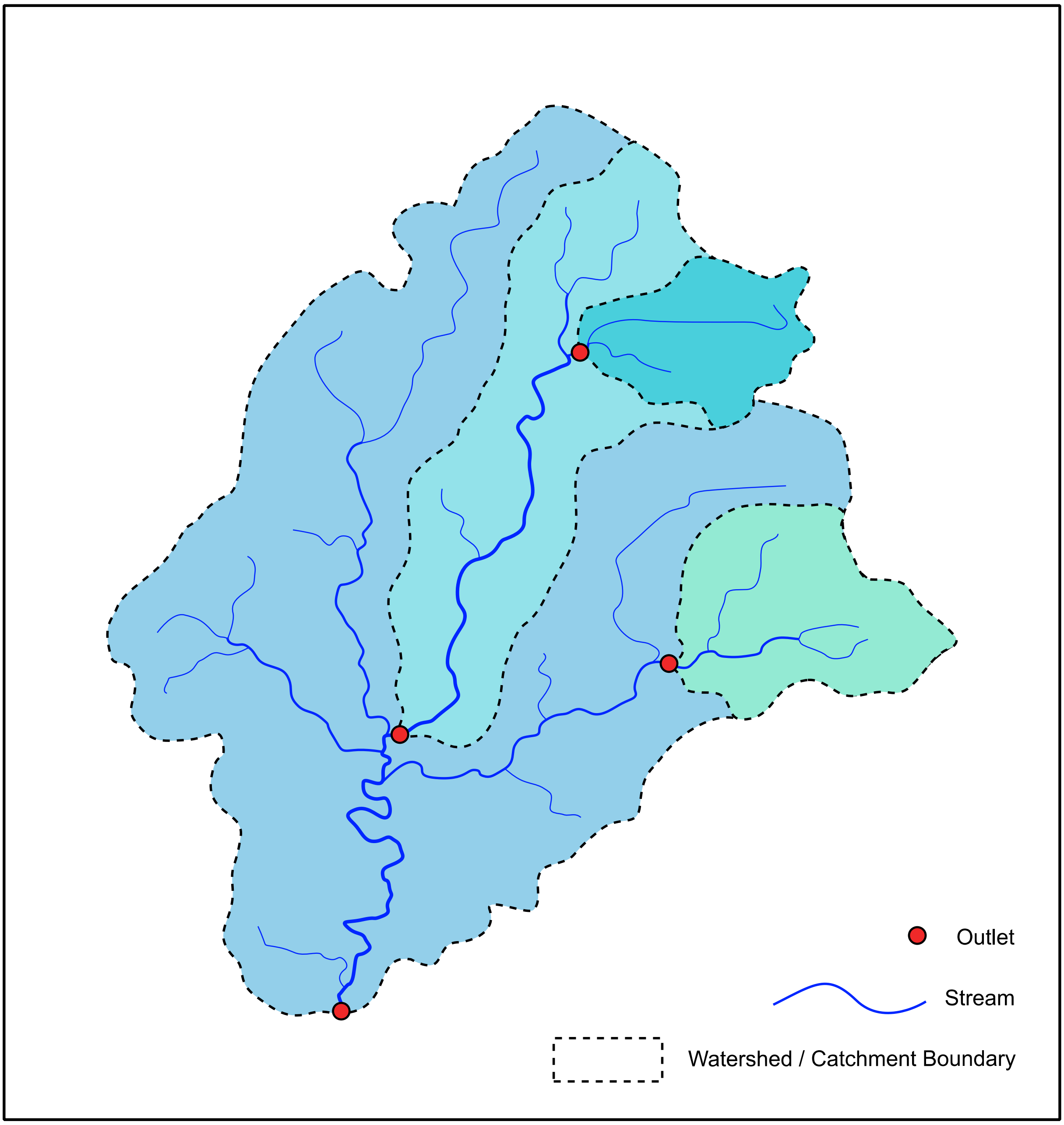

Figure 5. Illustration showing that catchments can be delineated at multiple scales depending on the location of the outlet, which makes it possible to have nested catchments (i.e., catchments within catchments).

A lack of consistency in the nomenclature used to denote these scales may further confuse matters (Kikoyo, 2023). Nevertheless, regardless of the geographical scale at which the principle of catchment management is applied, the logic which underlies the principle remains the same: the need to manage the system and its constituent parts holistically. The chief application of this principle is the establishment of management structures that facilitate research and cooperative administration at these scales (see "An Enabling Institutional Environment" below).

5. Participatory and Interdisciplinary Planning and Decision-Making

Given the complex nature of catchment systems, management at this scale requires a participatory approach which brings together a diverse network of actors and stakeholders, each of whom represent a variety of sectors, interests, and professional disciplines (GWP, 2000; Xie, 2006; Martínez-Santos et al., 2014; Smith & Jønch-Clausen, 2015; Tejada-Guibert et al., 2015; Ibisch et al., 2016; de Oliveira Vieira, 2020; GWP, 2022a; Bilalova et al., 2023). With respect to stakeholder participation, Dabrowski et al. (2013, p. 6) have noted that "IWRM involves complex socio-economic [and] socio-ecological processes that require healthy interaction from a full range of stakeholders, each of whom only have an element of knowledge on part of the complex systems involved." Therefore, argue Kasbohm et al. (2009, p. 6), stakeholder participation is "universally recognized as a key element in obtaining a balanced and sustainable utilisation of water." White (2013) has also recorded that, within the IWRM framework, there has been "increasing emphasis on stakeholder collaboration and the involvement of local communities in decision-making." Smith and Jønch-Clausen (2015, p. 5) explain that "IWRM sets out to reconcile multiple, competing uses for water, with legitimacy attained through public participation." A key aspect of this participatory management approach is the building of a shared vision towards which all actors can collaboratively work, while balancing conflicting interests and reaching mutually acceptable compromises (Jønch-Clausen & Fugl, 2001; Grigg, 2008; Hassing et al., 2009; UNESCO, 2009; Horlemann & Dombrowsky, 2010; Grigg, 2016). In addition, the issues faced by water managers are typically complex and multidimensional, often involving overlapping environmental, socio-political, and economic considerations (GWP, 2020). A reliance on technical solutions, which have historically dominated the field of water resources management, is therefore inadequate (Medema & Jeffrey, 2005; Katusiime & Schütt, 2020). In contrast, taking an integrated approach requires that responsible actors "draw from interdisciplinary founts of knowledge" (Grigg, 2016, p. 2). IWRM thus embraces the contributions offered by a range of different professional disciplines and skills, using an array of socio-technical and economic approaches to the management of water resources (Xie, 2006; Kidd & Shaw, 2007; Grigg, 2008, 2016; Meran et al., 2021; IWA, 2022; Parween, 2022). This approach has been fittingly described as a "pragmatic pluralism" by Katusiime and Schütt (2020, p. 3).

6. An Enabling Institutional Environment

The kind of coordinated, multisectoral, and participatory management described in the preceding paragraphs is only possible if the prevailing institutional environment enables actors to operate in an integrated manner (UNEP, 1992; Jønch-Clausen & Fugl, 2001; Lenton & Muller, 2009; UNESCO, 2009; Donoso & Bosch, 2015; Tejada-Guibert, 2015; Ison & Wallis, 2017; Meran et al., 2021; Awuah et al., 2023). In the context of IWRM, institutions broadly refer to the various rules and arrangements (formal and informal) which govern the values, roles, relationships, actions, and choices of stakeholders and other actors (Horlemann & Dombrowsky, 2010; Patterson et al., 2013; Lukat et al., 2022b; Awuah et al., 2023). These may include high-level policy and legislation, organisational and administrative structures at various levels, funding arrangements, and/or local plans and policies. The collective set of institutions in force within any given system may be referred to as the "institutional environment." According to guidelines published by UNESCO (2009, p. 6), "a key aspect of IWRM requires that the national government(s) create an enabling environment, including a legal framework, to facilitate a multi-sectoral coordinated basin-level approach." Thus, through its role in formulating policy and legislation, government becomes the primary enabler of IWRM and is responsible for ensuring that appropriate institutional arrangements are in place at the relevant levels (GWP, 2000; Pahl-Wostl et al., 2011b).

7. Informed Decision-Making Based on Shared Knowledge

Effective water resource management requires that stakeholders and policymakers have an adequate and holistic understanding of the complex, multidimensional dynamics of the catchment systems for which they are responsible. Thus, in order to achieve the best possible management outcomes, actors need to be informed about, inter alia, the drivers, pressures, states, impacts, and responses (DPSIR[4]) that characterise such systems (Xie, 2006; van der Keur et al., 2008; Kasbohm et al., 2009; Lenton, 2011; Ibisch et al., 2016; Stärz et al., 2016; de Oliveira Vieira, 2020; Meran et al., 2021). The GWP (2000, p. 51), for instance, explain that "the management of water resources requires an understanding of the nature and scope of the problem to be managed." Turton et al. (2007, p. 4) have similarly asserted that policymakers need to have "a thorough understanding of the functioning of the complex inter-linkages between ecosystems, water resource management options, and human activities that impact on the water resource." McDonnell (2008, pp. 132–133) has also argued that the provision of reliable and timely information is "fundamental to any good governance objectives to ensure that balanced, efficient and equitable decisions are made." Finally, Rogers et al. (2000, p. 509) have remarked that "ensuring that all stakeholders operate from a common knowledge base and with united purpose… will markedly reduce conflict and increase co-operative governance within a catchment." Effective integrated management therefore requires that all actors share an adequate understanding of the relevant issues, the latter being based on reliable data and information.

Consequently, an important aspect of the multisectoral, participatory, and interdisciplinary nature of IWRM is the integration of knowledge—from various fields and disciplines—into the decisions, policies, and plans that govern the management of water and related sectors/resources. However, the challenge of incorporating this diversity of knowledge into multi-stakeholder policymaking processes

[4] Understanding catchments according to the DPSIR framework is considered an important part of the integrated management of these systems (see, for example, Carr et al., 2007; Kasbohm et al., 2009; Grigg, 2016; Patrício et al., 2016; Sun et al., 2016; Grigg, 2021).

is an obstacle that persistently hinders the effective implementation of IWRM (Gooch & Stålnacke, 2010; Halbe et al., 2013; Reed et al., 2014; Olander et al., 2017; Oliver & Cairney, 2019; Grigg, 2021; Borden & Goodwin, 2022). This challenge is often experienced at what Gooch & Stålnacke (2010) have referred to as the "Science-Policy-Stakeholder Interface" (SPSI). The authors noted that "while the successful interaction and cooperation between research, policy and stakeholders is vital, it is often not straightforward and unproblematic" and have remarked that common experience has shown that such interactions are often "marked by frustration, misunderstandings, disappointment and a lack of substantial progress or positive results" (ibid., p. 141). According to Gooch & Stålnacke (2010), scientists typically complain that policymakers and managers do not take the knowledge that they generate into account when making management decisions. Conversely, policymakers complain that scientists do not provide the kind of knowledge that is both relevant and useful for the plans and policy decisions that they must make on a day-to-day basis. According to Olander et al. (2017), there remains a persistent gap between available research and the needs of decision-makers. In a recent opinion piece, Grigg (2021, p. 3) noted that this has been an enduring problem and has thus argued that those involved in water research should "do more to provide water managers with clear, credible and pertinent information." Therefore, in order to facilitate the incorporation of scientific knowledge into policy and decision-making processes, and in order to ensure that the decisions made by resource managers are rational, informed, and carefully considered, the availability of relevant, robust, and useful scientific information is of paramount importance (Gooch et al., 2010; Oliver & Cairney, 2019). Effective research needs to "address questions relevant to stakeholders and decision-makers and to include their values and perspectives in the knowledge production process" (Grizzetti et al., 2010, p. 67). Thus, argue Halbe et al. (2013, p. 2651), "methodologies are needed that deal with real-world complexity in order to find effective solution strategies, and facilitate knowledge transfer between science, policy, engineering and local communities."

8. Contextual, Adaptive, and Iterative Implementation Processes

In contrast to the claim by Bilalova et al. (2023, p. 2) that IWRM is "promoted as a universal blueprint for solving water related problems" it is frequently emphasised in the literature that no such blueprint exists for the implementation of IWRM (e.g., GWP, 2000; Jeffrey & Gearey, 2006; Xie, 2006; Funke et al., 2007; Lenton & Muller, 2009; Obeng, 2009; O'Keeffe, 2012; White, 2013; Tejada-Guibert, 2015; Grigg, 2016; GWP, 2020; Meran et al., 2021; Adom & Simatele, 2022; du Plessis, 2023). Instead, many authors have argued that the basic principles of IWRM should be expressed in an adaptive manner that is appropriate for local contexts (Lenton & Muller, 2009; Pahl-Wostl et al., 2011b; White, 2013; Tejada-Guibert, 2015; Grigg, 2016; Claros & de Oliveira Vieira, 2020; GWP, 2020; Adom & Simatele, 2022; Swatuk & Qader, 2023). For instance, the GWP (2004, p. 8) states that "IWRM is not a dogmatic framework, but a flexible, common-sense approach to water management." The implementation of IWRM should therefore follow a "pragmatic but principled approach" (Snellen & Schrevel, 2004, p.

21). White (2013) explains that “IWRM is not… a prescriptive description of how water should be managed, but rather it is a broad framework in which decision makers can collaboratively decide the goals of water management and co-ordinate the use of different instruments to achieve them.” Most authors have therefore argued that a flexible and iterative management approach, characterised by feedback loops and ongoing learning, is key to the successful implementation of IWRM (GWP, 2000; Medema & Jeffrey, 2005; van der Zaag, 2005; Anderson et al., 2008; Tejada-Guibert, 2015; Grigg, 2016; Smith & Jønch-Clausen, 2018; de Oliveira Vieira, 2020; GWP, 2022a; Lee et al., 2022b). IWRM can thus be described as a “flexible, situation-tailored, and area-specific” management system (Lee et al., 2022b, p. 1611), and, according to Pahl-Wostl et al. (2011b, p. 298), IWRM “provides an infinitely adaptable template of principles and strategies which can be shaped to address challenges from Australia to Zambia.” It is this flexible approach, according to du Plessis (2023, p. 30), that is one of IWRM’s primary advantages.

IWRM and the Land-Water Nexus

Although IWRM seeks to manage complex systems holistically, Mitchell (2005) has argued that, from a management perspective, not all aspects of the system are of equal importance as some variables may have a greater influence than others. It has also been argued that attempting to simultaneously co-manage every aspect of a catchment system would, in any case, be impractical (Biswas, 2004; Lenton & Muller, 2009). Pragmatism in IWRM thus encourages actors to focus on managing the most significant system variables (Mitchell, 2005; Kasbohm et al., 2009). Managing land use/land cover (LULC), which is considered to be one of the most influential variables in a catchment from a water management perspective, is therefore given particular emphasis in the IWRM literature (e.g., GWP, 2000, 2004; Calder, 2005; Mitchell, 2005; Bandaragoda, 2006; Kasbohm et al., 2009; Calder, 2012; Falkenmark et al., 2014; Setegen, 2015; Tejada-Guibert, 2015; Borchardt et al., 2016; Ibisch et al., 2016; Duda, 2017). The GWP (2000, p. 60) explain that “in the context of IWRM the management of land use is as important as managing the water resource itself since it will affect flows, patterns of demand and pollution loads.” The UNESCO guidelines for IWRM (2009, p. 4) have also noted that “cumulative land-uses in a river basin, such as urban development, agriculture and forest conservation, can have profound impacts on water resources in the basin and vice versa.” Bandaragoda (2006, p. 181) has asserted that the poor condition of water resources globally is largely due to the mismanagement of land and has thus contended that, in line with the principles of IWRM, it is “essential to clearly understand the land-water linkage, and how water movement through the landscape is linked to quality of water.” Locally, the South African White Paper on National Water Policy mandates that “since many land uses have a significant impact upon the water cycle, the regulation of land use shall, where appropriate, be used as an instrument to manage water resources within the broader integrated framework of land use management” (Principle 18; DWAF, 1997). The GWP (2000) has further argued that, in line with IWRM’s focus on managing social-ecological systems holistically, the relationship between LULC and water is most logically managed at the catchment scale, where land use policies should consider potential implications for local water resources. Falkenmark et al. (2014), however, have cautioned that while the land-water nexus is central to IWRM, not enough is currently being done to manage the two resources in a coordinated manner. Duda (2017, pp. 5, 22) has similarly described the ongoing lack of coordination between land use and water management as a "key failure," and warns that water management problems will persist unless land use is given due consideration within the IWRM framework (see also Bandaragoda, 2006). Lukat et al. (2023, p. 50) has also warned that a failure to give sufficient cognisance to the "nexus challenges" that typify water resources management may "accelerate the overexploitation or pollution of water resources." Falkenmark et al. (2014, pp. 391–392, 406) have therefore called for tools that give "greater visibility" to the land-water nexus, arguing that "for too long land issues have not been addressed properly within the IWRM discourse."

Models as Tools for the Implementation of IWRM

As argued above, the integration of scientific information into multi-stakeholder decision-making processes is essential for the effective implementation of IWRM. It is, nevertheless, a challenging task. The GWP has therefore advocated for the use of models to enable stakeholders and policymakers to develop a shared understanding of the complex dynamics that characterise catchment systems, thus empowering them to make rational data-driven decisions and formulate informed plans and policies (GWP, 2022b, 2022c, 2022d). Nearly five decades ago, in a book entitled *Systems Approach to Water Management,* Biswas (1976) declared that "the question is not whether we should use models for decision-making, but what type of model should we be using to obtain the best possible results." Precisely forty years later, Grigg (2016, p. 251) fittingly observed that within the IWRM framework "water managers [now] rely heavily on data and models to inform their decisions about complex management issues."

Jeffrey & Gearey (2006, p. 6) have explained the value of models for IWRM as follows:

> Modelling (in the broadest sense of the word) can make a significant contribution to closing the knowledge gap between the theory and practice of IWRM. In general terms models allow us to represent the world around us in alternative formats; to abstract, simplify, conceptualise, and structure our beliefs about how the world works. In so doing they support analysis, experimentation, theory testing, communication, and planning.

Several other authors and publications have confirmed that, in the context of IWRM, models are a key decision-support tool that actors can leverage in order to manage water resource systems more effectively (Pahl-Wostl et al., 2011b; Grigg, 2016; Ibisch et al., 2016; Stärz et al., 2016; Badham et al., 2019; de Oliveira Vieira, 2020; Swatuk & Qader, 2023). Principally, models can help reduce epistemological uncertainty among decision-makers, which results from an imperfect understanding of how these complex systems respond to internal and external changes or perturbations (van der Keur et al., 2008; Kasbohm et al., 2009; Grigg, 2016; Ibisch et al., 2016). The usefulness of models therefore lies in their ability to "simulate how systems behave and help predict outcomes of management strategies and scenarios" (Grigg, 2016, p. 251). Vollmer et al. (2023) have further argued that climate change will increase the uncertainty associated with managing complex catchment systems, making the use of models in this regard more vital than ever. The usefulness of models also lies in their ability to translate "raw" data into information that is useful and understandable to stakeholders and policymakers, allowing them to incorporate this knowledge more easily into their planning and decision-making processes. McDonnell (2008, p. 137) explains that "data alone cannot supply all the information required to support IWRM" and that "analysis involves bringing together the disparate datasets to consider the impacts, interactions and broader context of phenomena." The GWP (2017) have likewise noted that "integrated management approaches in particular require massive amounts of spatially and temporally varying data from many different sectors" and that "analytical tools [such as models] are needed to interpret the data in a way that makes it usable for decision makers." Without models to translate this "unsifted" data into meaningful knowledge, decision-making processes can become paralysed (Rogers et al., 2000, p. 506; McDonnell, 2008, p. 138). The GWP (2013, pp. 8, 11) have thus claimed that, when applied correctly, models can be "powerful and reliable tools for water managers" and can "assist in taking the IWRM process forward and helping decision-makers to make more rational decisions based on the best available information." Therefore, models directly address some of the main challenges faced at the Science-Policy-Stakeholder Interface (SPSI).

The Importance and Application of Catchment-Scale LULC-WQ Models

Models have a wide range of potential applications as decision-support tools in the context of water resources management. There are innumerable system variables and many complex processes and interactions for which various models can be developed. However, as noted above, LULC is one of the most influential—and yet, in the view of some authors, overlooked—system variables. It is therefore essential, under the IWRM framework, to provide stakeholders and policymakers with accurate information about the impacts of LULC on water resources. Models that quantify land use/water quality (LULC-WQ) interactions, thus providing actors with meaningful information about these processes at relevant scales, strongly align with the holistic systems-based approach of IWRM. Practically, the development of such models may also promote cross-sectoral integration by empirically demonstrating the critical link between water and land, and the consequent need for these two resources to be carefully co-managed by the relevant actors (thus giving "greater visibility" to the land-water nexus as called for by Falkenmark et al., 2014). This will also strengthen consensus-building and reduce uncertainty by reinforcing a common understanding among stakeholders of how the systems for which they are responsible function. Moreover, by providing insights into the relationship between LULC and water quality at the catchment scale, such models support IWRM's emphasis on devolved catchment-scale management. Furthermore, such models can be used to translate data (which in its "raw" form may make little sense to stakeholders and policymakers) into relevant and understandable knowledge, allowing these actors to make informed, proactive management decisions. Modelling the relationship between LULC and water quality at the catchment scale is therefore an important pursuit that is justified by, and supportive of, several of the key principles of IWRM. Moreover, as will be demonstrated in the following section, there is an urgent need to develop models of this kind in South Africa, where the implementation of IWRM has been hampered by sectoral fragmentation, particularly in the management of land use and water resources.

IWRM in South Africa and the Need for Models that Inform Integrated Land and Water Quality Management

In order to address the complex water resource management challenges that South Africa currently faces, and so avoid the looming water crisis, the effective implementation of IWRM is an urgent imperative (Movik et al., 2016; Malaza & Mabuda, 2019; DWS, 2021; Adom & Simatele, 2022; du Plessis, 2023). If one considers the national legislative environment, it is evident that there is a strong commitment to the principles of IWRM in the laws and policies that govern water resources management in South Africa (Herrfahrdt-Pähle, 2010; Mauck, 2012; van Koppen & Schreiner, 2014; Denby et al., 2016; Meissner et al., 2017; Stuart-Hill et al., 2020). On paper at least, water policy in South Africa today represents a fundamental departure from the previous technocratic, supply-driven, and administratively-fragmented management regime, and is now underpinned by principles that include equitable, efficient, and environmentally sustainable water management (Pollard, 2002; Herrfahrdt-Pähle, 2010; du Plessis, 2023). Taken together, these policies create what has been described by Herrfahrdt-Pähle (2010, p. 2) as a “holistic, decentralised and participatory approach to water management.” For this reason, South Africa is frequently lauded as being at the forefront of IWRM implementation (Herrfahrdt-Pähle, 2010; Schreiner, 2013; Movik et al., 2016; Karar, 2017; Stuart-Hill et al., 2020; du Plessis, 2023). Anderson et al. (2008, p. 666), for instance, observed that “much of South African water policy is considered to be some of the most progressive policy thinking in the world and is based on an IWRM approach.” Stuart-Hill et al. (2020, p. 2) have also noted that “South Africa’s water legislation is internationally recognised for its ambitious implementation of integrated water resource management.” Many authors have therefore claimed that, on a policy level, South Africa has created a strong enabling institutional environment for the implementation of IWRM.[5] Moreover, reports published by the United Nations on progress toward achieving the Sustainable Development Goals (SDGs) have suggested that the implementation of IWRM in South Africa (SDG Target 6.5) is

[5] See, for example, Pollard (2002), Jonker (2007), Anderson et al. (2008), Kahinda and Boroto (2009), Muller (2009), Herrfahrdt-Pähle (2010), Pahl-Wostl et al. (2011a), Mauck (2012), Schreiner (2013), Griffin et al. (2014), van Koppen and Schreiner (2014), Movik et al. (2016), Meissner et al. (2017), Palmer and Munnik (2018), Stats SA (2019a, 2019b), Stuart-Hill et al. (2020), Adom and Simatele (2022), and du Plessis (2023).

at a relatively advanced stage, especially with respect to the establishment of an enabling institutional environment (UNEP-DHI, 2020; UNEP, 2021; United Nations, 2023c).

Several other commentaries, however, have claimed that there has been a lamentable failure to translate the rhetoric of South Africa's progressive water policies into practice.[6] Recent accounts have reported what are described as "major implementation deficits" (Lukat et al., 2022a, p. 305) and have also argued that the core goals of IWRM have not been met due to persistent sectoral fragmentation in the management of water resources (Kahinda & Boroto, 2009; Palmer & Munnik, 2018; Adom & Simatele, 2022; du Plessis, 2023). The South African Department of Water and Sanitation (DWS, 2017c, p. 17) have themselves admitted that "water quality management arrangements are hampered by disintegrated institutional structuring, poor co-ordination and conflicting approaches between government departments and spheres of government." Thus, despite a strong commitment to IWRM on paper, translating this into practice in the South African context has been largely unsuccessful, leaving the management of water and related resources fragmented (Awuah et al., 2023; du Plessis, 2023).

One important manifestation of this failure, highlighted by several authors, is a critical lack of integration in the management of land and water resources at a time when South Africa is experiencing rapid and widespread land use change and associated environmental degradation (DEA, 2012; Claassen, 2013; Musakwa & Niekerk, 2013; Movik et al., 2016; DWS, 2017c; Knight, 2019b; Stats SA, 2019b; Adom & Simatele, 2022; DFFE, 2022a). Current transformations of the natural land surface by mining activities, agricultural expansion, and urbanisation are having significant and deleterious effects on the environment (DEA, 2012; Halpern & Meadows, 2013; Musakwa & Niekerk, 2013; Knight, 2019a; Skowno et al., 2021; DFFE, 2022b). These activities have resulted in the increased exploitation of natural resources, extensive loss of natural vegetation, widespread pollution, and general degradation of the natural environment (DEA, 2012; Gillson et al., 2012; Halpern & Meadows, 2013; Musakwa & Niekerk, 2013; du Preez et al., 2019; Jellason et al., 2021). From a water management perspective, several of South Africa's water quality issues (including salinisation, eutrophication, sedimentation, and bacterial contamination) can be linked to diffuse pollution generated by these land use changes.[7]

There is thus a clear and urgent need to develop strategies that are supportive of improved and integrated land and water resources management in South Africa. Moreover, as argued above, such strategies need to be based on relevant scientific knowledge that is communicated to policymakers and stakeholders in a way that makes sense to them. The *NWRS*, for instance, has acknowledged that there has been an "insufficient translation of data into appropriate information" and has noted that this is one of the

[6] See, for example, Funke et al. (2007), Merry (2008), Kahinda and Boroto (2009), Mauck (2012), Schreiner (2013), Karar (2017), Palmer and Munnik (2018), Stuart-Hill et al. (2020), Adom and Simatele (2022), Lukat et al. (2022a), Lukat et al. (2022b), and Awuah et al. (2023).

[7] See, for example, Slaughter and Mantel (2017), van der Hoven et al. (2017), Namugize et al. (2018), Nde and Mathuthu (2018), Malherbe et al. (2019a), Petersen et al. (2020), Dlamini et al. (2021), Koekemoer et al. (2021), Nde et al. (2021), Nkosi et al. (2021), and Senbore and Oke (2021).

primary shortcomings of water quality management in the country (DWS, 2021, p. 123). This being the case, the use of models to generate knowledge that can guide stakeholders and policymakers in the co-management of land and water resources, and thus help protect water resources from further degradation, is an important research endeavour in the South African context.

Conclusion

In a recent opinion piece published in *Nature Sustainability*, Vollmer et al. (2023, p. 233) have summarised the key principles of effective water governance as "cross-sectoral coordination… managed at the appropriate scale to reflect local conditions, and promotion of robust stakeholder engagement," and go on to note that "good governance has no blueprint, as context influences interpretation and implementation." While openly critical of IWRM, the authors actually offer a succinct synopsis of the essential elements of IWRM as described in the preceding paragraphs. Objectively, there is little doubt today that the principles of IWRM offer a valuable framework for the management of water and related resources, especially in the face of growing epistemological uncertainty associated with climate change (Ciampittiello et al., 2023). Furthermore, as argued above, the development of modelling strategies that can guide multi-stakeholder planning and decision-making processes by providing actors with timely and relevant information about the relationship between land use and water quality at the catchment scale is clearly in line with, and supportive of, many of the key principles of IWRM. Before reviewing the literature that documents the use of statistical methods for this purpose (the focus of Chapter 4), the next chapter briefly summarises the typical impacts of LULC on water resources.

CHAPTER 3:

An Overview of the Impacts of LULC on Surface Water Quality

"If there is an ailing river, a sick landscape may be the cause."
–Falkenmark et al. (1999, p. 33)

Introduction

Anthropogenic land use change is recognised as a force of global concern, causing environmental degradation across various ecosystems (including aquatic/hydrological systems) (Malek & Verburg, 2020; Gomes et al., 2021; Taylor & Rising, 2021; Bohenek & Sulliván, 2022; D'Arcy et al., 2022a; Liu et al., 2022; Xu & Xiao, 2022; Richardson et al., 2023). With respect to water quality, it seems almost impossible to overstate the significance of land use and land cover (LULC). Many publications, for instance, have established that LULC has a direct and decisive influence on hydrological systems. In one seminal article, Hynes (1975, p. 12) observed with remarkable prescience that "in every respect, the valley rules the stream" (see also Cooke et al., 2022). Several years later, in their own extensive treatise on the impacts of land use on water quality, Falkenmark et al. (1999, p. 33) also suggested that "if there is an ailing river, a sick landscape may be the cause." Wear et al. (1998, pp. 619, 627) have similarly argued that within catchment areas, "the use and condition of land in particular have a profound influence on water quality" and consequently concluded that land use is "clearly one of the most important factors determining water quality" (see also Gove et al., 2001; Griffith, 2002; Griffith et al., 2002a; Zhang et al., 2023b). According to Harris (2002, p. 343), "rivers and water bodies are the ultimate integrators of our land use decisions." Falkenmark (2011, p. 13) has similarly asserted that "a land-use decision is also a water decision." More recently, owing to the sensitivity of aquatic ecosystems to land use changes, Li et al. (2022b, p. 2) described rivers as the "sentinels" of their catchments. Aalipour et al. (2023, p. 2) have therefore concluded that there is an "undeniable relationship" between land use and water quality (see also Bohenek & Sulliván, 2022; Bowes et al., 2023).

The foregoing citations reflect what has become increasingly acknowledged among researchers and practitioners: the characteristics of a catchment, including land use and land cover, are key determinants of hydrology and water quality (Yirigui et al., 2019; D'Arcy et al., 2022a; Pandey et al., 2023). This chapter draws from a wide range of literature (including reference texts, reviews, and original research) to provide an overview of the typical impacts of different classes of LULC on water quality. The chapter specifically highlights the negative impacts that agriculture, urban development, mining operations, and commercial forestry may have on water resources. It also notes the ameliorative effect that natural vegetation can have by trapping and filtering contaminated surface runoff. It concludes, therefore, that maintaining natural vegetation cover in catchment areas is an important management strategy that can help to protect water resources from diffuse pollution.

Land Use versus Land Cover

Although the terms "land use" and "land cover" are often used interchangeably, a distinction can be made between the two (Horning et al., 2010; Parece & Campbell, 2015; Bohenek & Sulliván, 2022). Strictly speaking, *land cover* refers only to the natural (biotic) and artificial (abiotic) features that cover the Earth's immediate surface in broad categories that may, for example, include built-up land, cropland, forested land, or water (Anderson, 1976; Thompson, 1996; Schulze, 2000; Thenkabail, 2015; Heidkamp & Christian, 2022). According to Giri (2012, pp. 9, 226), land cover refers to the "actual vegetative, structural, or other surface cover resulting from a given land use" and so represents the visible evidence of different land uses. By contrast, *land use* refers to the human activities associated with a particular area of land in terms of utilisation, occupation, and/or management (Anderson, 1976; Thompson, 1996; Giri, 2012; Thenkabail, 2015; Heidkamp & Christian, 2022). It specifically refers to the manner in which the biophysical attributes of land are manipulated, managed, and exploited by humans (Schulze, 2000, p. 13). Jansen and Gregorio (2002, p. 98) have therefore defined land use as "the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it" (see also Horning et al., 2010).

With respect to the relationship between land use/land cover and water quality, Dabrowski et al. (2013, p. viii) have argued that "a distinction [can be] made between land use, associated with management practices influencing water quality, and land cover, which can be observed and mapped through earth observation technologies." The authors have further observed that it is difficult to determine the details of specific land use practices (such as the amount of fertiliser or pesticide applied to agricultural land) from remotely sensed earth observation data. Nevertheless, the authors have suggested that from a remote-sensing/earth-observation perspective, land cover may serve as a general proxy for land use (ibid., 2013, p. 75). In any case, thus defined, both land use (what people do on/with the land) and land cover (the land surface itself) influence water quality by determining not only the types and amounts of contaminants available for transport into receiving water bodies, but also how readily and by what pathways those contaminants may be mobilised. As such, the acronym LULC (i.e., land use/land cover) is frequently used in the literature (as well as in this study) to encompass both.

LULC as a Source of Diffuse Pollution

The impact of LULC on surface water quality is principally as a source of diffuse pollution (Falkenmark et al., 1999; Loague & Corwin, 2005; Bosman et al., 2018; Chapman et al., 2020; Kajitvichyanukul & D'Arcy, 2022; Zhang et al., 2023b). Simultaneously, according to Xu et al. (2023b, p. 1), streams and rivers are the “primary sink[s] of pollutants in terrestrial ecosystems.” It is this source/sink relationship, according to D'Arcy et al. (2022a, p. 14), that inextricably links land and water resources. According to Zhang et al. (2023b), there are a variety of complex pathways and processes by which diffuse pollution enters water bodies (see also Kajitvichyanukul & D'Arcy, 2022). For instance, contaminants may be naturally present on or within the land surface (as in the case of naturally occurring minerals and nutrients in soils) or later applied by humans (as in the application of fertilisers or pesticides). Various other land use activities may also expose or mobilise these pollutants, which are eventually transported during precipitation events into receiving water bodies through multiple pathways (Lintern et al., 2018). Thus, as Peters and Meybeck (2000, p. 185) have observed, “the quality of freshwater at any point on the landscape reflects the combined effects of many processes along water pathways.”

Furthermore, landscape characteristics— especially the extent of imperviousness surfaces, the presence or absence of vegetative cover, and the spatial configuration of land cover within the landscape—will additionally influence the hydrological response of a catchment (Falkenmark et al., 1999; Ding et al., 2016; Aalipour et al., 2022). Higher proportions of impervious land cover, for example, will result in a “flashier” hydrological response to precipitation events (i.e., reduced infiltration, shorter surface residence time, increased overland flow rates, shorter lag-times, reduced baseflow, and increased peak flow) (Schueler, 1994; Paul & Meyer, 2001; CWP, 2003). This has associated impacts on water chemistry and pollution rates. For instance, increased overland flow flushes contaminants that have accumulated on impervious surfaces directly into receiving water bodies, resulting in higher pollutant loads (Day & Dallas, 2011; Chapman et al., 2020). Initially this may be offset, to some degree, by increased streamflow in the receiving water body, resulting in greater dilution of the received contaminants (Day & Dallas, 2011; Chapman et al., 2020; D'Arcy et al., 2022a). However, in the long term, reduced baseflow will increase the relative concentration of pollutants in the receiving water body (Nobre et al., 2020; Li et al., 2022b; Deng et al., 2023; Roldán-Arias et al., 2023). Classes of LULC that are typically considered sources of diffuse pollution include urban/built-up areas, agricultural land, mines, and commercial forestry (Dallas & Day, 2004; Bosman & Kidd, 2009; Falkenmark, 2011; Chapman et al., 2020). As described in the following paragraphs, each of these land uses is typically associated with a specific suite of pollutants and associated water quality impacts (Dabrowski et al., 2013; de Mello et al., 2020; Mirzaei et al., 2020; D'Arcy et al., 2022b).

The Role of Natural Vegetation in Protecting Water Quality

While most anthropogenic classes of LULC are sources of diffuse pollution, areas of natural vegetation (i.e., native grasslands, shrublands, and forests) act as sinks, filtering out, assimilating, and transforming pollutants before they enter receiving water bodies, thus improving water quality (de Mello et al., 2017; Brogna et al., 2018; Yirigui et al., 2019; Sun et al., 2020; Bohenek & Sullivàn, 2022; Cheng et al., 2022; Caldwell et al., 2023; Feng et al., 2023b; Qiu et al., 2023; Woznicki et al., 2023). Natural vegetation also plays an important role in regulating overland flow rates, thereby reducing erosion and the overall pollutant load of surface runoff (Malherbe et al., 2019b; Yirigui et al., 2019; Sun et al., 2020; Caldwell et al., 2023). Riparian vegetation additionally helps to shade water, keep it cool, and so regulate dissolved oxygen concentrations (Vigil, 2003). Thus, in contrast to other classes of LULC, native forests and other natural vegetation are usually associated with improved water quality (Baker, 2005; Foley et al., 2005; de Mello et al., 2017; Brogna et al., 2018; Piffer et al., 2021; Cheng et al., 2022; Caldwell et al., 2023). The clearing of natural vegetation, and its transformation into other pollution-generating land uses, is therefore singularly detrimental to water quality (Harris, 2002; Allan, 2004b; Waite, 2014; Parece & Campbell, 2015; Brogna et al., 2017; Caldwell et al., 2023). This makes the preservation and/or restoration of natural vegetation within catchments and riparian zones an important water quality management strategy (Norris, 1993; Haycock et al., 2001; Stutter et al., 2012; de Mello et al., 2017; Sun et al., 2020; Cheng et al., 2022; Cooke et al., 2022). Pengelly and Fishburn (2002, p. 409) have concluded that "native vegetation is a valuable resource and an important key to maintaining the health of the land and waterways," while Piffer et al. (2021, p. 1) similarly suggested that "maintaining or restoring native vegetation cover is a promising intervention to sustain adequate water quality." A common strategy for protecting water quality from diffuse pollution is the establishment and maintenance of "buffer zones" of riparian vegetation (Norris, 1993; Haycock et al., 2001; Stutter et al., 2012; Sweeney & Newbold, 2014; Cole et al., 2020; Petersen et al., 2020). Cooke et al. (2022, p. 183) have summarised: "From reducing erosion and flood damage to maintaining cool water temperatures, filtering pollutants, protecting critical habitats, and enabling lateral connectivity, intact riparian zones mitigate many of the threats that degrade freshwater ecosystems."

The Typical Impacts of LULC on Surface Water Quality

Agricultural Land

There is an expansive body of literature documenting the manifold impacts of agricultural activities on water quality. These impacts are said to be considerable, well-established, and a major concern worldwide (Haygarth & Jarvis, 2002; Dallas & Day, 2004; Day & Dallas, 2011; Mateo-Sagasta et al., 2018; Chapman et al., 2020). Runoff from agricultural land has been described by Dallas and Day (2004, p. 123) as a "complex effluent" that typically contains elevated levels of nutrients, organic matter, dissolved salts, pesticides, sediments, and bacteria (see also Fraser, 2002; Vigil, 2003; Mateo-Sagasta et al., 2018; Chapman et al., 2020; Kronvang et al., 2020).

Perhaps the most widely reported impact of agriculture on water quality is the eutrophication of rivers and lakes due to the excessive input of nutrients—nitrogen and phosphorous—which may be applied to crops in the form of inorganic fertilisers, or present in the excreta of livestock (Haygarth & Jarvis, 2002; Baker, 2005; Meybeck et al., 2005; Dabrowski et al., 2013; Feld, 2013; Waite, 2014; Bosman et al., 2018; Mateo-Sagasta et al., 2018; Wepener et al., 2018; Bohenek & Sullіván, 2022). Nitrogen, when applied in excess of plant requirements, is highly mobile and easily leached from agricultural land by irrigation and/or precipitation. When land is cleared for planting, nitrogen loss increases as there are no plants to take up what is available in the soil (Haygarth & Jarvis, 2002; Bohenek & Sulliván, 2022). Phosphorous, while more resistant to leaching than nitrogen, is commonly transported along with the sediment particles to which it is often adsorbed, and even small amounts of phosphorous can have a significant impact on water quality (Haygarth & Jarvis, 2002; Chapman et al., 2020). Nutrient enrichment promotes excessive algal and macrophyte growth. This can result in a depletion of dissolved oxygen when these organisms respire, or when dead plant matter is decomposed by bacteria (Peters et al., 2005). Furthermore, blooms of cyanobacteria—a common symptom of eutrophication—can be toxic (Bohenek & Sulliván, 2022).

Another widely reported water quality impact associated with agricultural land (particularly when irrigated) is salinisation (Dallas & Day, 2004; Peters et al., 2005; Day & Dallas, 2011; Bosman et al., 2018; Mateo-Sagasta et al., 2018; Chapman et al., 2020). Although irrigation water may not contain high concentrations of dissolved salts, any solutes it does contain will remain in the soil when it evaporates. Over time, these salts build up in the soil profile and are eventually leached into nearby water bodies when there is sufficient runoff (Dallas & Day, 2004; Wepener et al., 2018). Additionally, irrigation tends to cause an increase in the water table, which draws dissolved minerals into the surface layers of the soil profile. These similarly accumulate in the soil as water evaporates and are eventually washed into receiving water bodies during precipitation events (Dallas & Day, 2004). The clearing of land for cultivation may also increase groundwater recharge and raise water tables, with similar results (ibid.).

Turbidity and sedimentation are additional water quality problems frequently associated with agricultural land (Haygarth & Jarvis, 2002; Dallas & Day, 2004; Foley et al., 2005; Peters et al., 2005; Bosman et al., 2018; Mateo-Sagasta et al., 2018; Chapman et al., 2020). Sediments originate from land disturbed by cultivation, as well as from cleared/harvested fields where there is little or no vegetative cover to prevent erosion. Livestock may also promote erosion and the mobilisation of sediments through overgrazing and hoof action. Sediments, apart from their primary physical impact on aquatic environments, may also transport other contaminants that become affixed to soil particles (including phosphorous, pathogens, and pesticides) (Day & Dallas, 2011).

The application of toxic agrochemicals (including pesticides, herbicides, and fungicides) may further impact aquatic ecosystems (Haygarth & Jarvis, 2002; Dallas & Day, 2004; Foley et al., 2005; Bosman et al., 2018; Mateo-Sagasta et al., 2018; Chapman et al., 2020). These may enter water bodies through atmospheric deposition when they are applied to crops (i.e., "spray drift"), via accidental spills or through improper disposal, or when pesticide residues are flushed by precipitation or irrigation from the fields to which they have been applied (Haygarth & Jarvis, 2002; Dallas & Day, 2004; Bosman & Kidd, 2009).

Organic and bacteriological contamination, derived primarily from animal waste, are other common impacts of agriculture on water quality (Haygarth & Jarvis, 2002; Dallas & Day, 2004; Meybeck et al., 2005; Peters et al., 2005; Mateo-Sagasta et al., 2018; Chapman et al., 2020; Bohenek & Sulliván, 2022). When organic matter in the water decomposes, potentially hypoxic conditions can develop as oxygen demand increases. Some bacterial species are also pathogenic and can cause disease in animals and humans. In some instances, animal waste may also contain traces of heavy metals which are added to animal feeds or given as food supplements (Haygarth & Jarvis, 2002; Mateo-Sagasta et al., 2018). Antibiotics, hormones, and steroids—so called "emerging pollutants"[8]—may also be present in the excreta of treated livestock (Peters et al., 2005; Day & Dallas, 2011; Mateo-Sagasta et al., 2018; Chapman et al., 2020; Bohenek & Sulliván, 2022). Finally, reductions in flow from agricultural withdrawals can further influence water quality by reducing base-flow, thus increasing the in-stream concentrations of contaminants (Bosman et al., 2018; Chapman et al., 2020).

Urban/Built-Up Land

Urban/built-up land is typically characterised by impervious surfaces and may include residential areas, informal settlements, commercial property, and industrial zones. Although urban land is often associated with point-source pollution (e.g., end-of-pipe discharges from wastewater treatment or industrial works), it is also a significant source of diffuse pollution. Overall, urban land tends to have a disproportionately negative impact on water quality relative to the area it occupies (Paul & Meyer, 2001; CWP, 2003; Dallas & Day, 2004; Chapman et al., 2020).

Point-source discharges in urban areas are usually linked to industrial activities or wastewater treatment. These effluents, especially when not properly treated, often contain elevated levels of nutrients, organic matter, bacteria, dissolved solids, heavy metals, synthetic compounds, oils, and pharmaceutical products (Vigil, 2003; Dallas & Day, 2004; Chapman et al., 2020; Ahmed et al., 2022). However, compared with diffuse pollution, point-source discharges are (in theory) easier to regulate (Loague & Corwin, 2005; Peters et al., 2005; Crooks et al., 2021; Day & Davies, 2023). Nevertheless, as point-source pollution remains a significant concern in urban areas, it has been argued that from a remote-sensing/earth-observation perspective, the spatial extent of built-up land in a given landscape may be used as a proxy for the amount of point-source pollution that might be expected (Ahearn et al., 2005; Bu et al., 2014; Yu et al., 2016; Procopio & Zampella, 2022).[9]

Stormwater runoff from built-up/urban areas contains a wide range of contaminants that may reach waterways as diffuse pollution. These accumulate on urban surfaces through various deposition

[8] These are also referred to as "contaminants of emerging concern" (CECs) in some publications (Salimi et al., 2017; Feng et al., 2023a).

[9] Admittedly, correlations between proportions of built-up land and point-source pollution loads in a landscape will vary depending on the average density of discharge points per unit area, making proportions of urban land an imprecise proxy for point-source contamination potential.

mechanisms until they are flushed into receiving water bodies during precipitation events (Peters & Meybeck, 2000; Dallas & Day, 2004; Chapman et al., 2020; Goodspeed et al., 2022). Diffuse urban pollution may also originate from leaks in sewerage systems and/or wastewater treatment works, as well as from seepages and/or spills at industrial sites (CWP, 2003; Vigil, 2003; Chapman et al., 2020; D'Arcy et al., 2022a). Leachate from landfills and waste dumps are another source of diffuse urban pollution (Bosman et al., 2018; Bohenek & Sulliván, 2022).

Owing to this diverse range of sources, urban stormwater usually contains elevated levels of most contaminants (Paul & Meyer, 2001; CWP, 2003; Ahmed et al., 2022). Elevated concentrations of nutrients, derived from a variety of activities and sources, are often found in urban runoff (Paul & Meyer, 2001; CWP, 2003; Meybeck et al., 2005; Dabrowski et al., 2013; Wepener et al., 2018; Chapman et al., 2020; Bohenek & Sulliván, 2022). Phosphorous contributions of urban areas are even said to rival that of agricultural land in some cases (Paul & Meyer, 2001, p. 342). High suspended solid and sediment loads are also common in urban runoff, derived especially from construction activities or from the detritus that collects on roads and parking areas (CWP, 2003; Vigil, 2003; Dallas & Day, 2004; Day & Dallas, 2011; Dabrowski et al., 2013). In addition, elevated levels of dissolved salts are frequently found in urban stormwater (Paul & Meyer, 2001; Vigil, 2003; Dabrowski et al., 2013; Bohenek & Sulliván, 2022). Hydrocarbons, heavy metals, and a "whole suite" of other persistent organic compounds are likewise typically present in urban runoff (Paul & Meyer, 2001, p. 345; CWP, 2003; Vigil, 2003; Meybeck et al., 2005; Dabrowski et al., 2013; Chapman et al., 2020). Moreover, although pesticides are commonly associated with agricultural activities, they are also used in urban and industrial settings and thus often present in urban stormwater (Paul & Meyer, 2001; Gevao & Jones, 2002; CWP, 2003; Meybeck et al., 2005; Dabrowski et al., 2013; Chapman et al., 2020; Bohenek & Sulliván, 2022). Bacterial contamination is also common in urban stormwater, especially in effluents derived from informal settlements where sanitation services are limited (Paul & Meyer, 2001; CWP, 2003; Dallas & Day, 2004; Meybeck et al., 2005; Day & Dallas, 2011; Dabrowski et al., 2013; Chapman et al., 2020; Bohenek & Sulliván, 2022). Acid rain, a consequence of the atmospheric pollution often associated with urban and industrial areas, is another water quality concern linked to urban land use (Bosman et al., 2018; Chapman et al., 2020). Finally, urban runoff may also include a range of so-called emerging pollutants, including pharmaceuticals, hormones, solvents, and microplastics (Meybeck et al., 2005; Chapman et al., 2020; Bohenek & Sulliván, 2022). The combined impacts of these contaminants include salinisation, acidification, turbidity, eutrophication, hypoxic conditions, and general toxicity. In addition, due to the increased proportion of impervious surfaces (which reduces permeability and increases overland flow rates), the total load of harmful material flushed into urban streams, especially during heavy rainfall events, is much increased (Paul & Meyer, 2001; CWP, 2003; Peters et al., 2005; Day & Dallas, 2011; Parece & Campbell, 2015; Chapman et al., 2020). This is compounded by generally reduced base-flows, thus elevating the in-stream concentration of these contaminants

(Bohenek & Sulliván, 2022). Unsurprisingly then, urban streams are some of the most seriously impacted in the world (Paul & Meyer, 2001).

Mining Operations

Pollution from mining operations is a worldwide problem that can have a significant impact on surface water quality (Dallas & Day, 2004; Dabrowski et al., 2013; García et al., 2016; Chapman et al., 2020; de Mello et al., 2020). While working mines are undoubtedly a source of pollution, Chapman et al., (2020, p. 129) have argued that decommissioned or abandoned mines tend to have a greater impact on water quality. This is due to the cessation of pumping operations and the resurgence and ingress of groundwater, which floods the exposed mine workings and becomes contaminated. When this contaminated water reaches the surface, it may flow into nearby water bodies. Leaks and spills from tailings dams are another common source of sediment and other contaminants (Peters et al., 2005). The nature of the effluent derived from mining activities logically depends on the type of mine, as well as on the underlying geology of the area being mined. Ore-extracting substances such as cyanide, for example, may be present in runoff derived from gold mines (Dallas & Day, 2004), while elevated concentrations of sulphate are a well-known impact of coal mining (Dabrowski et al., 2013). However, effluent from mines typically have a low pH, high levels of suspended solids, and contain a variety of heavy metals (Dallas & Day, 2004; Meybeck et al., 2005; Day & Dallas, 2011; Bosman et al., 2018; Chapman et al., 2020). This leads to an increase in acidity, turbidity, sedimentation, and heavy metal concentrations in receiving waters. Contaminants in waters affected by mining may also precipitate out as a yellow or orange-brown flocculate (Chapman et al., 2020; Bohenek & Sulliván, 2022). The most frequently documented water quality impact of mining is acid mine drainage (AMD) (Dallas & Day, 2004; Weiner, 2013; Bosman et al., 2018; Wepener et al., 2018; Boyd, 2020; Chapman et al., 2020; Bohenek & Sulliván, 2022). The very low pH levels that result from AMD are not only directly harmful to aquatic ecosystems, but can also have additional impacts by increasing the availability and/or toxicity of other chemicals (a phenomenon known as synergism) (Dallas & Day, 2004, pp. 22–23; Peters et al., 2005; Boyd, 2020; Chapman et al., 2020; Bohenek & Sulliván, 2022).

Commercial Forestry

The impacts of commercial forestry operations on water quality are varied (Fulton & West, 2002; Duffy et al., 2020). The disturbance of land by clearing, planting, and harvesting results in increased erosion and the mobilisation of several contaminants, including eroded soil and sediments, nutrients, organic matter, and other debris (Vigil, 2003; Dallas & Day, 2004; Peters et al., 2005; Day & Dallas, 2011; Dabrowski et al., 2013; Duffy et al., 2020). Increased nutrient loading is common, usually following the application of fertiliser to plantations or through the leaching of soils disturbed during clearing, planting, or harvesting processes (Dallas & Day, 2004; Peters et al., 2005; Day & Dallas, 2011; Dabrowski et al., 2013; Duffy et al., 2020). The application of pesticides to commercial forestry plantations may also impact nearby receiving waters (Dabrowski et al., 2013). The clearing of stands can also result in an increase in the water table owing to reduced water uptake by plants. As this water evaporates from the surface soil layers, salts are left behind which may later be flushed into streams when it rains. As such, common water quality impacts associated with commercial forestry plantations include turbidity and sedimentation, salinisation, nutrient loading, and pesticide toxicity.

Forestry operations also influence local hydrology and flow dynamics. Due to changes in interception and groundwater abstraction, streamflow may be reduced during afforestation and conversely increased during harvesting (Dallas & Day, 2004). Plantations of non-indigenous trees can present a major threat to water resources by using more water than the natural vegetation they replace, reducing streamflow levels by up to 50% in some cases (Jewitt, 2005). As indicated above, reduced flows may elevate the in-stream concentrations of many contaminants (Peters et al., 2005). Reduced interception due to clearing may also increase overland flow rates, thereby increasing the pollutant load of overland runoff. Notwithstanding the above, there is also evidence which suggests that commercial forestry plantations, when properly managed, can have positive impacts on water quality (Duffy et al., 2020).

Conclusion

This chapter has described some of the typical impacts of LULC on water quality.[10] The negative impacts of agricultural land, urban areas, mining operations, and commercial forestry plantations were reviewed. The role that natural vegetation can play in protecting water quality was also discussed. Acknowledging, therefore, that anthropogenic land uses tend to have a detrimental impact on water quality, and that the preservation and/or restoration of natural vegetation can help to mitigate these impacts, it follows that in order to protect water resources, land use must be carefully managed by limiting potentially harmful land use transformations (Cooke et al., 2022, p. 2). This involves ensuring that sufficient areas of natural vegetation are maintained within catchment areas and riparian zones to protect water resources from diffuse pollution. The development of accurate models of the relationship between land use and water quality, and the estimation of land use thresholds from these models, can inform such management practices. The next chapter thus reviews how statistical approaches have been used for this purpose in the existing literature.

[10] For further reference, Appendix 1 summarises the nature, sources, and typical effects of several water quality parameters/pollutants that are either derived from, or influenced by, LULC.

CHAPTER 4:

Statistical Approaches to Assessing the Impacts of LULC on Water Quality

"Hundreds of studies document statistical associations between land use and measures of stream condition using multisite comparisons and empirical models, and collectively these studies provide strong evidence of the importance of surrounding landscape and human activities to a stream's ecological integrity."
–Allan (2004b, p. 263)

Introduction

In accordance with the principles of IWRM (see Chapter 2), developing effective strategies to manage the negative impacts of land use/land cover (LULC) on water quality necessitates that relevant stakeholders and policymakers are well-informed about the nature and magnitude of these impacts (Attua et al., 2014; Fatehi et al., 2015; Chidamba et al., 2016; Lintern et al., 2018; Malherbe et al., 2019b; Zhang et al., 2019; Nde et al., 2021; Nkosi et al., 2021). Accordingly, the importance of studying the relationship between LULC and water quality, and the use of statistical methods for this purpose, is widely affirmed in the literature. Wang and Yin (1997, p. 103), for instance, have asserted that "pollution prevention requires a clear understanding of the impacts of land use on stream water quality at a watershed level." Dabrowski et al. (2013, p. iii), with reference to the South African context, have also affirmed that "understanding the influence of land-use, in all its forms, on the quality of water… can soundly inform both water quality management and land use management." According to Lacher et al. (2019, p. 621), "understanding statistically derived relationships between measures of LULC change and water quality, and applying that understanding to land use planning is essential for the long-term protection of water resources." Li et al. (2022b) have similarly recognised that "exploring linkages between riverine water quality and land use is of great importance for catchment management and water quality conservation." Finally, Gobry et al. (2023, p. 1) have asserted that "understanding the correlation among land-use/cover and water quality parameters is vital for future water quality management."[11]

Although Wilson and Weng (2010, p. 1096) have reported that the relationship between land use and water quality "has not been extensively studied," there is in fact a large body of academic literature

[11] While none of the quoted publications explicitly refer to IWRM, the resonance of these assertions with the paradigm is clear.

dating back to the 1970s which demonstrates the use of statistical approaches to investigate, quantify, and/or model relationships between LULC and water quality. To undertake a review of this literature, potentially relevant publications were initially identified by conducting searches on the Scopus, Google Scholar, and Web of Science databases using appropriate Boolean search terms (see Table 1).

Table 1. Boolean search terms used to identify relevant publications.

<table>
<tr><td></td><td colspan="2">AND</td></tr>
<tr><td rowspan="5">OR</td><td>Land use</td><td rowspan="5">Water Quality</td></tr>
<tr><td>Land cover</td></tr>
<tr><td>Land-use</td></tr>
<tr><td>Land-cover</td></tr>
<tr><td>LULC</td></tr>
</table>

The results of these searches were further refined by manually reviewing document titles and abstracts for relevance. Articles which featured the use of statistical methods to investigate the relationship between landscape characteristics (including land use and land cover) and water quality were retained for review.[12] As the review progressed, citations in these articles were checked to locate additionally relevant material that had not been identified in the original searches. Supplementary research tools (e.g., Connected Papers) were also used to highlight key publications and trace links through the literature to other relevant articles. The aim of this largely heuristic, semi-systematic approach was to curate a representative (rather than exhaustive) collection of relevant literature.

A survey of the selected literature—which included approximately 300 peer-reviewed primary research and review articles—revealed several common themes and findings. Many of these findings, especially as they relate to typical source/sink dynamics, are now well established (Yao et al., 2023). However, it is also evident that, despite the wealth of research and published material available, there are still a number of knowledge gaps, areas of persistent uncertainty, and methodological issues that need to be addressed by further research (see Shen et al., 2015, p. 417; Wang et al., 2023b, p. 2). What follows is a high-level, critical review of these studies, in which common methods, findings, and limitations are noted and discussed. Particular attention is paid to the determination of LULC thresholds for the management of water quality.[13] Drawing the discussion together, the review closes by presenting a case for the estimation of thresholds of natural vegetation for the integrated management and protection of water quality.

[12] In a limited number of cases, and only to the extent that these provided additionally relevant insights, studies which used complex process-based hydrological models (rather than statistical approaches; see below) were also reviewed.

[13] Where relevant, additional threshold-related literature was consulted to provide conceptual context for this discussion.

The Advantages of a Statistical Approach

A number of complex "process-based" models have been developed that allow researchers to predict the impact of several catchment variables (including LULC) on both hydrology and water quality (Fatichi et al., 2016; Giri & Qiu, 2016; Yuan et al., 2020; Goodspeed et al., 2022; Horton et al., 2022; Wang et al., 2022). Well-known examples include the Soil & Water Assessment Tool (SWAT), the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) application, the Water Quality Analysis Simulation Program (WASP), the Agricultural Catchments Research Unit (ACRU) model, and the Water Quality Systems Assessment Model (WQSAM). However, these models have extensive data requirements and must be carefully calibrated to ensure accurate results (Giri & Qiu, 2016; Malherbe et al., 2019b; de Mello et al., 2020; Goodspeed et al., 2022; Yao et al., 2023). Consequently, they have been criticised as "typically data intensive and time-consuming" (Dabrowski et al., 2013, p. 14) as well as "over-parameterized, overly complex, and difficult to use" (Fatichi et al., 2016, p. 45). A recent South African study by Mararakanye et al. (2022) illustrates this point, and demonstrates that the performance of these models can be affected by a lack of data (see Appendix 5). Thus, while these models have been effectively used in cases where sufficient data and technical expertise are available, many researchers have sought alternative approaches (Giri & Qiu, 2016; Ullah et al., 2018; Łaszewski et al., 2022).

A variety of comparatively simple statistical approaches have therefore been widely used to quantify relationships between LULC and water quality (Giri & Qiu, 2016; Lintern et al., 2018; Rodríguez-Romero et al., 2018; Ullah et al., 2018; Cheng et al., 2022; Mashala et al., 2023; Yao et al., 2023). Sliva and Williams (2001) have asserted that, when coupled with Geographical Information Systems (GIS), statistical methods are effective for understanding the complex relationships involved in catchment management. According to Rothenberger et al. (2009, p. 521), such methods provide "a simple but effective analytical approach with predictive power." Studies by du Plessis et al. (2014, p. 2945; 2015, p. 648) have also affirmed that statistical approaches can "promote informed and accurate decision making within the water management sector" and thereby improve coordination at the interface between science, policy, and stakeholders. Gorgoglione et al. (2020, p. 2) have similarly argued that such models can "facilitate informed decision making in the design of measures to mitigate pollution impacts on receiving water bodies." According to a review by Giri and Qiu (2016), the relative simplicity of statistical models, coupled with their accuracy and predictive power, has made them attractive alternatives for many researchers (see also Ullah et al., 2018; Łaszewski et al., 2022). Cheng et al. (2022, p. 16) have thus reported that statistical approaches are now widely used in exploring the relationship between LULC and water quality, while Yao et al. (2023) have likewise affirmed that such approaches have proven to be effective alternatives to the data-intensive, complex process-based models mentioned above.

Indicators of Water Quality

The typical aim of the studies reviewed is to assess the statistical relationship between LULC (as an explanatory/independent variable) and water quality (as a response/dependent variable). To this end, various indicators have been used to estimate and measure water quality (Liu et al., 2010). Appendix 2 lists the most common indicators and cites examples of studies in which they have been used. Most studies used one or more physiochemical or microbiological water quality parameters as response variables (e.g., electrical conductivity, dissolved and/or suspended solids, pH, nutrient concentrations, dissolved oxygen, temperature, faecal coliform counts etc.). Several other studies used biological indices to measure water quality (i.e., assessments based on the diversity and/or abundance of aquatic species). The authors of these studies have argued that bioassessments have the advantage of being sensitive to, and thus reflecting, the combined effects (acute and chronic) of multiple physiochemical variables on aquatic ecosystems (Clapcott et al., 2012; Manfrin et al., 2016; Clément et al., 2017; Dalu et al., 2022; Prakoso et al., 2023). Abbasi and Abbasi (2011, p. 331) explain that “aquatic organisms, especially the community structure of organisms such as plankton, macroinvertebrates, fishes and benthos, fairly reflect not only the current water quality but also the overall ecosystem health of a water body.” Also worthy of mention are studies in which spectral indices derived from remote-sensing/earth-observation data were used to estimate the trophic state of water bodies (Bonansea et al., 2021; Baltodano et al., 2022).

In addition, several studies have used composite physiochemical water quality indices (WQIs) as response variables. The authors of these studies have advocated for the use of WQIs because of their ability to translate the observed measurements of multiple physiochemical parameters into a single unitless score of overall water quality (Umwali et al., 2021; Paná et al., 2022; Pandey et al., 2023). This is advantageous because water quality, when considered holistically, is a function of the cumulative effects of multiple parameters (Wang & Zhang, 2018). For example, du Plessis et al. (2015, p. 650) has emphasised the need to consider “a wide variety of water quality parameters… in order to obtain a holistic and accurate view of a water body’s water quality in terms of environmental and human health.” Moreover, Gossweiler et al. (2019, p. 2) have contended that “water quality as a whole is not clearly defined by studying these parameters separately.” The use of a WQI thus enables researchers to assess the cumulative impact of multiple individual variables which, in combination, determine the overall state of water resources. According to Schiff & Benoit (2007, p. 713) “multiparameter water quality indices have been used to serve a variety of functions by providing a simple, objective way of judging and ranking water quality that is more robust than any individual parameter.” This is especially important when considering the complex suite of pollutants contained in runoff derived from multiple land uses and their cumulative effect on water quality in catchment systems (Rhodes et al., 2001; Tsegaye et al., 2006; Schiff & Benoit, 2007; Shukla et al., 2018).

Land Use/Land Cover Data

Owing to the limitations of existing land cover maps, many researchers have elected to generate land cover data for their respective study areas from satellite imagery using a variety of GIS-based land cover classification procedures (e.g., Ding et al., 2015; Liu & Yang, 2018; Wang & Zhang, 2018; Gossweiler et al., 2019; Mallya & Rwiza, 2021; Senbore & Oke, 2021; Obubu et al., 2022; Torres-Bejarano et al., 2022; Waturu et al., 2023). In these studies, both supervised (e.g., Hua, 2017) and unsupervised (e.g., Baltodano et al., 2022) approaches have been used, including a variety of classification algorithms (e.g., maximum likelihood, support vector machine, and random forests). In such cases, satellite imagery of varying spectral and spatial resolution was obtained from a range of earth observation sensors, including MODIS (e.g., Bonansea et al., 2021), SPOT (e.g., Song et al., 2020), Sentinel (e.g., Palma et al., 2020), and Landsat (e.g., Torres-Bejarano et al., 2022). Cheng et al. (2022) confirm that medium-resolution satellite imagery (e.g., Landsat) is the main source of LULC data in these studies. Several other studies, however, have used existing land cover datasets (such as national thematic land cover maps) (e.g., Shupe, 2013; Midway et al., 2015; Martin et al., 2017; Malherbe et al., 2019a; Barnard et al., 2021; du Plessis, 2021; Allafta & Opp, 2022; Heidkamp & Christian, 2022; Ma et al., 2022; Paná et al., 2022). The principal advantage of using existing land cover maps is convenience, allowing researchers to save the time and effort required to generate accurate land cover maps from satellite imagery. However, existing data may not always be suitable for these studies. For instance, the spatial resolution of existing datasets may be too coarse for accurate estimations of land cover to be made at smaller analytical scales (e.g., within smaller sub-catchments). In addition, existing land cover maps for the specific period and/or area of interest may not be available. However, it may also be argued that existing land cover datasets—generated by professional GIS specialists with superior expertise, more experience, and greater access to financial and technological resources—are likely to be more accurate than those generated for ad hoc studies by researchers whose strengths and expertise lie in other areas.

Statistical Methods

Various statistical methods have been used to investigate the impacts of LULC on water quality, including Pearson's and Spearman's correlation analysis, principal component analysis (PCA), redundancy analysis (RDA), cluster analysis (CA), analysis of variance (ANOVA), and Kruskal–Wallis tests (a non-parametric version of ANOVA) (Pei et al., 2023).[14] Typically, these methods are used to

[14] More recently, artificial intelligence and machine learning approaches, including Random Forests (RF) and Artificial Neural Network (ANN) models, have been used to predict water quality from land use data (see Gazzaz et al., 2015; Park et al., 2021; Varadharajan et al., 2022; Zhang et al., 2022b; Bhatt et al., 2023; Venkateswarlu & Anmala, 2023). The results of these studies are promising, and it has been proposed that the use of artificial intelligence may promote the development of "more accurate, computationally tractable, and scalable models… [that have]… the potential to accelerate decision-relevant predictions and process understanding of river water quality" (Varadharajan et al., 2022, pp. 1, 13). Nevertheless, the effectiveness of comparatively simple statistical methods such as those noted above has been widely demonstrated in the published literature.

test for statistically significant relationships among (or between) LULC and water quality variables. They may also be used to test for significant differences in water quality between sites or across samples, which differences may then be attributed to variations in LULC. Reviews by Giri and Qiu (2016), Ullah et al. (2018), Cheng et al. (2022), and Mashala et al. (2023) provide further detail on how these methods have been applied. Various forms of regression analysis have also been used to develop statistical models of the relationship between LULC and water quality (Huang & Klemas, 2012; Ullah et al., 2018; Mashala et al., 2023). One such study reported that regression analysis was "very useful… for the quantification and prediction of water quality in relation to land cover change" and concluded that the technique has considerable utility as "a key tool for improved decision-making within the water management sector" (du Plessis et al., 2014, p. 2964). Examples of studies in which these methods have been used are given in Appendix 3.

Temporal versus Spatial Perspectives

When investigating the relationship between LULC and water quality, researchers tend to adopt either a spatial (i.e., cross-sectional) or temporal (i.e., longitudinal) perspective. The cross-sectional approach, which is by far the most common, involves investigating possible correlations between LULC and water quality across multiple independent locations at a particular "moment" in time (typically a period of several months over which conditions are averaged).[15] Together, these locations are intended to provide a statistical sample that is representative of varying types and degrees of LULC in the study area, spanning a continuum of minimally to highly impacted sites (i.e., a "human disturbance gradient" as described in Soranno et al., 2011, pp. 141, 144). Across this sample, LULC and water quality data from each location are paired in order to examine relationships between these two variables (Nobre et al., 2020; Yao et al., 2023). Commonly used statistical methods for this approach include correlation analysis, regression analysis, and principal component analysis. While this approach is especially useful when historical land use or water quality data for the region of interest are either unavailable or unreliable (a common problem in developing countries), it has the disadvantage of introducing additional explanatory variables into the sample, which can make it difficult to ascribe variation in water quality to differences in LULC (i.e. variation in environmental variables such as geology, climate, and topography between sites may also explain differences in water quality; see below).

A related spatial approach is to compare water quality between sites (or groups of sites), each of which are representative of distinct LULC conditions, in order to determine whether differences in water quality between these locations may be attributed to differences in LULC. Statistically, these sites

[15] Recent examples of cross-sectional studies include Chen and Olden (2020), Huang et al. (2020), Mirzaei et al. (2020), Mwaijengo et al. (2020), Palma et al. (2020), Park and Lee (2020), Song et al. (2020), Barnard et al. (2021), Crooks et al. (2021), Dymek et al. (2021), Hanna et al. (2021), Li et al. (2021), Liu et al. (2021), Umwali et al. (2021), Vera Mercado and Engel (2021), Zhang et al. (2021), Aalipour et al. (2022), Allafta and Opp (2022), Heidkamp and Christian (2022), Kuranchie et al. (2022), Łaszewski et al. (2022), Li et al. (2022b), Zhang et al. (2022b), Zhong et al. (2022), and Zhou et al. (2022).

represent distinct land use “populations”, between which statistically significant differences in water quality may be attributable to the differences in LULC.[16] In these instances, frequently used statistical methods include *t*-tests, ANOVA, or Kruskal–Wallis tests.

In longitudinal studies, researchers typically investigate the impacts of changes in LULC on water quality at a single location over a given period of time (usually several years/decades).[17] For instance, researchers may observe changes in water quality over time at a given location, associated with either urban or agricultural expansion during the same period, thus allowing this relationship to be modelled using time-series data. The primary benefit of using time-series data from a single location is that it essentially eliminates the problem of between-site variation among other variables (a common limitation of cross-sectional studies), meaning that changes in water quality can be attributed to land use with greater confidence.

General Trends

There has been remarkable consistency in the findings of the reviewed studies, especially in terms of the overall influence—whether positive or negative—that different classes of LULC tend to have on water quality. In the vast majority of studies, for example, it has been reported that urban and agricultural land have a statistically significant and overwhelmingly negative impact on water resources (i.e., as proportions of urban and agricultural land increase, water quality tends to become increasingly impaired). Increased impervious surface cover, which is typically associated with urban land use, has also been consistently linked to water quality impairment. Several studies have also reported negative water quality impacts associated with areas of bare/disturbed ground. Conversely, many studies have reported that proportions of natural vegetation (typically forests) are positively correlated with water quality (or, alternatively, that a loss of vegetative cover is detrimental to water quality). It is therefore widely acknowledged that while increased proportions of urban and agricultural land cover tend to be correlated with negative water quality impacts, undeveloped areas of natural vegetation are generally associated with improved water quality (Ullah et al., 2018; Fernandes et al., 2021; Wang et al., 2021; Cheng et al., 2022; de Mello et al., 2022; Li et al., 2022b; Caldwell et al., 2023; Qiu et al., 2023; Siqueira et al., 2023; Xu et al., 2023a; Zhang et al., 2023b). These studies have further established that the loss of natural vegetation in catchments is universally detrimental to water quality (Prakoso et al., 2023; Qiu et al., 2023). Also noteworthy, although far less consistent, are the findings of studies in which Normalised Difference Vegetation Index (NDVI) values, being indicative of photosynthetic activity

[16] Recent examples include Petersen et al. (2020), Ramião et al. (2020), Dlamini et al. (2021), Mahabeer and Tekere (2021), Clark et al. (2022), Dalu et al. (2022), de Mello et al. (2022), Makgoale et al. (2022), and van Deventer et al. (2022).
[17] Recent examples of studies that have taken a temporal (i.e., longitudinal) perspective include Dunea et al. (2020), Tahiru et al. (2020), Bonansea et al. (2021), Mallya and Rwiza (2021), Molekoa et al. (2021), Senbore and Oke (2021), Baltodano et al. (2022), Mararakanye et al. (2022), Obubu et al. (2022), Gobry et al. (2023), and Goswami et al. (2023).

and thus the vegetative condition of landscapes, were significantly correlated with several water quality indicators (e.g., Griffith et al., 2002a; Chu et al., 2013; Masocha et al., 2017; Chen et al., 2021; Senbore & Oke, 2021; Wang et al., 2021; Torres-Bejarano et al., 2022; Pandey et al., 2023). Appendix 4 lists examples of publications in which the above findings have been reported. The consistency of these results, although unsurprising given what is now known about the typical impacts of land use on water resources, is nevertheless remarkable considering that these studies have not only been conducted across a range of different geographic contexts, but also in view of the wide variety of methods and metrics used when conducting the analyses (i.e., despite these contextual and methodological differences, the majority of the studies have reported similar findings).

Defining and Classifying Natural Vegetation

As noted in the preceding section, one of the key findings reported in the literature is that the extent of natural vegetation in a landscape tends to be positively associated with improved water quality. However, an important assumption worth noting is that, in the context of these studies, forests are often presumed (whether implicitly or explicitly) to be representative of natural vegetation. Tiner (2004, p. 228) for instance lists "the percent of *forest* in the watershed" (emphasis added) when describing common means by which LULC change and habitat disturbances have been measured in similar research. This assumption is further illustrated in a recent article by Caldwell et al. (2023, p. 2), in which the importance of "natural land cover" for maintaining water quality is discussed, and which opens with the universal assertion that "*forests* and water are inextricably linked… and millions of people depend on *forests* for clean and reliable drinking water supplies" (emphasis added). In most studies this association is similarly implicit: while the term "natural vegetation" is not always used explicitly, its equivalence with forests is implied when forested land is juxtaposed against land cover classes which, in the context of the study, typify anthropogenic disturbance (such as urban or agricultural land). Thus, in such studies, forested land, by implication, represents undisturbed (i.e., naturally vegetated) areas.[18] In other studies, however, "natural vegetation" or "natural land cover" may be explicitly defined as, or represented by, forested land.[19] This assumed equivalence may be explained by the fact that most of the existing research has been conducted in temperate regions in the northern hemisphere, where forests are generally the dominant class of indigenous vegetation. [20]

[18] See, for example, Death and Collier (2010), Miller et al. (2011), Feld (2013), Ye et al. (2014), Ding et al. (2015), Midway et al. (2015), Chen et al. (2016), Brogna et al. (2017), Clément et al. (2017), de Mello et al. (2017), de Mello et al. (2018), Morse et al. (2018), Cecílio et al. (2019), Song et al. (2020), Vera Mercado and Engel (2021), Wang et al. (2021), de Mello et al. (2022), Zhong et al. (2022), Liu et al. (2022), Prakoso et al. (2023), Qiu et al. (2023), and Wang et al. (2023a).
[19] See, for example, Maloney and Weller (2011), Yu et al. (2013), Zhang et al. (2021), and Allafta and Opp (2022).
[20] See the section titled "Geographic Bias in the Existing Research and the State of Research in South Africa" below.

Some studies, by contrast, have explicitly broadened their classification of naturally vegetated areas to include other vegetative land cover classes, such as shrubland,[21] grassland,[22] and wetlands.[23] In a particularly relevant study by Iñiguez-Armijos et al. (2014, pp. 1–3), which aimed to investigate the influence of vegetation cover on water quality and thereby determine how much vegetation is required to sustain healthy streams, the authors explicitly aggregated "all types of native vegetation" into a single land cover class (see also Sponseller et al., 2001; Shiels, 2010; Bierschenk et al., 2012; and Pandey et al., 2012, in which studies similar approaches were taken). Similarly, when proposing new remotely-sensed indicators for monitoring the condition of "natural habitat" in watersheds, Tiner (2004, pp. 230–231) defined the latter as "plant communities represented by forests, meadows, marshes, swamps, and shrub thickets" and continued to suggest that "for a watershed, natural habitat integrity can be measured by extent to which a watershed is represented by forests, grasslands, and other natural ecosystems."

Although the rationale by which natural vegetation is defined and/or classified in these studies is seldom discussed, it is by no means a moot point. For instance, in biomes in which forests are *not* the dominant class of indigenous vegetation (e.g., savannas or grasslands), it may be inappropriate to assume that areas of forested land are adequately representative of the extent of natural land cover in a given landscape. Therefore, when investigating the impacts of LULC on water quality it may be more appropriate, in some contexts, to select other vegetative land cover classes, or aggregations thereof, when defining or classifying natural vegetation (e.g., shrublands or grasslands).

Moreover, as noted by Cole et al. (2020, p. 3), the morphological and functional traits of different plant species can influence their impact on water resources. For instance, depending on their physiological, structural, and life-cycle characteristics, different plant species may be more or less effective at intercepting and removing contaminants from overland flow, and thus at protecting water resources from diffuse pollution. For instance, in a study by Petersen et al. (2020, p. 347) comparing the nature of runoff generated by different categories of LULC, it was concluded that "the vegetation structure (mixture of trees, shrubs and herbs) and composition (vegetation taxonomic type) of the riparian buffer zone play an important role in the buffering capabilities [of these areas]."

Therefore, while grassland is typically expected to act as a detention medium by trapping contaminants in overland flow before they reach receiving waters, there is evidence which suggests that grassland may not consistently serve as an effective buffer against diffuse pollution (and may, especially when

[21] See, for example, Tiner (2004), Nash et al. (2009), Shiels (2010), Bonansea et al. (2016), Manfrin et al. (2016), Yu et al. (2016), Gebel et al. (2017), Petersen et al. (2017), Shi et al. (2017), Gossweiler et al. (2019), Malherbe et al. (2019a), Malherbe et al. (2019b), and Ogbozige and Alfa (2019).

[22] See, for example, Tiner (2004), Uuemaa et al. (2007), Nash et al. (2009), Shiels (2010), Bonansea et al. (2016); Xu et al. (2016), Shi et al. (2017), Tromboni and Dodds (2017), Gossweiler et al. (2019), Malherbe et al. (2019a), Malherbe et al. (2019b), Ogbozige and Alfa (2019), Palma et al. (2020), de Mello et al. (2022), and Zhang et al. (2022a).

[23] See, for example, Booth et al. (2002), Tiner (2004), Shiels (2010), Xu et al. (2016), and Malherbe et al. (2019a).

degraded or used to graze livestock, be a source of contaminated runoff).[24] In addition, while commercial forestry is typically expected to have a negative impact on water quality (especially during planting and/or harvesting phases when soil is disturbed or when fertilisers are applied), such plantations, if carefully managed, may in fact provide beneficial ecosystem services that improve water quality and protect water resources from diffuse pollution (Ide et al., 2019; Malherbe et al., 2019b; Duffy et al., 2020). Therefore, it may be similarly inappropriate to assume that *all* locally occurring classes of natural vegetation will provide water resources with effective protection from diffuse pollution, while simultaneously assuming that all other classes of vegetative land cover (e.g., commercial forestry) are detrimental to water quality.

Therefore, as research into the impacts of land use on water quality gradually extends into regions in which forests may not be the only, nor the dominant, category of indigenous vegetation, the question of how natural vegetation should be defined and/or classified should be decided on a case-by-case basis, taking both local conditions and the specific aims/objectives of the study into account. This not only applies to the classification of remotely sensed data using GIS, but also when using existing land cover datasets. When classifying remotely sensed data, researchers need to define appropriate thematic classification schemes by which to classify the different spectral classes of natural vegetation as they appear in the satellite imagery. For example, these may be classified into individual sub-classes of natural vegetation (e.g., "forests", "woodland", "shrubland", "grassland", or "wetlands") or into a single aggregate class of "natural vegetation" or "natural land cover". When using existing land cover datasets, researchers may consider which of the existing thematic land cover classes, as they appear in the map, can or should be aggregated into a single aggregate class that is representative of natural vegetation in the study area (if this is desired and supportive of the research aims). In either case, it should not be assumed that any single vegetative land cover class (such as forests) would be satisfactorily representative of natural vegetation in a given area, nor that an aggregation of all locally occurring vegetation would automatically provide the best representation of land cover with good buffering potential. Instead, when assessing the relationship between LULC and water quality, consideration should be given to developing contextually appropriate metrics by which to define and/or classify natural vegetation.

The Significance of Landscape Configuration

Given that certain land cover classes are typically sources of diffuse pollution, and that others act as sinks, it follows that the overall *composition* of the landscape (i.e., the proportion of the landscape occupied by different classes of LULC) will have an impact on water quality (Griffith, 2002; Shen et

[24] See, for instance, Ahearn et al. (2005), Amiri and Nakane (2006), Xiao and Ji (2007), Ding et al. (2013), Shen et al. (2014), Chen et al. (2016), Vrebos et al. (2017), Asare et al. (2018), Lacher et al. (2019), Chen et al. (2021), Dymek et al. (2021), and Zhou et al. (2022).

al., 2015; Aalipour et al., 2023). However, it has also been suggested—and subsequently demonstrated in several studies—that the *configuration* of a landscape may also significantly influence the relationship between LULC and water quality.[25] Whereas composition refers to the extent of each class of land cover within a landscape (without explicitly considering the arrangement or location of land cover patches), configuration relates to the spatial arrangement, position, and/or distribution of land cover within a given landscape (Griffith et al., 2002b; Thomas et al., 2020; Ene & McGarigal, 2023e; Xu et al., 2023b; Zhang et al., 2023b). Ding et al. (2016, p. 206) explain that composition metrics are only "coarse predictors of water quality" and that they "do not discriminate between different landscape configurations, such as the patch size, patch shape, edge configuration or spatial interconnection of patches of land use types within a landscape." D'Arcy et al. (2022a, p. 2) confirm that while the composition of a landscape determines the types of pollutants available for mobilisation, other landscape characteristics, including configuration, influence "the extent to which pollutants… are likely to be exposed and mobilised by weather conditions." Several authors have therefore contended that landscape composition may not be sufficient, on its own, to account for variations in water quality. These authors have noted that the configuration of a landscape may influence (among other hydrological processes) the nature, pathways, and quantity of surface runoff generated during precipitation events (which, in turn, will influence the contaminant loads mobilised and transported into receiving water bodies from the land surface) (Shen et al., 2015; Song et al., 2021; Aalipour et al., 2023; Mo et al., 2023). Consequently, these authors have emphasised the importance of considering configuration as a potentially significant variable when investigating the influence of LULC on water quality (Kearns et al., 2005; Huang & Klemas, 2012; Slaughter & Mantel, 2017; Gorgoglione et al., 2020; Wang et al., 2021; Wu & Lu, 2021; de Mello et al., 2022; Zhang et al., 2022a; Deng et al., 2023; Yao et al., 2023).

Landscape configuration may be measured using a number of landscape pattern metrics (LPMs), which include estimates of aggregation and/or fragmentation, patch size and/or patch density, as well as the diversity of land cover types contained within the landscape (McGarigal, 2001; Griffith et al., 2002b; Uuemaa et al., 2009; Zhou et al., 2012; Yu et al., 2013; Wang et al., 2014; Zhang et al., 2019; Liu et al., 2021). Some of these metrics measure configuration at the *landscape level* (i.e., the diversity and/or spatial arrangement of all land cover types within a landscape), whereas other metrics measure configuration at the *class* or *patch level* (i.e., the spatial arrangement of patches of a specific class of land cover within a landscape) (Xu et al., 2023b). While the majority of studies focus on landscape-

[25] See, for example, Hunsaker and Levine (1995), Johnson et al. (1997), Lammert and Allan (1999), Griffith (2002), Strayer et al. (2003), Kearns et al. (2005), King et al. (2005), Snyder et al. (2005), Uuemaa et al. (2007), Lee et al. (2009), Uuemaa et al. (2009), Huang and Klemas (2012), Liu et al. (2012), Zhou et al. (2012), Bateni et al. (2013), Yu et al. (2013), Bu et al. (2014), Qiu and Turner (2015), Shen et al. (2015), Chaplin-Kramer et al. (2016), Chen et al. (2016), Ou et al. (2016), Clément et al. (2017), Shi et al. (2017), Lintern et al. (2018), Wang and Zhang (2018), Zhang et al. (2019), de Mello et al. (2020), Mirzaei et al. (2020), Thomas et al. (2020), Chiang et al. (2021), Dymek et al. (2021), Aalipour et al. (2022), Cheng et al. (2022), Zhang et al. (2022a), Zhong et al. (2022), Zhou et al. (2022), Aalipour et al. (2023), Xu et al. (2023a), Xu et al. (2023b), and Zhang et al. (2023b).

level configuration, Huang and Klemas (2012) and Xu et al. (2023b) have both suggested that class-level assessments of configuration may be more appropriate.

Relevant to the current study is the common assumption that as natural vegetation cover becomes more fragmented, its ability to act as a sink/buffer is reduced (Gergel et al., 2002; Lee et al., 2009; Shupe, 2013; Yirigui et al., 2019; Cole et al., 2020; de Mello et al., 2020; Thomas et al., 2020; Fernandes et al., 2021; de Mello et al., 2022; Bowes et al., 2023; Zhang et al., 2023a). Figure 6 below illustrates two hypothetical catchments, each containing the same amount of natural vegetation but exhibiting different degrees of fragmentation. The vegetation in the catchment on the left is arranged in larger, more aggregated patches, whereas the patches of vegetation in the catchment on the right are smaller, less regular, and more fragmented.

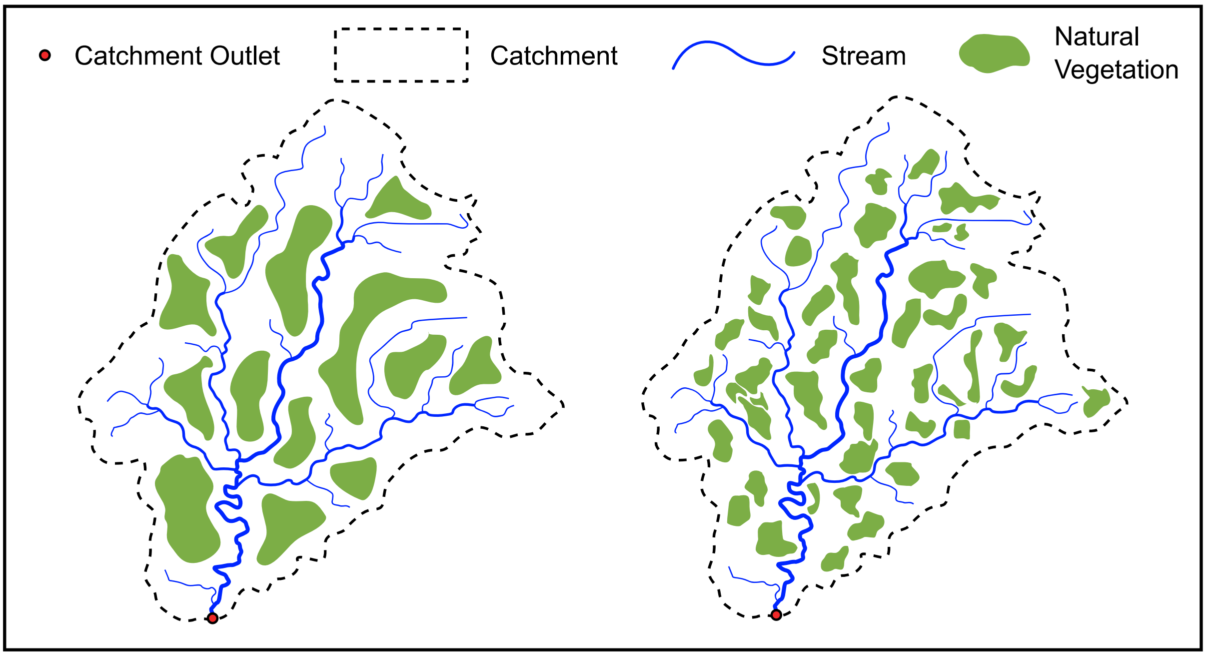

Figure 6. Illustration showing two hypothetical catchments, each containing the same amount of natural vegetation but demonstrating different degrees of class-level fragmentation. Patches of natural vegetation in the catchment on the left are more aggregated, while those in the catchment on the right are more fragmented.

The size, shape, and spatial arrangement of patches of natural vegetation in a landscape (i.e., their configuration and the degree to which they are fragmented) are likely to influence their ability to trap and intercept surface runoff and thus act as sinks for transported contaminants (Yirigui et al., 2019). According to Lintern et al. (2018, p. 15), for example, “small and fragmented forests… are… not as effective at reducing the contaminants contained in runoff from other sources (e.g., urban, agricultural land uses) within the catchment.” Xu et al. (2023a, p. 10) have thus emphasised the necessity of maintaining “large and intact” areas of forest to protect water resources. In addition, Wang et al. (2021) suggest that fragmentation may also be indicative of anthropogenic disturbance within a landscape and may therefore signify the presence of other pollution-generating land uses (see also Griffith, 2002, p. 855).

Several studies have tested the relative influence of landscape configuration on water quality, and many have found that increased fragmentation—especially of natural vegetation such as forests—is associated with poorer water quality. Lee et al. (2009), for instance, found that oxygen demand in rivers increased when surrounding forests became more fragmented. Similarly, Ye et al. (2014) and Ding et al. (2016, p. 212) found that greater fragmentation reduced the ability of vegetation to intercept surface runoff and contain diffuse pollution. Shen et al. (2014, p. 96) reported that "large area[s] of unfragmented forest" are important for diffuse pollution control in urban catchments. Liu and Yang (2018, pp. 11, 12) found that landscape fragmentation was an important driver of water quality degradation and thus recommended that management plans should focus on increasing the "extent and density" of natural landscapes to improve water quality in urban stream systems. Yirigui et al. (2019) found that while the relative amount of riparian forest cover had a positive relationship with biological indices, increased fragmentation of forest cover was negatively correlated with stream health. Bateni et al. (2013) reported that non-fragmented natural vegetation was positively correlated with water quality, while Zhang et al. (2019, p. 84) similarly found that "non-broken large forest land patches" were more effective at filtering contaminants. Wu and Lu (2021) also concluded from the results of their study that the fragmentation of riparian vegetation was likely to reduce its effectiveness as a sink. Similarly, when comparing water quality across catchments, de Mello et al. (2022) observed that forest fragmentation had a negative impact on water quality. Liu et al. (2021, p. 7) also observed that "scattered" forest land tends to be linked with poor water quality (being correlated in their study with increased chemical and biological oxygen demand). Another study also found that when the dominant land cover type in a landscape was forest or grassland, aggregation between patches was linked to better water quality (Zhong et al., 2022). In a recent meta-analysis, Qiu et al. (2023) reported that the fragmentation of forest landscapes is usually associated with increased nitrogen pollution.[26]

While the assumption that fragmented patches of natural vegetation will be less effective at intercepting contaminated runoff is reasonable, and notwithstanding the evidence which supports this supposition, this may not always be the case (see, for example, Lee et al., 2009; Qiu & Turner, 2015; Clément et al., 2017; Thomas et al., 2020; Liu et al., 2021; Qiu et al., 2023; Yao et al., 2023). For instance, it is logical to presume that contiguous patches of vegetative cover within riparian zones are more likely to effectively intercept surface runoff than fragmented patches. However, when considered at other scales, it is conceivable that smaller, more irregular patches of natural vegetation, which are evenly distributed throughout the landscape, may be more effective at filtering overland flow than a single aggregated patch of natural vegetation that is far removed from the receiving water body (and thus not in a position, literally speaking, to intercept overland flow). Thus, depending on the location of vegetation within a landscape, patches that are more fragmented may, in theory at least, be more effective at intercepting

[26] From these citations, it is once again evident that forests are typically presumed to be representative of natural land cover in these studies.

surface runoff (Thomas et al., 2020). Clément et al. (2017, p. 627) thus concluded that "there remains significant uncertainty regarding the effect of the spatial configuration of different types of land cover on water quality" (see also the conclusions of Mo et al., 2023; Qiu et al., 2023). Nevertheless, it is often concluded that, rather than considering either one or the other, the potential influence of both landscape composition *and* configuration should be investigated (Uuemaa et al., 2007; Lee et al., 2009; Yu et al., 2013; Qiu & Turner, 2015).

Location and Scale

The location of LULC within a catchment in relation to receiving water bodies has also been found to significantly influence its relationship with water quality (Morse et al., 2018). Therefore, the nature and strength of these relationships, in so far as they are estimated from statistical analyses, will be determined to a large degree by the scale at which the analysis is conducted (Fernandes et al., 2021; Cheng et al., 2022).[27] In other words, the relationship between LULC and water quality, and analyses thereof, are said to be "scale-dependent" (de Oliveira et al., 2017; Lintern et al., 2018; Lacher et al., 2019; Zhang et al., 2019; Song et al., 2020; Li et al., 2022b; Torres-Bejarano et al., 2022; Siqueira et al., 2023; Xu et al., 2023a). The importance of considering scale when investigating the impacts of LULC on water quality has thus been confirmed in many publications.[28]

Studies that investigate the relationship between LULC and water quality typically test for correlations at four different scales: (1) whole catchment, (2) riparian buffer zone, (3) local contributing area, and (4) riparian-reach buffer zone (Iñiguez-Armijos et al., 2014; de Oliveira et al., 2017; de Mello et al., 2020; Song et al., 2020; Fernandes et al., 2021; Łaszewski et al., 2022; Zhou et al., 2022; Mashala et al., 2023; Wang et al., 2023a; Xu et al., 2023a). In the context of these studies, the catchment is usually defined as the area of land drained by a stream network, upstream of a point at which water quality is monitored (i.e., the catchment outlet). At the whole-catchment scale, LULC is measured across the full extent of the catchment. At the riparian buffer zone (RBZ) scale, LULC is measured within a linear buffer of specified width that runs along the entire length of the primary watercourse and its tributaries. At the local contributing area (LCA) scale, a circular buffer of specified radius is extended from the outlet and clipped to the boundaries of the catchment. At the riparian-reach buffer zone (RRBZ) scale,

[27] In this context "scale" refers to the size and location of the area under analysis within a catchment, rather than to the size of the catchment itself.

[28] See, for example, Steedman (1988), Allan and Johnson (1997), Fitzpatrick et al. (2001), Gove et al. (2001), Sliva and Williams (2001), Buck et al. (2004), King et al. (2005), Schiff and Benoit (2007), Magierowski et al. (2012), Pratt and Chang (2012), Shupe (2013), Yu et al. (2013), Ye et al. (2014), Shen et al. (2015), Ding et al. (2016), Ou et al. (2016), Martin et al. (2017), Shi et al. (2017), Grimstead et al. (2018), Lintern et al. (2018), Mainali and Chang (2018), de Mello et al. (2020), Mwaijengo et al. (2020), Song et al. (2020), Vera Mercado and Engel (2021), Zhang et al. (2021), Heidkamp and Christian (2022), Kuranchie et al. (2022), and Zhong et al. (2022).

the linear buffer extends a specified distance upstream of the outlet along the watercourse. Figure 7 below illustrates each of these analytical scales.

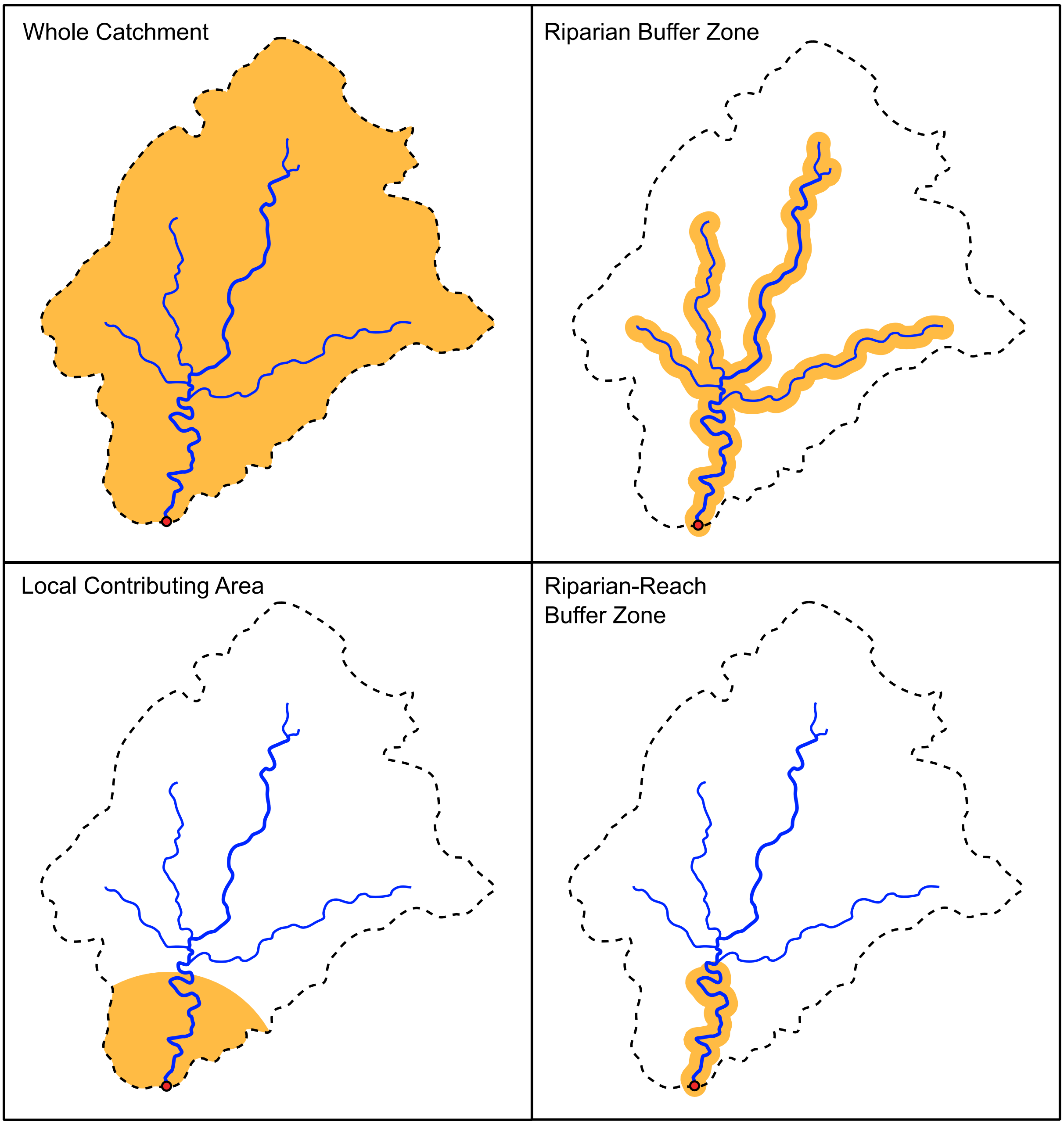

Figure 7. Illustration showing the spatial scales (shaded orange) at which relationships between LULC and water quality are typically tested: whole-catchment (upper left); riparian buffer zone (RBZ) (upper right); local contributing area (LCA) (lower left); riparian-reach buffer zone (RRBZ) (lower right).

A key question is whether LULC across the whole catchment, versus LULC adjacent to water bodies, is most significant in terms of its influence on water quality (de Mello et al., 2020; Song et al., 2021; Cheng et al., 2022). It is commonly assumed, for instance, that anthropogenic LULC directly adjacent to rivers and streams (i.e., riparian land use) is likely to have the most significant impact on water quality (Johnson et al., 1997; Gove et al., 2001; Tiner, 2004; Waite et al., 2010; Miller et al., 2011; Ou et al., 2016; Ramião et al., 2020; Han et al., 2023; Roldán-Arias et al., 2023; Xu et al., 2023b). Similarly, vegetation within riparian areas, which has the potential to intercept contaminated runoff generated in other areas, is often seen as the “last line of defence” for water quality protection (Song et al., 2021, p. 1). However, the cumulative effects of LULC across the entire catchment may be too great to be effectively mitigated or offset by riparian land use (Brabec et al., 2002; Allan, 2004a, 2004b; Brabec, 2009; Tran et al., 2010; Tromboni & Dodds, 2017; Ramião et al., 2020; Thomas et al., 2020). Thus, despite the logical importance of managing LULC within riparian areas, land use decisions across the entire catchment may be equally as important—if not more important—as those made within riparian zones (Brabec et al., 2002; de Mello et al., 2020; Ramião et al., 2020).

Of the multiscale studies reviewed, several reported that the influence of LULC adjacent to water bodies (e.g., within riparian buffer zones) was more significant in terms of its impact on water quality than LULC at the whole-catchment scale.[29] Conversely, a number of studies have reported that LULC at the whole-catchment scale was more significant than riparian LULC.[30] To further complicate matters, several studies have described “multiscale effects” (wherein some water quality parameters were more significantly correlated to LULC at the whole-catchment scale, while other water quality parameters were more strongly influenced by LULC within riparian areas).[31] Noting the varying results of these studies, Bohenek and Sullliván (2022) have concluded that considering the impacts of LULC at both the whole-catchment and riparian buffer zone scales is advisable.

The results of studies in which the influence of land use within riparian buffers of varying width have been compared have been inconsistent (Han et al., 2023). For example, several studies found that LULC within a 100 m riparian buffer zone was most significant (e.g., Shen et al., 2015; Nava-López et al., 2016; Ou et al., 2016; Mainali & Chang, 2018). Other researchers, however, reported that LULC had the most significant influence on water quality at greater buffer widths, including 200 m (e.g., Dai et al., 2017), 400 m (e.g, Wang & Zhang, 2018), 1000 m (e.g., Xu et al., 2016; Huang et al., 2020), and 1100 m (e.g., Zhong et al., 2022).[32]

[29] See, for example, Osborne and Kovacic (1993), Johnson et al. (1997), Basnyat et al. (1999), Lammert and Allan (1999), Fitzpatrick et al. (2001), Roy et al. (2003), King et al. (2005), Schiff and Benoit (2007), Riseng et al. (2010), Tran et al. (2010), Iñiguez-Armijos et al. (2014), Shen et al. (2015), Nava-López et al. (2016), Shi et al. (2017), Wang and Zhang (2018), Huang et al. (2020), Wu and Lu (2021), Zhong et al. (2022), and Zhou et al. (2022).
[30] See, for example, Omernik et al. (1981), Steedman (1988), Hunsaker and Levine (1995), Roth et al. (1996), Allan et al. (1997), Sliva and Williams (2001), Sponseller et al. (2001), Griffith et al. (2002b), Jarvie et al. (2002), Allan (2004a), Buck et al. (2004), Young et al. (2005), Zampella et al. (2007), Death and Collier (2010), Magierowski et al. (2012), Nielsen et al. (2012), Pratt and Chang (2012), Ding et al. (2016), Brogna et al. (2017), Clément et al. (2017), de Mello et al. (2018), Park and Lee (2020), Łaszewski et al. (2022), and Deng et al. (2023).
[31] See, for instance, Jarvie et al. (2002), Strayer et al. (2003), Uriarte et al. (2011), Zhou et al. (2012), Chen et al. (2016), de Mello et al. (2018), Zhang et al. (2019), Song et al. (2020), Heidkamp and Christian (2022), and Kuranchie et al. (2022).
[32] In the reviewed studies, riparian buffer widths ranged from 30 m (e.g., de Mello et al., 2018) to 2000 m (e.g., Chen et al., 2016), while the buffer width at which the influence of LULC was most frequently assessed appears to be 100 m (e.g., Johnson et al., 1997; Lammert & Allan, 1999; Sliva & Williams, 2001; King et al., 2005; Schiff & Benoit, 2007; Li et al., 2009; Nielsen et al., 2012; Waite, 2014; Shen et al., 2015; Chen et al., 2016; Nava-

Song et al. (2021) have noted that, among the factors that have contributed to ongoing uncertainty regarding the influence of LULC at different scales, a lack of methodological clarity is a common problem. One issue that has not been considered when investigating the influence of riparian LULC on water quality is the scale (or spatial resolution) of the stream network layer for which riparian buffer zones are delineated in a GIS environment. For instance, a low-resolution (i.e., large-scale) stream network layer would contain only major rivers and some higher-order tributaries. By contrast, a high-resolution (i.e., small-scale) GIS layer would also include lower-order tributaries. As a greater number of lower-order tributaries are included in the network, the total area occupied by the riparian buffer zones delineated for this layer will occupy a greater proportion of the catchment area (see Figure 8).

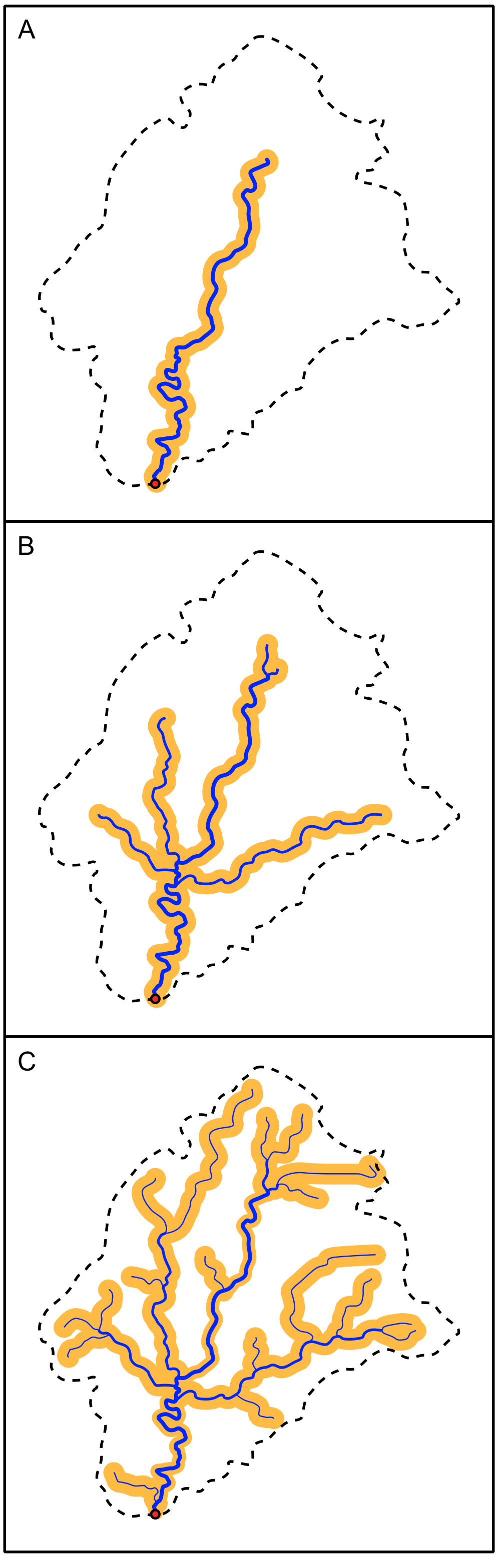

Figure 8. Illustration demonstrating that the scale (and thus apparent density) of the stream network used to delineate riparian buffer zones will determine the land area occupied by the latter (orange) relative to the total area of the catchment.

An important implication of this is that as the apparent density of the stream network increases, the difference between the land area contained within the delineated riparian buffer zones and the land area of the catchment itself will become increasingly insignificant (thus making comparisons between the influence of riparian versus catchment wide land use less meaningful). This is evident in Figure 8, where the successive inclusion of increasingly lower-order tributaries means that the area occupied by the riparian buffer zones (shaded orange) will increase as a proportion of the total area of the catchment. Therefore, in addition to the width of the delineated riparian buffer zones, the scale (or resolution) of the stream network layer used to delineate the buffers must also be considered.

In addition, when LULC is measured within a local contributing area (i.e., a radial buffer measured from the catchment outlet and clipped to the boundaries of the

López et al., 2016; Ou et al., 2016; Slaughter & Mantel, 2017; Mainali & Chang, 2018; Wang & Zhang, 2018; Zhang et al., 2019; Wu & Lu, 2021; Zhong et al., 2022).

catchment), the proportion of the LCA relative to the total area of the catchment will depend on the size and shape of the catchment itself. For instance, the area occupied by an LCA with a radius of 1 km may be relatively small in proportion to the total catchment area of a large catchment. However, in a smaller catchment, an LCA of the same width will occupy a larger proportion of the catchment. In very small catchments, the same LCA may occupy such a large proportion of the catchment that it no longer represents localised land use. This is shown in Figure 9 below, where an LCA based on the same radius in each catchment occupies very different proportions of the total catchment area due to differences in the size of the catchments. This means that across a statistical sample of catchments that differ in size and shape—which, in any real-world investigation, will necessarily be the case—an LCA of specified radius will not represent a consistent analytical scale of land use (in so far as it is intended to represent localised land use around a particular drainage point) against which the influence of land use at other scales can be compared. Consider that in Figure 9 below, while the LCA in the larger catchment indeed represents land use within a short distance of the catchment outlet, in the smaller catchment an LCA of the same radius represents land use occupying more than half of the total catchment area (its designation as a "*local* contributing area" is therefore questionable).

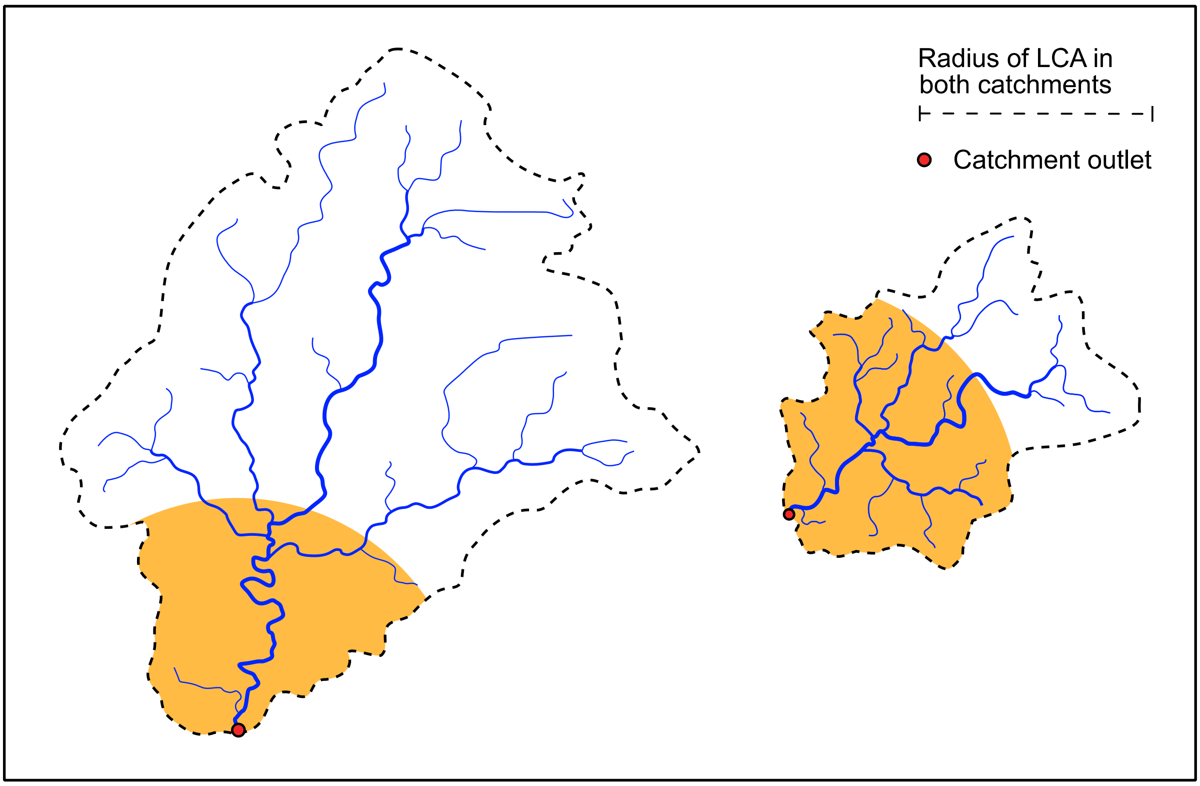

Figure 9. Illustration showing that the relative area occupied by LCAs of the same radius differs significantly owing to differences in the size and shape of the catchments.

Considering these issues and the uncertainty that persists with respect to the significance of scale, many authors concede that the question of scale-dependency remains largely unresolved.[33] According to Xu

[33] See, for instance, Ding et al. (2015), Yu et al. (2016), Brogna et al. (2018), Zhang et al. (2019), Park and Lee (2020), Song et al. (2020), Liu et al. (2021), Song et al. (2021), Vera Mercado and Engel (2021), Wu and Lu

et al. (2023b), for example, there remains considerable uncertainty regarding the most appropriate scales at which to conduct research into, and manage the effects of, LULC on water quality. What is clear is that the impacts of LULC on water quality vary at different scales. However, the processes that govern these multiscale impacts are complex, and the early conclusion reached by Johnson et al. (1997, p. 194) remains apt:

> Although the functions that riparian ecotones play in moderating stream water chemistry are well described the relative influence of the riparian zone [versus] the catchment on ambient water chemistry is known to be variable and is not well understood.

As such, it is recommended by several authors that a multiscale perspective is necessary when developing integrated land and water quality management strategies, and that such strategies should likewise be informed by multiscale analyses (Strayer et al., 2003; Schiff & Benoit, 2007; Zhou et al., 2012; Ding et al., 2016; de Mello et al., 2018; Park & Lee, 2020; Song et al., 2021; Pei et al., 2023).

Potentially Confounding Factors

Notwithstanding the remarkable consistency of the findings reported in the literature with respect to the typical impacts of different classes of LULC on water quality (discussed above), the relationship between land use and water quality is complex and influenced by several additional factors (Ye et al., 2014; Nobre et al., 2020; Li et al., 2022b; Caldwell et al., 2023). Thus, although the influence of LULC on water quality is of principal interest in these studies, it is not the only significant variable. Several other factors, including catchment size and topography, local geology and soil type, as well as climatic conditions and seasonal variations in temperature and precipitation, can all have additional impacts—direct and indirect—on water quality (Vigil, 2003; Dallas & Day, 2004; Baker, 2005; Day & Dallas, 2011; Fatehi et al., 2015; Lintern et al., 2018; Nobre et al., 2020; Bowes et al., 2023; Qiu et al., 2023; Yao et al., 2023). Consequently, the relationship between LULC and water quality in any given area is further complicated by a variety of additional, geographically specific, and potentially confounding (in the statistical sense) environmental variables (Caldwell et al., 2023). The potential influence of these additional variables is significant for two related reasons, discussed in turn below.

Inherent Regionality

Firstly, the influence of local environmental variables—especially geology and climate—will mean that the relationship between land use and water quality is often specific to a particular region (Baker, 2005; Morse et al., 2018; Chiang et al., 2021; Bohenek & Sullilván, 2022; Li et al., 2022b). Local geology, for instance, has a profound influence on water quality and largely determines its natural chemical characteristics (Day & Dallas, 2011; Chapman et al., 2020; Clark et al., 2022; Procopio & Zampella,

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(2021), Zhang et al. (2021), Cheng et al. (2022), Kuranchie et al. (2022), Łaszewski et al. (2022), Li et al. (2022b), Zhong et al. (2022), Deng et al. (2023), Mashala et al. (2023),Mo et al. (2023), Xu et al. (2023a), and Xu et al. (2023b).

2022). Thus, background water chemistry—that is, water quality conditions typical of a region in the absence of anthropogenic influence—will vary from region to region depending on the natural physiographic attributes that characterise these regions. According to Day and Dallas (2011, p. 68), "the physical attributes and chemical constituents of natural fresh waters differ from continent to continent, and even from region to region, because they are influenced by climate, geomorphology, geology, and soils" (see also Dallas & Day, 2004). In addition, some local factors may moderate the impact of land use on water quality by influencing the mechanisms and pathways by which contaminants are mobilised and transported from the landscape into receiving water bodies (Slaughter & Mantel, 2017; Malherbe et al., 2019a; Helsel et al., 2020; Procopio & Zampella, 2022). For instance, both the geomorphology and precipitation patterns of a given region will determine runoff characteristics, thus influencing the rate at which contaminants are flushed into receiving waters (Day & Dallas, 2011; Pratt & Chang, 2012; Yu et al., 2016; Dai et al., 2017; Nobre et al., 2020; Ramião et al., 2020; Fernandes et al., 2021; Allafta & Opp, 2022). Together, the combined influence of these factors will mean that relationships between LULC and water quality are inherently regional. Consequently, it may not be appropriate to extrapolate the results of studies conducted in one region, characterised by a particular set of environmental attributes, to other regions with dissimilar characteristics (which thus reinforces the need for region-specific research) (Dallas & Day, 2004; Chiang et al., 2021).

Analytical and Methodological Implications

Secondly, these variables, if not properly accounted for, may confound statistical analyses of the relationship between LULC and water quality and reduce the predictive power of statistical models (King et al., 2005; Magierowski et al., 2012; Slaughter & Mantel, 2017; Ramião et al., 2020; Liu et al., 2021; Winton et al., 2021). In other words, as these variables may themselves have a direct impact on water quality, their influence makes it difficult to isolate the effects of LULC and thus assign causality (Magierowski et al., 2012; Ott & Longnecker, 2016; Ramião et al., 2020; Crooks et al., 2021; Dymek et al., 2021; Wu & Lu, 2021). It has recently been observed, for example, that "the relationship between land use and water quality is difficult to establish because it depends on many factors, such as hydrology, soil properties, topography, seasonality and historical land use or its spatial distribution in the catchment" (Ramião et al., 2020, p. 1). The challenge of isolating the influence of LULC is further complicated when interaction effects and multicollinearity exist between these variables (Detenbeck et al., 1993; Allan, 2004b; Tu, 2011a; de Oliveira et al., 2017; Wang et al., 2021; Li et al., 2022b; Bowes et al., 2023; Yao et al., 2023).

Therefore, as several publications have stressed, the potentially confounding influence of these variables either needs to be minimised in the design of the study, or otherwise accounted for statistically when analysing the relationship between LULC and water quality (Feld, 2013; du Plessis et al., 2014; Waite, 2014; Ding et al., 2015; Slaughter & Mantel, 2017; Lintern et al., 2018; Winton et al., 2021; de Mello et al., 2022; Kuranchie et al., 2022; Simpson et al., 2022). The former is most frequently achieved by limiting the inter-site variability of these factors across samples (thereby emphasising differences in LULC), while the latter is usually achieved by incorporating these variables in multivariate statistical analyses (such as multiple regression or redundancy analysis). When conducting statistical analyses, limiting the inter-site variability of potentially confounding environmental factors is usually achieved by conducting investigations on a regional basis. Conducting studies within areas that are relatively uniform (in terms of local climate, geology, soil type, and topography) enables researchers to isolate the influence of the variable of interest (i.e., LULC) within the sample. In other words, as far as possible, LULC should be the only variable that differs between the sites/catchments being studied, thus emphasising its impact on water quality and improving the explanatory power of the statistical models (Klein, 1979; Lenat & Crawford, 1994; Grimstead et al., 2018; de Mello et al., 2022). Performing studies within distinct ecoregions, which are defined as having shared ecological attributes, is one means of reducing inter-site variability. Slaughter and Mantel (2017, p. 500), who used this approach when modelling the impacts of land cover on diffuse nutrient inputs in selected biomes in South Africa, explain that "since it can be assumed that broad regional characteristics will affect the relationships between land cover and non-point load inputs, these relationships should be investigated on a regional scale."

It may also be possible to improve the performance of statistical models of the relationship between LULC and water quality by incorporating these additional variables into multivariate statistical analyses (Clapcott et al., 2012; Magierowski et al., 2012; Chatterjee & Simonoff, 2013). However, as noted above, caution must be taken to avoid multicollinearity between the included explanatory variables, which may muddy the waters—if the pun will be excused—of any statistical analysis (Tu, 2011a; Magierowski et al., 2012; de Oliveira et al., 2017; Helsel et al., 2020; Li et al., 2022b; Mashala et al., 2023).

Seasonality

Several studies have also observed that water quality naturally varies according to season, and that seasonal differences in precipitation, discharge, and temperature may also influence the impact of LULC on water quality.[34] On the one hand, seasonal differences in precipitation will affect the mobilisation and transport of contaminants from the land surface into water bodies in overland runoff, typically resulting in greater pollutant loads in overland flow during the wet season. On the other hand, however, seasonal variations in discharge and streamflow will also influence the in-stream concentration of contaminants through dilution (Day & Dallas, 2011; Nobre et al., 2020; D'Arcy et al.,

[34] See, for example, Rhodes et al. (2001), Ye et al. (2014), Ding et al. (2015), Farrell et al. (2015), Moodley et al. (2015), Yu et al. (2016), van der Hoven et al. (2017), Lintern et al. (2018), Mainali and Chang (2018), de Mello et al. (2020), Kim et al. (2020), Palma et al. (2020), Dlamini et al. (2021), Umwali et al. (2021), Wang et al. (2021), Winton et al. (2021), Wu and Lu (2021), Zhang et al. (2021), Kadir et al. (2022), Li et al. (2022b), Zhang et al. (2022a), Zhou et al. (2022), Deng et al. (2023), Han et al. (2023), Wang et al. (2023b), and Xu et al. (2023b).

2022a; Li et al., 2022b; Deng et al., 2023; Roldán-Arias et al., 2023; Zhang et al., 2023a). While precipitation patterns are related to regional climatic characteristics, the specific effect of seasonality is temporal (i.e., intra-annual) variation in water chemistry within the same region. Therefore, if one desires to reduce the influence of intra-annual seasonal variability, it will be necessary to design water quality sampling regimes that cover both wet and dry seasons, possibly over several annual cycles, thus allowing for the estimation of average annual conditions (see, for instance, Nde & Mathuthu, 2018; Nde et al., 2021).

The "Ghost of Land Use Past"

Another potentially confounding factor worthy of mention is the "ghost of land use past" (a phenomenon also referred to in the literature as the "legacy effect" of land use on water quality) (Harding et al., 1998; Allan, 2004a; Feld, 2013; Tayyebi et al., 2015; Martin et al., 2017; Vrebos et al., 2017; Morse et al., 2018; Chen & Olden, 2020; de Mello et al., 2020; Ramião et al., 2020). These terms refer to the fact that the impacts of land use on water resources may not be immediately apparent and may take several years to manifest, with changes in water quality lagging behind changes in LULC (Zhang et al., 2023b). This may mean that any observed water quality impacts are, in fact, due to the influence of LULC conditions several years in the past, rather than to present-day LULC. This is a particularly difficult factor to account for, and so most studies simply pair water quality data with LULC data from the same period.

Thresholds

In the context of environmental studies, thresholds generally refer to "tipping points" at which abrupt, possibly irreversible, and generally undesirable changes occur in the condition of ecological systems, driven by external—typically anthropogenic—disturbances or perturbations (van Nes et al., 2016; Munson et al., 2018; Zhang et al., 2018). According to Lenton (2013, p. 21), thresholds are "ubiquitous, occurring in a variety of systems across a range of spatial and temporal scales and involving many environmental processes." Thresholds are widely considered to be one of the most effective regulatory tools for managing the cumulative effects of human development on the environment, and thus awareness of the existence and/or location of these thresholds is crucial for environmental decision-making (Muradian, 2001; Huggett, 2005; Antoniuk, 2006; Kelly et al., 2015; Zhang et al., 2018).

Polasky et al. (2011, p. 400) explain that thresholds "can be useful in organising thinking about complex problems by focusing attention on critical boundaries that have major consequences if crossed." The idea of thresholds as "boundaries" which quantify levels of anthropogenic perturbation that should not be exceeded in order to avoid irreparable or catastrophic environmental changes is also apparent in the "planetary boundaries" discourse (Rockström et al., 2009; Rockström et al., 2014; Steffen et al., 2015; Gleeson et al., 2020; Richardson et al., 2023). In this respect, they delineate a safe operating space in which permissible levels of socioeconomic development can occur without causing irreversible ecological harm (ibid.). Thresholds are particularly attractive in the context of environmental management as they provide quantifiable, non-arbitrary, and defensible targets that can be used to guide complex decision-making and planning processes (Ficetola & Denoël, 2009; Foley et al., 2015; Kelly et al., 2015; Tomal & Ciborowski, 2020). As summarised by Johnson (2013, p. 58), "the threshold concept has much intuitive appeal: there is a strong theoretical foundation for nonlinear dynamics, critical response points are integrated easily within regulation, and regulatory thresholds allow the consideration of both current and potential future effects of development." Examples from around the world demonstrate that incorporating thresholds into conservation strategies can facilitate improved management outcomes (Foley et al., 2015; Kelly et al., 2015).

Thresholds can be used to inform both proactive and retroactive management strategies (Tomal & Ciborowski, 2020). Concerning the former, thresholds can be used to set pre-emptive limits on pollution, land use development, and other forms of ecological disturbance before irreversible or unacceptable harm is caused (Huggett, 2005; Kennet, 2006; Johnson, 2013; Kelly et al., 2015; Grimstead et al., 2018). In instances where thresholds cannot be identified or predicted until they have been breached, they may be used to set targets for retrospective ecological restoration (Huggett, 2005; Lenton, 2013; Kelly et al., 2015). However, Dodds et al. (2010, p. 988), who argue that proactive protection is preferable, have explained that "managers should be aware that human actions might result in undesirable rapid changes and potentially an unwanted alternative stable state, and that recovery from that state might require far more resources and time than avoiding entering the state in the first place would have required" (see also Groffman et al., 2006; Ye et al., 2014; Foley et al., 2015).

Nonlinear "Ecological" Thresholds versus Regulatory Thresholds

Nonlinear "ecological" thresholds are premised on the idea that ecosystems often exhibit multiple stable states and that external pressures—such as pollution or habitat loss—can trigger sudden (i.e., nonlinear) transitions from one state to another (Muradian, 2001; Huggett, 2005; Groffman et al., 2006; Steffen et al., 2015; Zhang et al., 2018). While ecosystems often have the ability to resist changes driven by external perturbations, and may subsequently recover and return to the original state if given enough time—a quality known as "resilience"—at a certain point the pressures exerted upon a system may become great enough to overcome this resistance, resulting in an abrupt and potentially irreversible transition from one ecological state to another (Muradian, 2001; Groffman et al., 2006; Zaccarelli et al., 2008; Martin et al., 2009; Scheffer, 2009; Johnson, 2013; Rockström et al., 2014; Capon et al., 2015). Such ecological tipping points are often illustrated by the idea of a sphere being driven over a "hill" (i.e., a threshold) from one "valley" (i.e., stable state) to another (Dodds et al., 2010; Lenton, 2013; Capon et al., 2015; Zhang et al., 2018). This is shown in Figure 10 below, where an environmental disturbance begins to shift the ecosystem from its natural state (A) towards the threshold (B). The resistance/resilience of the system is represented by the steep walls of the valleys and the tendency of the sphere to return to its original state (Capon et al., 2015). However, if the disturbance is large enough to overcome the system's resistance and exceed the threshold, the system may rapidly accelerate towards another (undesirable) stable state (C). If this occurs, more effort (in terms of time and resources) may be required to return the system to its original state (illustrated in Figure 10 by the steeper valley walls of the alternative stable state).

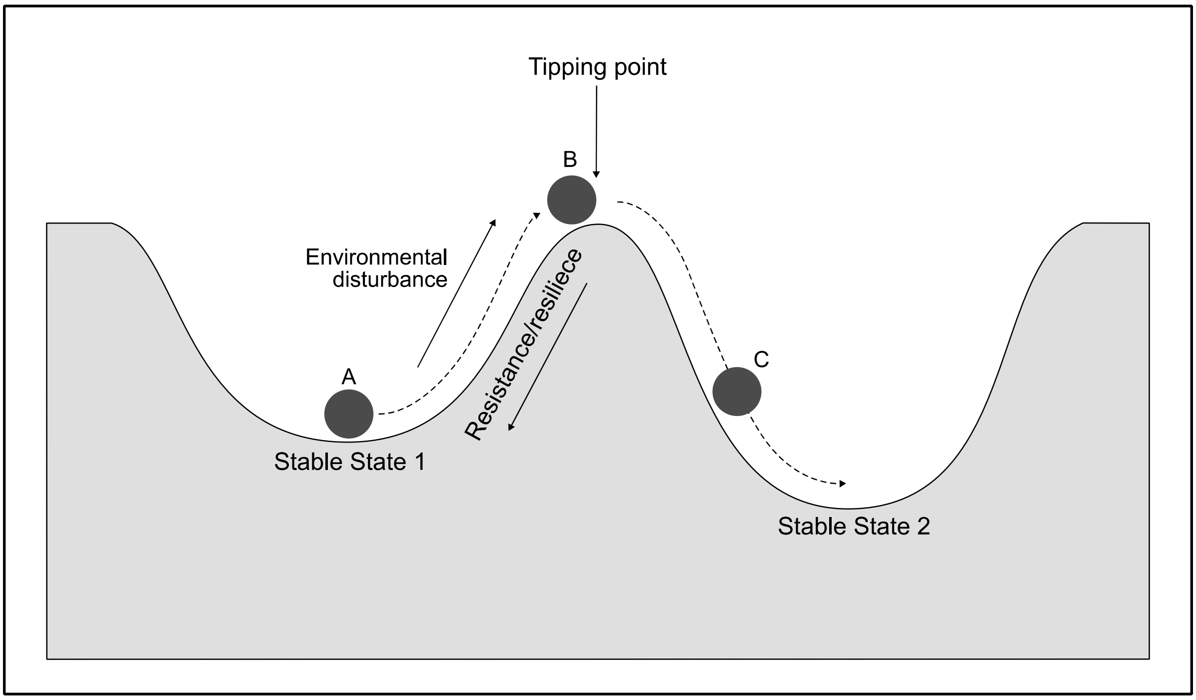

Figure 10. Illustration showing how an ecological threshold may be explained by a sphere being driven over a hill (i.e., a tipping point) from one valley (i.e., stable state) to another by an environmental disturbance (see Dodds et al., 2010; Lenton, 2013; Capon et al., 2015; Zhang et al., 2018).

Ecological thresholds, as described above, are typically characterised by:

- Sudden or dramatic (i.e., nonlinear) changes in an ecological system's condition triggered when the degree of disturbance (typically some form of anthropogenic perturbation) reaches or exceeds a critical value.
- The likelihood that such changes may be triggered by comparatively small environmental disturbances.
- A transition from one stable ecological state to another, with the attendant possibility that this change may be irreversible (referred to as "hysteresis").[35]

Turner (2005, p. 1970) thus defines ecological thresholds as "the point at which there is an abrupt change in an ecosystem quality, property or phenomenon, or where small changes in an environmental

[35] These characteristics are fundamental to what Munson et al. (2018) have referred to as the "sensu strictu" definition of ecological thresholds, and are found in the descriptions and definitions of thresholds given in Muradian (2001), Scheffer et al. (2001), Bennett and Radford (2003), Walker and Meyers (2004), Huggett (2005), Turner (2005), Groffman et al. (2006), Martin et al. (2009), Scheffer (2009), Dodds et al. (2010), Johnson (2013), Guntenspergen and Gross (2014), Kelly et al. (2014), Foley et al. (2015), D'Amario et al. (2019), and Armstrong McKay et al. (2022).

driver produce large responses in the ecosystem." The nonlinear nature of ecological thresholds is illustrated in Figure 11 below.

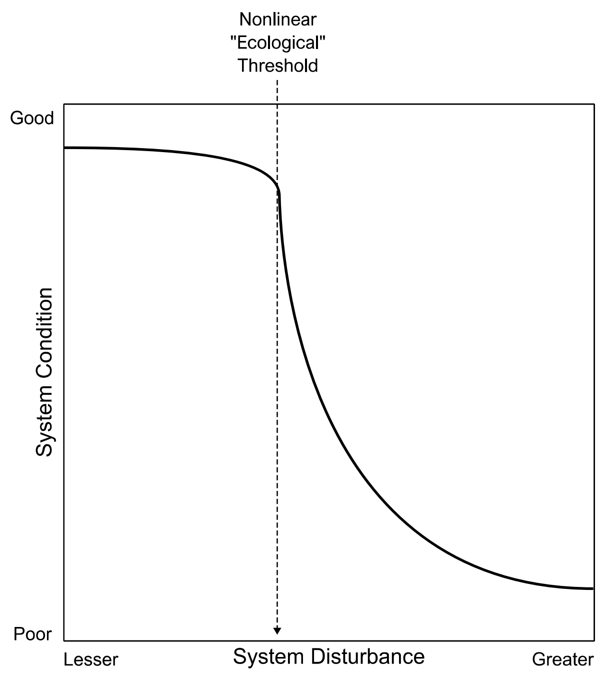

Figure 11. Illustration showing a nonlinear ecological threshold triggered when system disturbance reaches a critical level, resulting in an abrupt deterioration in system condition (adapted from Steffen et al., 2015).

Although there is abundant evidence to suggest that ecological systems may respond abruptly to perturbations (as illustrated above in Figure 11), not all environmental thresholds are defined by nonlinear responses (Johnson, 2013; Kelly et al., 2014). Often, argues Antoniuk (2006), the cumulative effect of human development on the environment is not characterised by a distinctive or observable "breakpoint" (i.e., nonlinearity). Instead, a threshold may be defined as the point at which the degree of environmental disturbance—and the resultant deterioration in ecological condition—becomes intolerable according to some socially, politically, or scientifically defined notion of acceptability (regardless of whether the ecological system in fact exhibits a nonlinear response) (Kelly et al., 2014). When framed in this way, these are typically referred to as "regulatory thresholds", "management thresholds", or "decision thresholds" (Kennet, 2006; Martin et al., 2009; Johnson, 2013; Guntenspergen & Gross, 2014; Kelly et al., 2014). Antoniuk (2006, pp. 2, 12) has described them as "technically or socially-based standards that identify the point at which an indicator changes to an unacceptable condition" and has noted that they reflect "the desired balance between human activities and ecological and social sustainability." These thresholds are therefore somewhat subjective, reflecting "acceptable" trade-offs between socioeconomic development and environmental interests (Antoniuk, 2006; Martin et al., 2009; Johnson, 2013). Recognising that not all thresholds are nonlinear in nature, Polasky et al. (2011, p. 398) have described them simply as "a defined target level or state based on the avoidance of unacceptable outcomes or an ecologically defined shift in system status." Therefore, as Hilderbrand et al. (2010) have maintained, although not all systems exhibit abrupt or nonlinear responses to external pressures, the threshold concept can still be used to describe and manage ecological responses to anthropogenic disturbances. The concept of a regulatory threshold is illustrated in Figure 12 below.

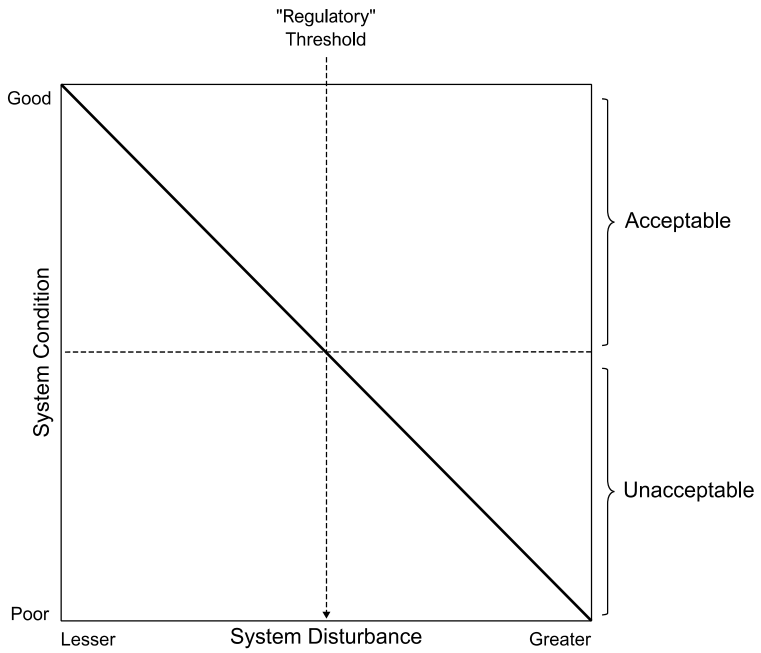

Figure 12. Illustration showing how a regulatory threshold is defined as the point at which the degree of environmental disturbance, and the resultant deterioration in system condition, becomes intolerable according to some socially, politically, or scientifically defined notion of acceptability.

Target and Precautionary (Tiered) Thresholds

Given the uncertainty involved in determining thresholds, Dodds et al. (2010) have suggested a precautionary approach to ecosystem management when thresholds are used to guide decisions. Similarly, Holzer and Olson (2021) discuss the widespread use of "precautionary buffers" in environmental management to account for this uncertainty and thus prevent long-term or irreversible harm that may occur if the thresholds adopted are insufficiently protective. In line with the precautionary principle, these buffers are created by placing regulatory thresholds "upstream" of critical ecological thresholds. This establishes a system of tiered thresholds, with precautionary and/or target thresholds in place to prevent levels of disturbance being reached that exceed nonlinear tipping points (Antoniuk, 2006; Johnson, 2013). Figure 13 below illustrates how precautionary and target thresholds relate to one another, as well as to nonlinear thresholds.

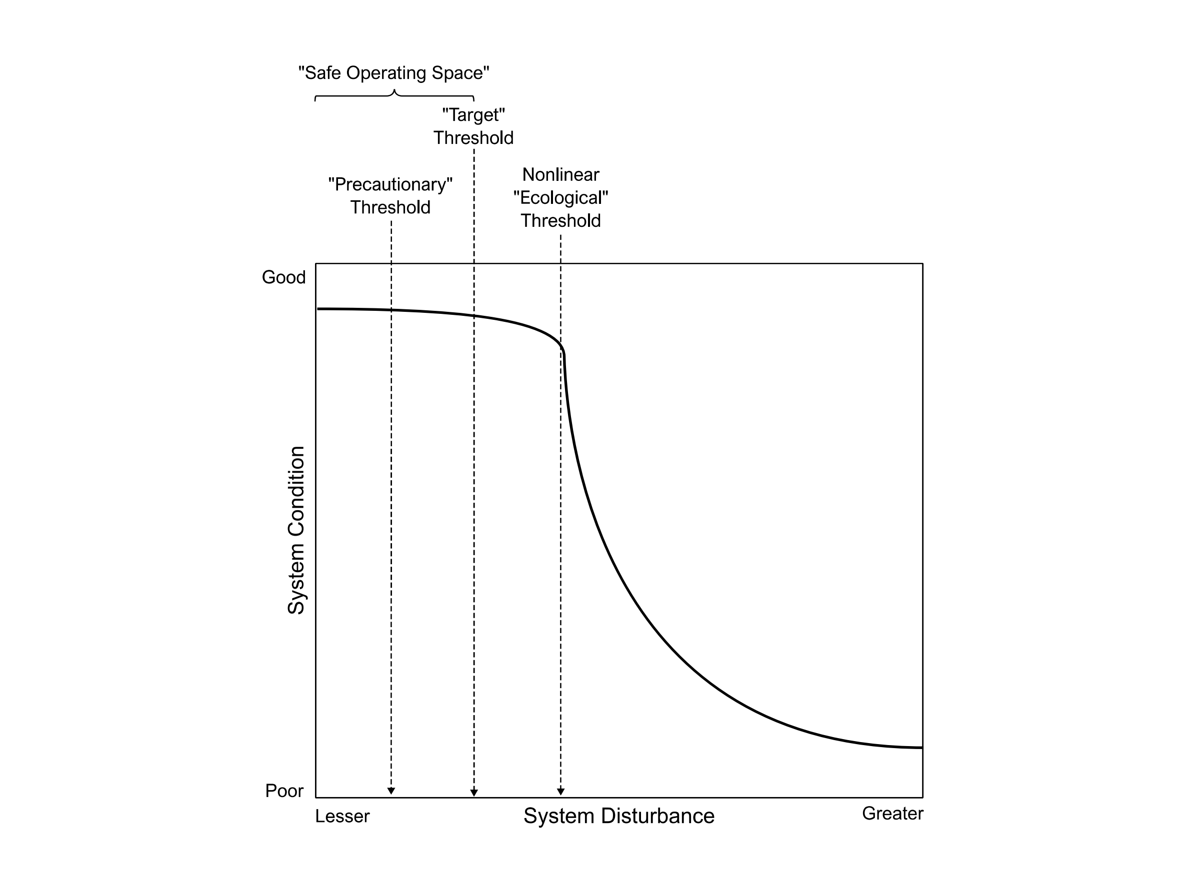

Figure 13. Illustration showing a system of tiered thresholds (adapted from Antoniuk, 2006; Johnson, 2013; Steffen et al., 2015).

Precautionary thresholds, which are intentionally conservative and thus placed ahead of target thresholds and/or ecological tipping points, are designed to alert environmental managers to the fact that these thresholds are being approached and that interventions may be required to prevent unwanted ecological harm. Target thresholds, as with regulatory thresholds more generally, represent “tolerable” degrees of environmental disturbance according to socially, politically, or technically defined standards. In cases where nonlinear thresholds exist, target thresholds are usually placed some distance ahead of these critical tipping points so as to avoid potentially irreparable environmental harm. If precautionary and/or target thresholds are exceeded, however, a critical nonlinear threshold may be reached, the latter representing an ecological tipping point beyond which catastrophic and potentially irreversible environmental harm is likely. The precautionary and target thresholds are therefore designed to create a “buffer” or “safe operating space” for anthropogenic activity that reduces the risk of critical nonlinear thresholds being breached (Rockström et al., 2009; Steffen et al., 2015; Clift et al., 2017; Rockström et al., 2018; Richardson et al., 2023).

Land Use Thresholds in the Context of Water Quality Management

Several studies have demonstrated that aquatic ecosystems may undergo abrupt (i.e., nonlinear) changes in response to changes in their surrounding landscapes.[36] Tayyebi et al. (2015, p. 103), for instance, have observed that "research has demonstrated that land use tipping points in water quality and aquatic health occur when a certain percentage of watershed or catchment exceeds a certain amount of urban and agricultural land use." While questioning the evidence for this claim, Capon et al. (2015, p. 124) nevertheless have acknowledged that "freshwater ecosystems frequently are cited as exemplars of regime shifts and multiple stable states." Dodds et al. (2010) have described some of the statistical techniques commonly used for estimating the location of nonlinear thresholds in these studies, including breakpoint regression, nonlinear curve fitting, cumulative frequency distributions, and changepoint analysis. In addition, several other authors have also identified regulatory LULC thresholds (as opposed to nonlinear thresholds), defining these as the point at which changes in LULC cause a transition in water quality (or stream condition) from one regulatory class to another (e.g., from "fair" to "poor") (e.g., Klein, 1979; Steedman, 1988; Booth & Jackson, 1997; May et al., 1998; Fitzpatrick et al., 2001; Brabec et al., 2002; Roy et al., 2003; Sutjiningsih, 2017; Nusantara et al., 2020; Zhong et al., 2022). Moreover, a number of publications have explicitly recognised the value that such land use thresholds offer to policymakers and planners by providing these actors with objective targets that can be incorporated into integrated land and water resource management strategies.[37] Finally, as alluded to by Tayyebi et al. (2015) in the quote above, thresholds that have been identified in the existing literature typically relate to proportions of either urban or agricultural land at various spatial scales. By contrast, thresholds of natural vegetation have received far less attention from researchers.

Thresholds of Urban and Impervious Land Cover

According to Grimstead et al. (2018), most threshold-related studies have been conducted in urban settings (see also Yao et al., 2023). Consequently, the majority of LULC thresholds described in the literature relate to either urban land use or impervious land cover (Liu et al., 2021). As noted several years ago by Arnold and Gibbons (1996), there has been remarkable consistency in the findings of these studies. Firstly, as observed by Allan (2004b), responses of aquatic systems to changes in the extent of urban/impervious cover in the surrounding landscape are almost invariably nonlinear. It also seems almost universal, as reported by Song et al. (2020), that significant aquatic degradation occurs when urban or impervious cover in a catchment exceeds 10–15%. The results of several studies support this

[36] See, for example, Wang and Yin (1997), Roy et al. (2003), King et al. (2005), Turner (2005), Donohue et al. (2006), Schiff and Benoit (2007), Zampella et al. (2007), Tayyebi et al. (2015), Nava-López et al. (2016), Clément et al. (2017), Masocha et al. (2017), Tromboni and Dodds (2017), Grimstead et al. (2018), D'Amario et al. (2019), Li et al. (2021), Zhong et al. (2022), and Mo et al. (2023).

[37] See, for instance, Booth et al. (2002), Allan (2004a), Donohue et al. (2006), Dodds et al. (2010), Clapcott et al. (2012), Magierowski et al. (2012), Tromboni and Dodds (2017), Grimstead et al. (2018), D'Amario et al. (2019), Chen and Olden (2020), Liu et al. (2021), and Xu et al. (2023a).

assertion.[38] Thus, based on the available evidence, the conclusion reached by Schueler (1994, p. 8) several years ago remains appropriate:

> Many independent lines of research… converge toward a common conclusion: that it is extremely difficult to maintain predevelopment stream quality when watershed development exceeds 10 to 15% impervious cover.

This being the case, Brabec (2009, p. 425) has observed that thresholds of impervious cover "are now commonly used as benchmarks of water quality planning and protection in local, watershed, and regional planning efforts."

Thresholds of Agricultural Land Cover

Although thresholds of urban and impervious cover dominate the literature, several publications have also reported thresholds of agricultural land use.[39] However, the results of these studies have been far less consistent than those of studies conducted in urban catchments. Subsequently, the thresholds of agricultural cover reported in the literature have varied widely. In Wisconsin, USA, for instance, Wang et al. (1997) reported an "obvious decline" in habitat quality and Index of Biotic Integrity (IBI)[40] scores when catchment-wide agricultural land cover exceeded 50%. In the same study, however, some sites maintained relatively good aquatic habitat quality and biotic integrity even when agricultural land cover reached 80% (see also Wang et al., 2003). In another study conducted in Wisconsin, Fitzpatrick et al. (2001, pp. 1498, 1504) found that fish IBI scores transitioned from "good" to "fair" or "poor" when the extent of agricultural cover in the catchment exceeded 30%, but also reported that "as little as 10 percent agriculture in the stream network buffer related to fish IBI scores of fair or poor." In Tasmania, Australia, Magierowski et al. (2012, p. 773) reported catchment-scale thresholds of agricultural (grazing) land cover of between 40 and 60%, beyond which in-stream macroinvertebrate communities were likely to be "substantially affected." In yet another Wisconsin-based study, Qiu and Turner (2015, pp. 1, 12) reported that "surface-water quality responded nonlinearly to percent cropland" and further observed that water quality (phosphorous loading) improved when agricultural cover was below approximately 60%. Grimstead et al. (2018), when investigating the impacts of agriculture on aquatic invertebrate communities in Ontario, Canada, found that benthic macroinvertebrate community traits

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[38] See, for instance, Klein (1979), Schueler (1994), Arnold and Gibbons (1996), Booth and Jackson (1997), Wang and Yin (1997), Paul and Meyer (2001), Brabec et al. (2002), Roy et al. (2003), Allan (2004b), King et al. (2005), Groffman et al. (2006), Schoonover and Lockaby (2006), Schiff and Benoit (2007), Zampella et al. (2007), Clapcott et al. (2012), Tayyebi et al. (2015), Kim et al. (2016), Tromboni and Dodds (2017), D'Amario et al. (2019), Chen and Olden (2020), Medupin et al. (2020), and Zhong et al. (2022).

[39] See, for example, Wang et al. (1997), Fitzpatrick et al. (2001), Wang et al. (2003), Allan (2004b), Riseng et al. (2010), Huang and Klemas (2012), Feld (2013), Tayyebi et al. (2015), Grimstead et al. (2018), D'Amario et al. (2019), and Li et al. (2021).

[40] The Index of Biotic Integrity (IBI), developed initially by Fausch et al. (1984), is a widely used biological index for the assessment of aquatic systems (Canning & Death, 2019). It uses metrics related to taxonomic richness, functional groups, and community composition, to assess the health of aquatic ecosystems and reflect the degree to which these systems have been impacted by anthropogenic disturbances such as water pollution.

showed threshold responses when agricultural cover in the catchment exceeded 70%. D’Amario et al. (2019), when analysing data from existing studies conducted in southern Ontario, Canada, also detected significant changes in water quality when agricultural cover reached between 34 and 45%. In a recent global survey, Chen and Olden (2020, p. 4956) reported a wide range of agricultural land use thresholds, ranging from as low as 2.5% (in New Zealand) to 72.5% (in Belgium), above which “significant changes” in fish community composition and/or species richness were observed. Ding et al. (2021, p. 4) reported that aquatic macroinvertebrate taxa declined “sharply” when the proportion of agricultural land within 1 km riparian buffer zones in the Hun-Tai River Basin in China reached between 23 and 40%, with an estimated threshold value of 25.82%. Finally, in a study conducted in the Dan River Basin in China, Xu et al. (2023a, p. 7) observed that “abrupt changes” in nitrogen and phosphorous concentrations were likely to occur if proportions of agriculture within a 100 m riparian buffer zone exceeded 26–29%. While the wide range of thresholds published in these studies may be attributable to differences in the metrics and methods used, as well as to the additional influence of regional environmental variables, Allan (2004b, p. 273) nevertheless concluded that “the wide range of responses reported from streams draining agricultural landscapes clearly indicates that extent of agriculture is not by itself sufficient” as an indicator for threshold estimation.

Thresholds of Natural Vegetation

The land use thresholds described above represent thresholds in the narrow sense (i.e., maximum limits of urban and/or agricultural development that should not be exceeded if water resources are to be protected). They are explicitly framed in this manner, for example, in the review by Chen and Olden (2020). However, viewed from the opposite perspective, rather than setting limits on urban or agricultural expansion in order to protect water quality, the findings of several studies provide evidence which suggests that, for a given region, it may be possible to determine minimum thresholds of natural vegetation cover required to protect aquatic systems (see, for example, the conclusion of Hanna et al., 2021).[41] Nash et al. (2009, pp. 358–359), for instance, concluded that “while controlling and meeting human need, maintaining and preserving natural land cover by a *certain level* may help in providing healthier surface water quality” (emphasis added). In addition, both Attua et al. (2014, p. 66) and Cecílio et al. (2019, p. 49) have argued that maintaining an “adequate” level of natural vegetation in catchments can improve water quality. While the reported thresholds of natural vegetation vary significantly, in a review of the existing literature Morse et al. (2018) have suggested that water quality tends to deteriorate when proportions of forests fall below 60–90% of the total catchment area. However, the authors have also acknowledged that specific threshold values will largely depend on local factors. Therefore, a key question—and one that remains largely unanswered to date—is what “certain level” of natural

[41] Some examples include Steedman (1988), Black et al. (2004), Death and Collier (2010), Tran et al. (2010), Feld (2013), Attua et al. (2014), Iñiguez-Armijos et al. (2014), Midway et al. (2015), Clément et al. (2017), de Mello et al. (2017), and Zhong et al. (2022).

vegetation might be considered “adequate” for the protection of water resources and the maintenance of water quality in a given region (Brabec et al., 2002; Death & Collier, 2010; Iñiguez-Armijos et al., 2014; Hanna et al., 2021).

Geographic Bias in the Existing Research and the State of Research in South Africa

While Łaszewski et al. (2022) have reported that research into the impacts of LULC on water quality has expanded globally in recent years, several reviewers have maintained that most of the existing studies have been conducted in temperate regions of the United States and Europe (e.g, Baker, 2005; Tromboni & Dodds, 2017; Kronvang et al., 2020; Bohenek & Sullibán, 2022; Prakoso et al., 2023). As a consequence of this geographic bias, far less is known about the influence of LULC on water quality in other regions, especially in disparate climatic regions and less economically developed countries (ibid.). While the literature presently surveyed confirms the foregoing, the relatively recent proliferation of related research in China[42] and, to a lesser extent, South America[43] is noteworthy.

In view of South Africa’s pressing water quality problems, there is an unquestionable need for further research into the impacts of land use on water resources (Kundu et al., 2015; du Plessis, 2019b; Riddell et al., 2022; du Plessis, 2023). Notwithstanding a rich history of hydrological flow and discharge modelling, Slaughter and Mantel (2017, p. 499) have argued that water quality research and modelling in South Africa is relatively undeveloped and constrained by a lack of data, technical expertise, and funding. While these constraints certainly present a hurdle to research, there have been, especially in recent years, several studies conducted in South Africa which relate to the impacts of LULC on water quality.[44] A survey of this literature reveals that the majority of these studies simply confirm what now amounts to common knowledge regarding the typical impacts of LULC on water quality, generally observing that agricultural and urban areas have negative impacts on water resources. Moreover, in several studies, rather than testing for statistically significant associations between LULC and water

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[42] See, for example, Ding et al. (2015), Shen et al. (2015), Chen et al. (2016), Ding et al. (2016), Ou et al. (2016), Xu et al. (2016), Yu et al. (2016), Dai et al. (2017), Liu and Yang (2018), Zhang et al. (2019), Wang et al. (2020), Wu and Lu (2021), Li et al. (2022a), Zhong et al. (2022), Zhou et al. (2022), Deng et al. (2023), Han et al. (2023), Liu et al. (2023), Ma et al. (2023), Mo et al. (2023), Pei et al. (2023), Wang et al. (2023a), Wang et al. (2023d), Xu et al. (2023a), Yao et al. (2023), and Zhang et al. (2023b).

[43] See, for instance, Carpio and Fath (2011), Iñiguez-Armijos et al. (2014), Calijuri et al. (2015), de Mello et al. (2017), de Oliveira et al. (2017), Tromboni and Dodds (2017), de Mello et al. (2018), Simedo et al. (2018), de Mello et al. (2020), Gorgoglione et al. (2020), Nobre et al. (2020), Bonansea et al. (2021), Piffer et al. (2021), de Mello et al. (2022), de Souza et al. (2022), Paná et al. (2022), Torres-Bejarano et al. (2022), Roldán-Arias et al. (2023), and Siqueira et al. (2023).

[44] These include studies by Walsh and Wepener (2009), Dabrowski and de Klerk (2013), Slaughter and Mantel (2013), du Plessis et al. (2014, 2015), Moodley et al. (2015), Chidamba et al. (2016), Petersen et al. (2017), Slaughter and Mantel (2017), van der Hoven et al. (2017), Asare et al. (2018), Namugize et al. (2018), Nde and Mathuthu (2018), Malherbe et al. (2019a); Malherbe et al. (2019b), Petersen et al. (2020), Barnard et al. (2021), Dlamini et al. (2021), du Plessis (2021), Koekemoer et al. (2021), Mahabeer and Tekere (2021), Molekoa et al. (2021), Nde et al. (2021), Senbore and Oke (2021), Makgoale et al. (2022), Mararakanye et al. (2022), van Deventer et al. (2022), and Dube et al. (2023).

quality, the authors simply draw speculative (albeit plausible) conclusions regarding the likely impacts of land use on water quality (thus failing to empirically demonstrate any links between the two). In addition, very few publications offer any specific or quantifiable management targets (e.g., thresholds). Nevertheless, despite these shortcomings, it is evident that there is growing appreciation in South Africa of the need to better understand the impacts of LULC on water quality. Appendix 5 provides a critical review of several of these studies.

The Case for Estimating Minimum Thresholds of Natural Vegetation for the Integrated Management and Protection of Water Quality

As outlined above, a large body of research has demonstrated that it is possible to use statistical methods to produce accurate models of the relationship between several physiochemical and biological indicators of water quality and various metrics of LULC. Furthermore, several published studies have shown that it may be possible to identify "specific and quantifiable" thresholds of LULC in order to inform strategies for the integrated management of land and water resources (Xu et al., 2023b, p. 10). However, by virtue of the fact that the relationship between land use and water quality is highly complex, no single LULC metric can fully account for the overall impact that LULC will have on water resources in a given landscape (Klein, 1979; Zampella et al., 2007; Brabec, 2009; Dabrowski & de Klerk, 2013; Shen et al., 2015). Brabec et al. (2002, p. 510) remind the reader that "any indicator [of LULC] is merely a proxy for the complex set of actions and events that affect water quality." Thus, although thresholds of urban and agricultural land cover are frequently reported in the literature, they are subject to significant limitations. For instance, notwithstanding the remarkably consistent results of studies in which thresholds of urban or impervious cover have been reported, such thresholds may have limited utility in situations where urban land is neither the only, nor the most influential, class of LULC (e.g., in agricultural catchments or in catchments containing mixed/multiple land uses). A noteworthy example of the confounding influence that other classes of LULC can have on statistical analyses is reported in a study by King et al. (2005). When attempting to model the relationship between urban land cover and nitrate concentrations, the authors found that the influence of agricultural land across the sample was sufficiently significant to reverse the true correlation between these variables (ibid., p. 144). Similarly, due to the additional influence of agriculture in their own study, Zampella et al. (2007, p. 601) likewise concluded that "urban land cannot be used as the sole estimator of water-quality conditions." Similarly, proportions of agricultural land cover may not be a suitable predictor of water quality in situations where other classes of LULC may also be significant. Furthermore, the literature shows that, for a variety of reasons, determining consistent thresholds of agricultural cover has proven difficult in the past (see, for instance, Allan, 2004a). As Rhodes et al. (2001, p. 3640) have observed, “degradation of water quality often results from multiple land use activities, and separating the impact of mixed sources of nonpoint source pollution is difficult.”

This being the case, many studies have used multivariate statistical approaches in an effort to account for the combined influence of different classes of LULC on water quality (see Appendix 3). However, several authors have noted that the inclusion of multiple classes of LULC as explanatory variables in multivariate models can be problematic when proportions of these classes exhibit covariation within the landscape (e.g., Detenbeck et al., 1993; Allan, 2004b; King et al., 2005; Tu, 2011a, 2011b; Magierowski et al., 2012; de Oliveira et al., 2017; Wang et al., 2021; Li et al., 2022b; Procopio & Zampella, 2022; Mashala et al., 2023). Due to the fact that multicollinearity has the effect of reducing the predictive power and accuracy of statistical models, Tu (2011a, p. 158) has cautioned that “multivariate regression analysis involving multiple land variables is not appropriate for analysing the impact of land use change on water quality due to the significant relationships among land use variables.” Thus, Tu (2011a, p. 158) goes on to argue, “a bivariate correlation analysis [should be] used to analyse the relationship between each land use variable and each water quality parameter in order to avoid the potential multicollinearity among land use variables.”

This situation presents researchers with something of a conundrum. In many contexts it may not be appropriate to use proportions of either urban or agricultural land cover as metrics on which to base thresholds for the integrated management and protection of water resources. Nor can these metrics be accommodated together as explanatory variables in multivariate analyses without encountering problems associated with multicollinearity. The hypothetical usefulness of a single integrative metric, which is able to account for the complex relationship between LULC and water quality in any given context, and which can be incorporated into relatively simple bivariate statistical analyses, is thus plainly evident. While urban and agricultural land cover are arguably unsuitable for this purpose, natural vegetation may be a more suitable, and hitherto overlooked, alternative for the estimation of thresholds that can be used to inform integrated land and water resource management strategies. In support of this supposition, Morse et al. (2018, p. 4) have affirmed that the extent of natural vegetation in a catchment is “a major—if imperfect—determinant of water quality.” Likewise, with reference to relationships between LULC and water quality, Bohenek and Sulliván (2022, p. 453) have stated that “the amount and condition of catchment and riparian vegetation are particularly critical variables” (see also Miller et al., 2011; Bierschenk et al., 2012; de Mello et al., 2018; 2022).

As noted above, it has been widely demonstrated that natural vegetation, by virtue of its ability to intercept and filter contaminated overland runoff originating from other land uses, has a universally positive relationship with water quality. Therefore, through its role as a buffer of diffuse pollution in the context of water quality management, and provided that it has been appropriately classified for the region of interest, natural vegetation has general applicability as a LULC metric in all landscapes, regardless of prevailing land use conditions. Moreover, while covariation between LULC variables can be problematic when conducting multivariate statistical analyses, when using natural vegetation as a metric for modelling and threshold estimation, multicollinearity may actually offer a unique advantage: As the extent of natural vegetation in a catchment will be inversely proportional to the extent of other classes of LULC in the same landscape (e.g., urban and agricultural land use), the amount of natural vegetation in a catchment not only reflects the buffering capacity of the landscape,[45] but may be additionally indicative of the degree of anthropogenic disturbance in the landscape by reflecting the presence and/or extent of other land uses (Wang et al., 2021). For these reasons, it is proposed that natural vegetation, when appropriately classified as a distinct class of LULC, may have superior utility as a metric for modelling and threshold estimation.

However, several important considerations must be borne in mind if such an approach is to be adopted. Firstly, as reasoned above, in the context of these studies it is important to determine how best to define and classify natural vegetation in a contextually appropriate manner. Thus, for the purposes of estimating minimum thresholds of natural vegetation for the management of water quality, it must first be established which classes of locally occurring vegetation may be aggregated into a single land cover class that offers the best protection from diffuse pollution. Furthermore, issues of scale and configuration, which have both been highlighted in the literature as potentially significant factors, demand due consideration when attempting to identify thresholds of natural vegetation. In other words, the question of how much natural vegetation cover is sufficient for the protection of water quality (a question of landscape composition) must be complemented by questions relating to the significance of the location of this vegetation in relation to receiving water bodies, as well as the degree to which fragmentation may affect its efficacy as a sink (questions of scale and configuration, respectively). These factors, if found to be significant, will necessarily influence the estimation and application of any minimum thresholds of natural vegetation. For instance, as noted above, previous research suggests that a multiscale approach is most appropriate when investigating relationships between LULC and water quality, with the attendant possibility that different thresholds may apply at different spatial/analytical scales (see, for instance, Grimstead et al., 2018). Moreover, it is also necessary, as reasoned above, to adopt methodological approaches that are able to minimise, or otherwise account for, the potentially confounding influence of other factors (including local environmental variables, seasonality, and catchment size). Furthermore, as a consequence of the influence of these variables, any estimated thresholds may also be regionally specific, thus emphasising the need for local studies conducted at appropriate regional scales.

[45] In this context, a landscape's buffering capacity refers to its ability to retain, assimilate, and/or transform contaminants contained in overland runoff before they pollute receiving water bodies (Goyette et al., 2018; Valera et al., 2019).

With these caveats in mind, the development of methods by which researchers can accurately estimate minimum thresholds of natural vegetation for the integrated management and protection of water quality would provide stakeholders and policymakers with valuable decision-support tools. This would be particularly advantageous in the South African context, where, despite the strong rhetoric of IWRM, the lamentable state of the country's water resources can be attributed (at least in part) to a failure on the part of those responsible to effectively manage the impacts of LULC on water resources in an integrated manner. The production of knowledge that can support the integrated management of land and water resources is critical if South Africa is to meet its own environmental and socioeconomic developmental goals.

Conclusion

There is little doubt, based on the wealth of research available, that LULC has a major influence on water quality. Consequently, in line with the principles of IWRM, understanding and regulating the impacts of LULC on water resources is a key concern. Relatively simple statistical models of the relationship between LULC and water quality have significant potential as key decision-support tools that can enable stakeholders and policymakers to gain a better understanding of, and therefore make informed decisions regarding, the complex catchment systems under their management. In cases where these models can be used to determine critical land use thresholds, actors are also provided with objective targets that can guide the development of integrated, scale-appropriate management strategies. This chapter reviewed the extensive body of literature in which the use of statistical approaches for this purpose is demonstrated. While there is remarkable consistency in the published findings—in so far as urban and agricultural land are typically associated with negative water quality impacts while natural vegetation tends to be associated with improved water quality—there are also several knowledge gaps, areas of persistent uncertainty, and methodological issues which are apparent in the literature. These include ongoing uncertainty regarding the potential significance of spatial scale and landscape configuration when investigating the impacts of LULC on water quality. Other issues relate to the potentially confounding influence of additional variables (including local environmental factors such as geology and climate) which, unless properly accounted for, may undermine the accuracy of the models and make it difficult to isolate the impacts of land use on water quality. Finally, while thresholds of urban and agricultural land use have been reported in the literature, they are subject to several limitations and may not be applicable in certain situations. It is thus concluded that natural vegetation, while hitherto largely overlooked, may be a superior metric for the estimation of land use thresholds that can subsequently be used to inform integrated land and water management strategies in a variety of contexts. The remainder of this thesis documents the estimation of minimum thresholds of natural vegetation within a distinct drainage region that straddles the Western and Eastern Cape provinces of South Africa, and discusses the relevance of these thresholds, and the methods used to estimate them, for the integrated management of land and water resources in the country.

CHAPTER 5

Study Area

"Water and its surrounding environments interact with each other and change their mutual properties through feedbacks that are complex, and can vary spatially and temporally."
— Knight (2019b, p. 91)

According to Day and Dallas (2011, p. 70), "Southern Africa is diverse in climate, geomorphology, geology and soils, and also in its terrestrial and aquatic biotas, and so different parts exhibit differences in water chemistry even when unaffected by human activities." Given that the influence of these factors can complicate statistical analyses (which seek to isolate the impacts of LULC on water quality, as described in the previous chapter), it is important to conduct studies within regions that are, as far as possible, relatively homogenous with respect to these variables (thus highlighting differences in LULC and making it easier to assign causality to the latter with greater confidence). It was with this consideration in mind that the present study area was selected.

South Africa is divided into 22 primary drainage regions, which are further divided into secondary, tertiary, and quaternary sub-catchments (Pitman et al., 1998). The present study area comprises an aggregation of 35 of these secondary catchments (see Figures 14 and 15), and was identified in a study by Day et al. (1998) as a region within which surface waters share similar chemical characteristics. According to the authors, while the conductivity of the surface waters varies across the region, the rivers form a distinct group typically characterised by low pH, low alkalinity, and a high sodium to calcium ratio (ibid., 1998, p. 194). By virtue of these shared chemical characteristics, which are primarily attributable to the region's geology (see below), comparisons between water quality at different sites within this region can be made for the purposes of study and management (Day & King, 1995; Day et al., 1998). Importantly, any significant deviations from these shared "background" water quality characteristics within this region may be indicative of human impacts on the water resources.

The study area covers approximately 71,000 km^2 and extends for about 1,500 km along the western, southern, and south-eastern coast of South Africa, from 18°12'25"E 31°43'11"S (near the town of Vredendal in the Western Cape) to 27°7'46"E 33°29'57"S (near the town of Port Alfred in the Eastern Cape) (see Figures 14 and 15). It also straddles the administrative border between the Western Cape and Eastern Cape provinces, and similarly extends across three of South Africa's Water Management Areas (namely the Berg-Olifants, Breede-Gouritz, and Mzimvubu-Tsitsikamma WMAs) (see Figure 16). Several of South Africa's Strategic Water Source Areas (SWSAs) also overlap with the extent of the study area (see Figure 17). SWSAs are regions which supply disproportionately large volumes of water per unit area and are therefore considered of strategic significance for water security from a national planning perspective (Le Maitre et al., 2018; Stats SA, 2023). They are estimated to support at least 50% of the population, 64% of the economy, and supply about 70% of the water used by irrigated agriculture (CER, 2023a). Due to their disproportionate importance, the protection of SWSAs is a national priority (CSIR, 2023; Stats SA, 2023).

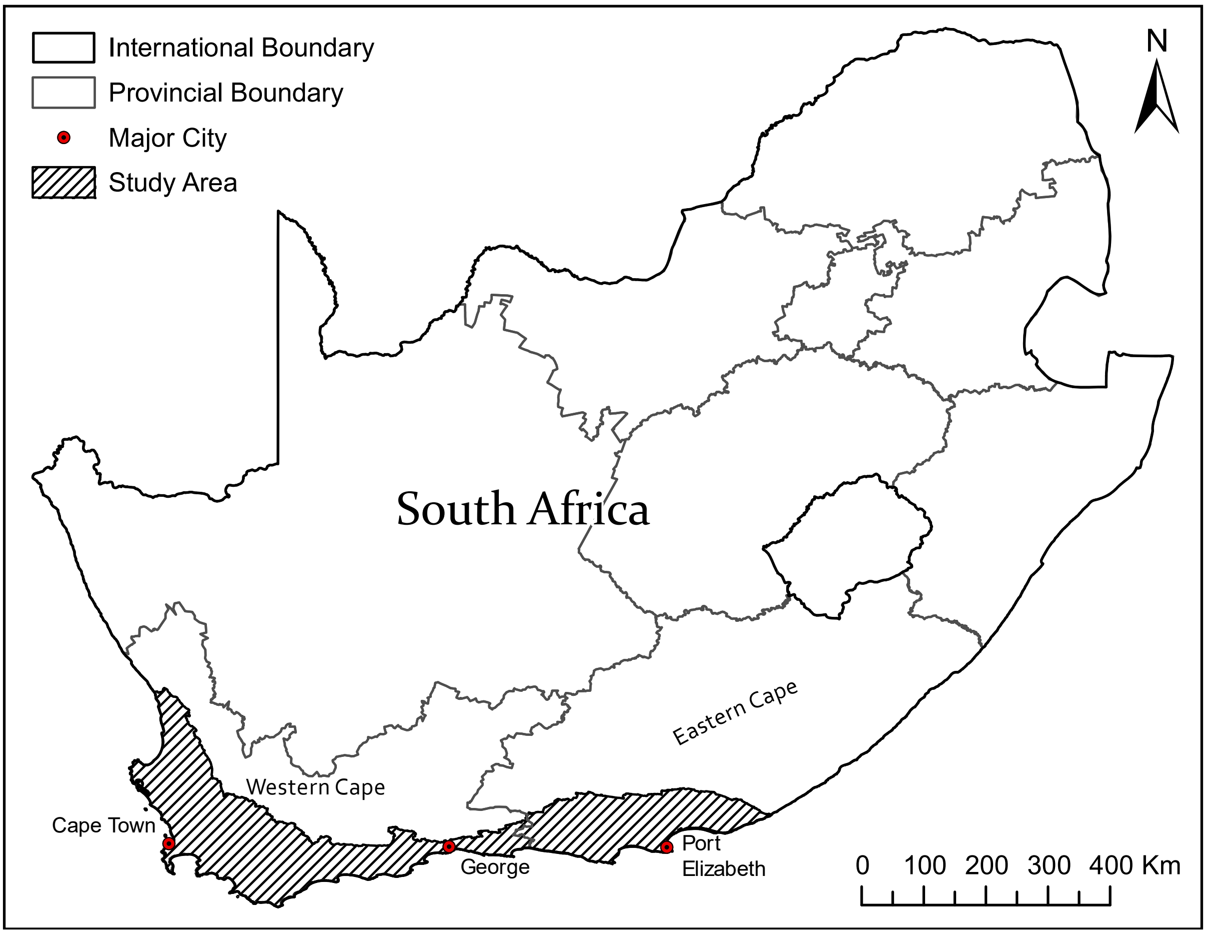


Figure 14. Map showing the location of the study area in within South Africa's national borders. Geospatial data obtained from HDX (2023).

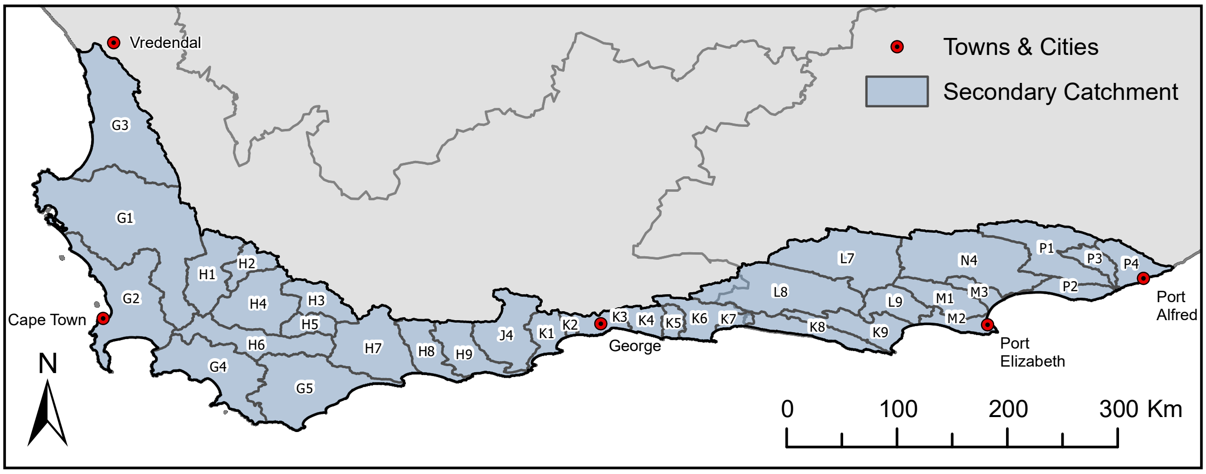


Figure 15. Map showing the extent of the study area and the 35 secondary catchments of which it is composed. Geospatial data obtained from Bailey and Pitman (2016); DWS (2023); HDX (2023).

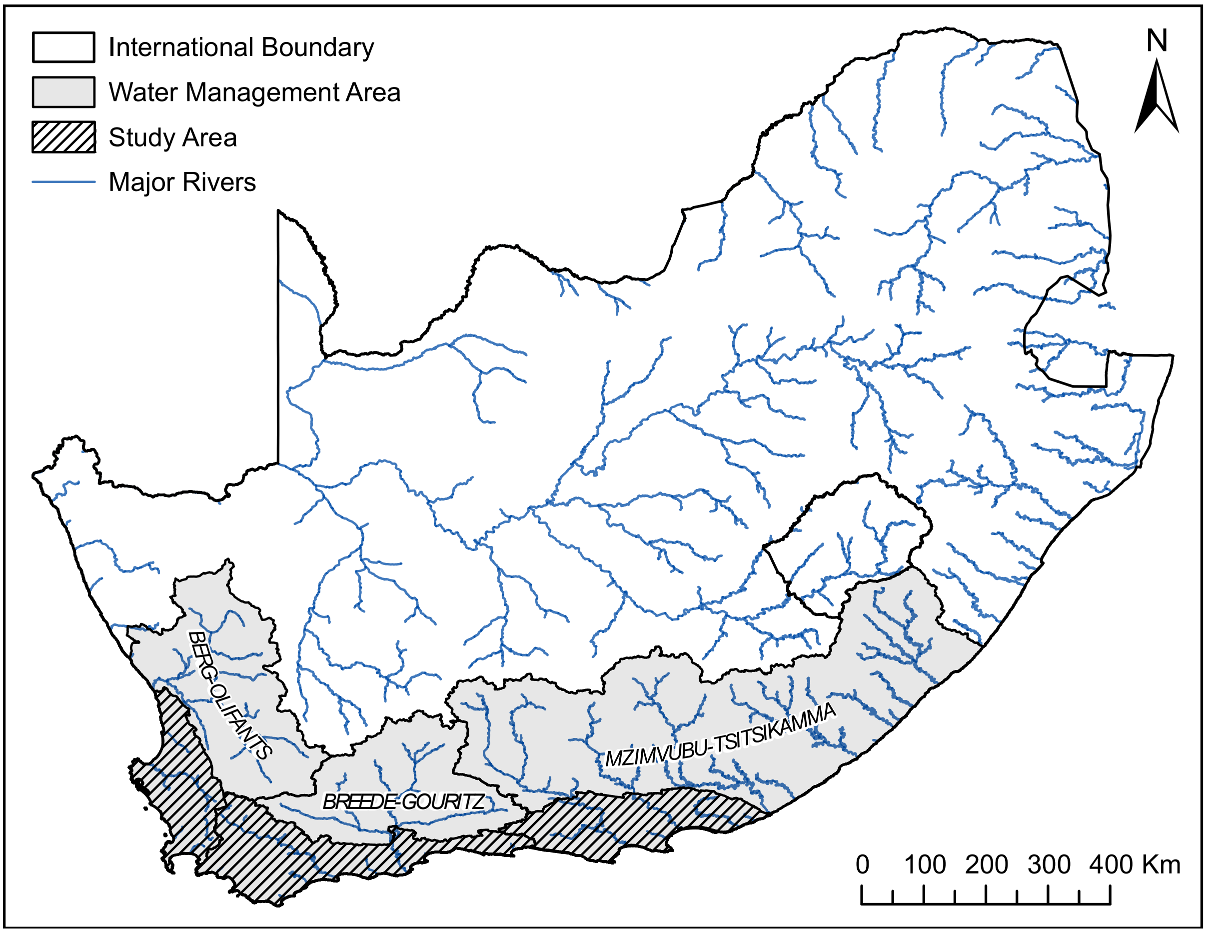


Figure 16. Map showing the study area in relation to the three Water Management Areas (WMAs) across which it extends. Geospatial data obtained from Bailey and Pitman (2016); DWS (2023); HDX (2023).

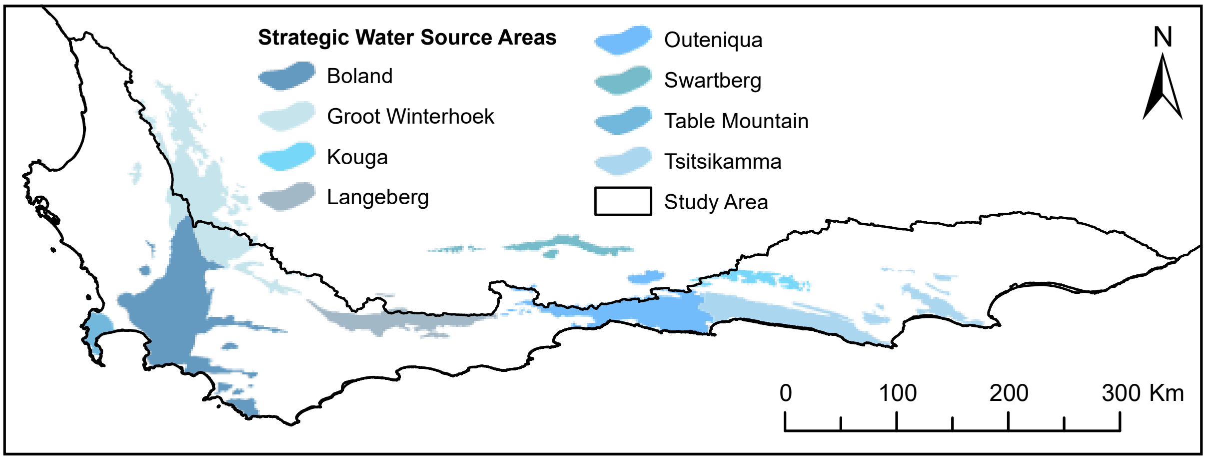


Figure 17. Map showing the location of several Strategic Water Source Areas (SWSAs) relative to the study area. Geospatial data obtained from Bailey and Pitman (2016); DWS (2017d); Lötter and Le Maitre (2021).

Compared to the national average temperature of 17.5°C, the mean annual temperature across the study area is approximately 16.9°C (Fick & Hijmans, 2017; World Bank Group, 2021). Mean annual precipitation across the study area is approximately 498 mm, which is comparable to the national average of 464 mm per year (ibid.). However, there are discernible precipitation gradients within the study area, as shown in Figure 18. As is evident from the map, some locations receive considerably more precipitation per year than the annual average (namely the areas near the Hottentots-Holland Nature Reserve in the south-west, Tsitsikamma National Park along the southern coast, and the town of Port Alfred).

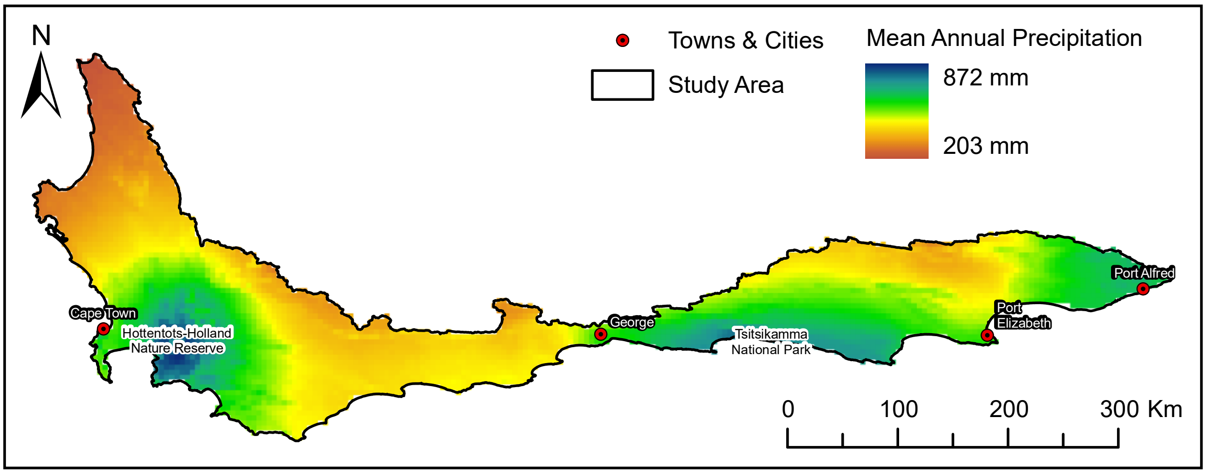


Figure 18. Map showing mean annual precipitation of the study area. Precipitation data obtained from Fick and Hijmans (2017).

Geologically, the study area is dominated by the sandstones, shales, and mudstones of the Cape Supergroup (which occupies approximately 60% of the study area). The rest of the area is composed of the Kalahari Group (16%), the Malmesbury, Kango and Gariep Groups (11%), the Uitenhage Group (6%) and the Cape Granite Suite (3%) (Johnson & Wolmarans, 2008; SANSA, 2015; Knight & Rogerson, 2019). Geological variation across the study area is shown in Figure 19.

> Sedimentary rocks, such as those of the Cape Supergroup, may have been derived from sand particles that were already strongly weathered when they were consolidated… Very little soluble material is present in these rocks, and so even less can be leached out. Waters flowing over such rocks usually have very low concentrations of salts, including nutrients, and the bulk of dissolved material is derived from rain, snow and other forms of precipitation, in which the major ions are sodium and chloride. Such waters are said to be 'rainfall dominated' or 'precipitation dominated' and are very soft, pure and unbuffered.

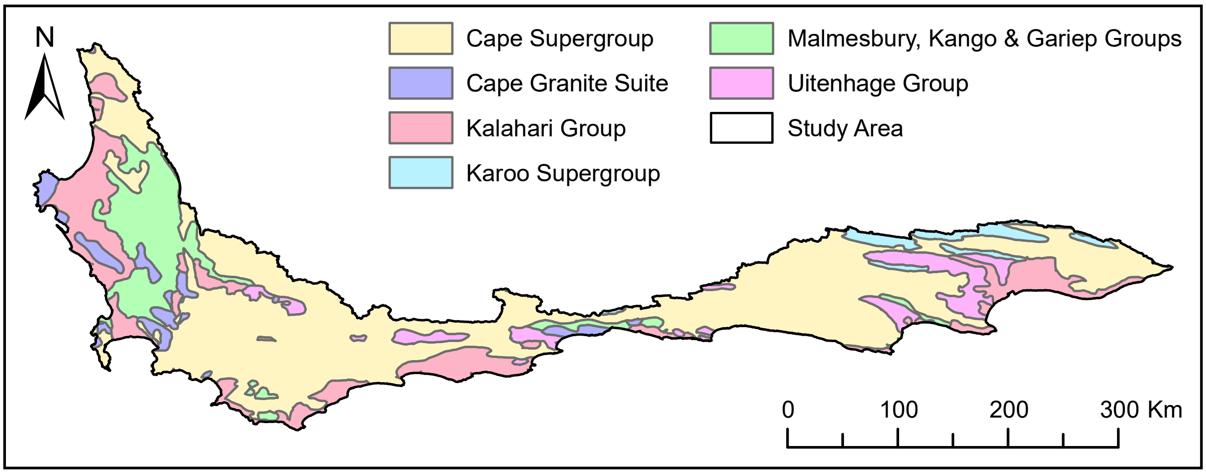


Figure 19. Map showing the geology of the study area. Geological data obtained from SANSA (2015) and modified according to Johnson and Wolmarans (2008); Knight and Rogerson (2019).

For the purpose of water resources management, in addition to drainage regions, South Africa has been further divided into several distinct ecoregions, each of which is defined according to physiographic, climatic, geological, and vegetative characteristics (Kleynhans et al., 2005). While the study area nominally contains six different ecoregions (see Figure 20), the predominant characteristics of these ecoregions are fairly similar (as shown in Table 2). Taken together, the Southern, South Western, and South Eastern Coastal Belt ecoregions account for approximately 59% of the study area (21%, 20%, and 18%, respectively). The Southern Folded Mountains on their own occupy an additional 31% of the region. The Western Folded Mountains and Western Coastal Belt account for the remaining 10% of the study area. Topographically, while the western part of the study area (i.e., the South Western Coastal Belt) is mainly composed of plains of moderate relief, the rest of the region is dominated by mountainous and hilly areas of moderate to high relief (i.e., the South Eastern Coastal Belt, Southern Coastal Belt, and the Southern and Western Folded Mountains). The vegetation indigenous to the region is predominantly fynbos or renosterveld, with areas of afromontane forest and succulent thicket. The study area also tends to receive the majority of its precipitation in winter months, although some areas receive rainfall throughout the year. Mean annual precipitation for the region varies (as described above), with similar fluctuations in runoff. Detail is provided in Table 2 below.

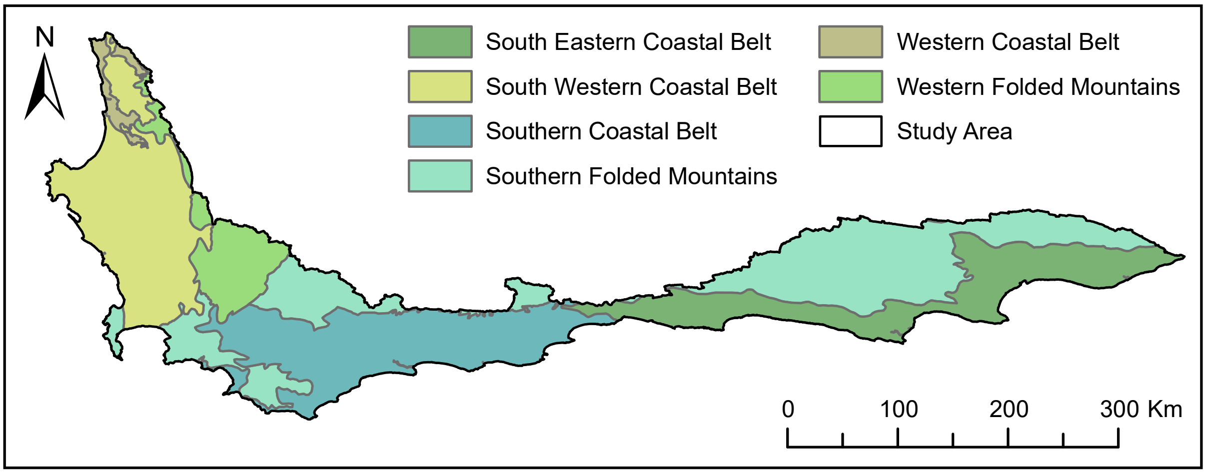


Figure 20. Map showing the ecoregions that occur within the study area. Ecoregion data obtained from DWS (2019).

Table 2. Characteristics of the ecoregions within the study area. Data from Kleynhans et al. (2005).

	Southern Folded Mountains	Southern Coastal Belt	South Western Coastal Belt	South Eastern Coastal Belt	Western Folded Mountains	Western Coastal Belt
Approximate Proportion of Study Area (%)	31	21	20	18	8	2
Physiography	Closed hills; mountains; moderate and high relief	Closed hills; mountains; moderate and high relief	Plains; moderate relief	Hills and mountains; moderate and high relief	Closed hills; mountains; moderate and high relief	Plains; low relief
Dominant Vegetation Types	Grassy fynbos; mountain fynbos	South and south-west coast renosterveld	West coast renosterveld	Mesic succulent thicket; afromontane forest	Mountain fynbos	Lowland succulent karoo
Rainfall Seasonality	Very late summer to winter to all year	Winter to all year	Winter	All year to very late summer, to winter	Winter	Winter
Mean Annual Precipitation	Generally low but moderate to high towards the south	Moderate	Moderate in a limited area in the south, decreasing to low in the north	Moderate to high	Varies from moderate/high in the south to low in the north	Very low/arid
Mean Annual Runoff (Simulated)	Predominantly moderate	Moderate	Very low in the north to moderate/high in the south	Moderate to very high	Very high in the south	Very low

According to the latest national land cover data (DFFE, 2020), the study area consists mainly of shrubland (38%), cultivated land (30%), forested land (15%), and grassland (11%). Built-up land makes up approximately 3% of the total study area, while the remaining area is divided between Barren Land, Water Bodies, and Wetlands. Less than 0.1% of the land area is occupied by land designated as Mines and Quarries. Current land cover in the study area is shown in Figure 21.

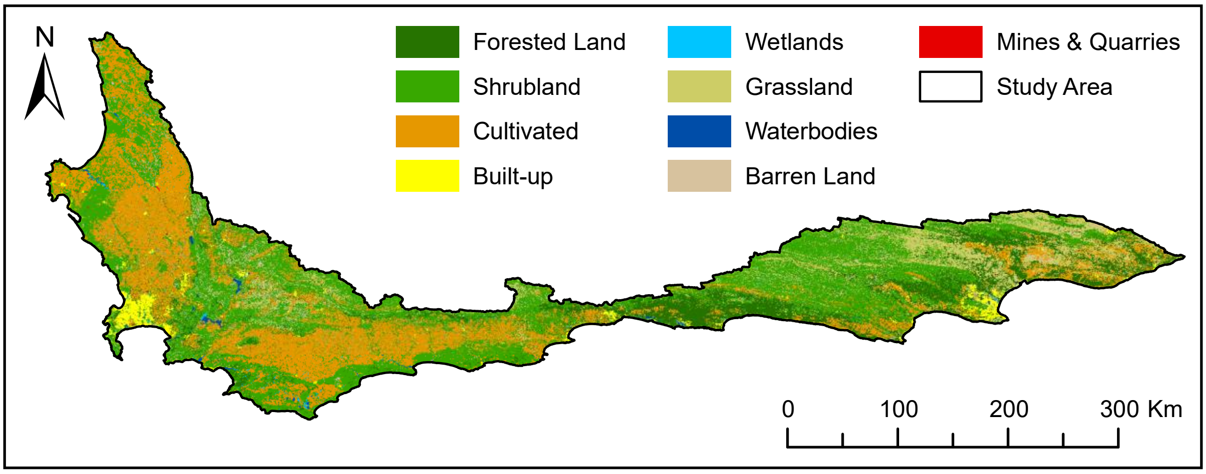


Figure 21. Map showing current (2020) land use/land cover for the study area. SANLC data obtained from DFFE (2023).

In conclusion, although the study area shows some spatial variation in terms of precipitation, geology, and ecology, these differences are slight and unlikely to have a major impact on water quality in the absence of anthropogenic influences. Instead, the shared geological, climatic, and ecological characteristics of the area (described above) mean that, under unimpacted conditions, background water chemistry of the surface waters is fairly similar. As noted above, this assertion is supported by the findings of Day et al. (1998), who found that surface waters in this area were distinct from other regions in terms of their natural chemical characteristics (see also Day & King, 1995). By virtue of this, differences in pollution levels in the catchments across this region could be more confidently attributed to anthropogenic disturbances, including LULC transformations, in subsequent statistical analyses.

CHAPTER 6:
Methods and Results

"The formulation of scientifically justified guidelines for the management of anthropogenic impacts on river health requires a better understanding of the quantitative linkages among river-system parameters."
—Magierowski et al. (2012, p. 726)

Data Sources and Sample Selection

Water Quality Data

Water quality data for this study were obtained from the National Chemical Monitoring Programme (NCMP) database, supplied on request by the Resource Quality Information Services (RQIS) sub-directorate of the South African Department of Water and Sanitation (DWS). The RQIS maintains a large national database of multivariate water quality records from an extensive network of monitoring sites located on lakes, dams, and rivers across South Africa (Nomquphu, 2005; Huizenga et al., 2013; DWS, 2015; Ramjukadh et al., 2018; DWS, 2022b). However, despite the wide geographical coverage of the NCMP network, as well as the fairly regular sampling undertaken at most sites, there are periods and locations for which there are large gaps in the database (DWS, 2022b).

Land Use/Land Cover (LULC) Data

Land use/land cover (LULC) data were obtained from the Environmental Geographical Information Systems (E-GIS) platform managed by the South African Department of Forestry, Fisheries and the Environment (DFFE, 2023). Of the available land cover products, the 2013/14 South African National Land Cover (SANLC) map was selected for this study. The map was derived from multi-seasonal Landsat 8 (OLI) imagery, acquired between April 2013 and March 2014, using an "operationally proven" semi-automated modelling procedure (Geoterra Image, 2015, pp. 6–7). The map has an overall classification accuracy of 82.53% and a 30 m spatial resolution (ibid.).

An existing land cover product was chosen for two reasons. Firstly, the SANLC datasets, which are freely and publicly available from the DFFE, offer a classification accuracy that was unlikely to be improved upon by conducting an ad hoc land cover classification procedure for the region of interest (this assertion is made considering the significant amount of time, expertise, and financial capital invested in the production of the available national land cover products, which far surpassed the resources available for the present study). Furthermore, the accuracy of the 2013/14 SANLC map is very close to the benchmark of 85% quoted in several reference texts (e.g., Giri, 2012; Congalton & Green, 2019; Stehman & Foody, 2019). Secondly, if the methods developed in this study are to be replicated in other regions of South Africa, the use of existing national land cover maps means that the same land cover datasets can be easily used for future studies, making results—especially estimated thresholds of natural vegetation—more comparable. The use of existing land cover products has been favoured for similar reasons in a number of other studies, including several conducted in South Africa using the same SANLC products (e.g., Dabrowski & de Klerk, 2013; Malherbe et al., 2019a; Barnard et al., 2021; du Plessis, 2021; Fynn & Abiye, 2022).

Sample Selection

To develop accurate models of the relationship between land cover and water quality, data were required from an unbiased cross-sectional sample of sub-catchments that would be representative of the range of conditions found in the study area. The NCMP water quality monitoring sites located within the study area represented possible locations for which sub-catchments could be delineated using digital elevation model (DEM) data (each sub-catchment, thus delineated, would approximate the land area drained by the respective sampling point). Metrics of natural vegetation, calculated for these sub-catchments, could thus be paired with water quality data to provide a sample for further statistical analysis and modelling. Based primarily on the years for which water quality data were available at the sampling sites located within the study area, the decision was made to pair data from the 2013/14 SANLC map with water quality data from the NCMP database from the same period (i.e., the 2013/14 map was the most recent land cover product available that corresponded to a period during which regular water quality sampling had taken place at most of the NCMP monitoring sites in the study area).

Of the sampling sites located within the study area, 211 represented locations along rivers for which water quality data were available after 1990 (before which date Ramjukadh et al., 2018, have identified a pH anomaly in the data). A systematic review of each of these sites was undertaken to identify suitable locations for inclusion in the statistical sample of sub-catchments used to generate the regression models. The following criteria were used to select sites according to the data requirements of the statistical modelling procedures:

1. The site represented a pour-point[46] from which an independent[47] sub-catchment could be delineated.

[46] A "pour-point" is the terminology used in the ArcGIS software environment to refer to the lowest point in a watershed towards which all flow is directed (i.e., a catchment's outlet) (Bajjali, 2018).

[47] The statistical requirement of independence (i.e., that the measurements of one observation should be in no way related to, or influenced by, the measurements of other observations) necessitated that sub-catchments should not be nested. Thus, in instances where the selection of two eligible NCMP sites would have resulted in one of the delineated sub-catchments being contained within the other (i.e., nesting of sub-catchments), a choice needed to be made between the two. In such cases, the site that offered most comprehensive water quality record was usually retained. In order to determine eligibility according to this criteria, the land area drained by each of the sites was estimated visually using a 1:50,000 stream network layer (available from DWS, 2023) in conjunction with sub-basin boundaries from the global HydroBASINS datasets (Lehner & Grill, 2013). This made it possible to determine whether the inclusion of any two sites would result in the nesting of sub-catchments, thus violating the requirement of independence.

2. At least 15 monthly water quality samples had been recorded at the site between January 2013 and December 2014.[48, 49]
3. Data were available for the following water quality parameters: electrical conductivity (EC), ammonium nitrogen (NH_4-N), nitrite-and-nitrate nitrogen (NO_2+NO_3-N), orthophosphate (PO_4), sulphate (SO_4), and pH.[50]

A total of 58 sites met these criteria and were thus selected for inclusion in the sample of sub-catchments used for further statistical analyses. While this is not, sensu stricto, a truly independent or random sample, the following sections will demonstrate that the selected sites offered a reasonably representative cross-sectional sample of sub-catchments, widely distributed across the study area, and covering a range of land use conditions. Appendix 6 provides further details of the sites selected. The locations of the sites within the study area are shown on the map below (Figure 22). Each of the monitoring sites listed in the NCMP database are designated unique identifying numbers which were retained in this study to identify the monitoring points and the sub-catchments delineated for each.

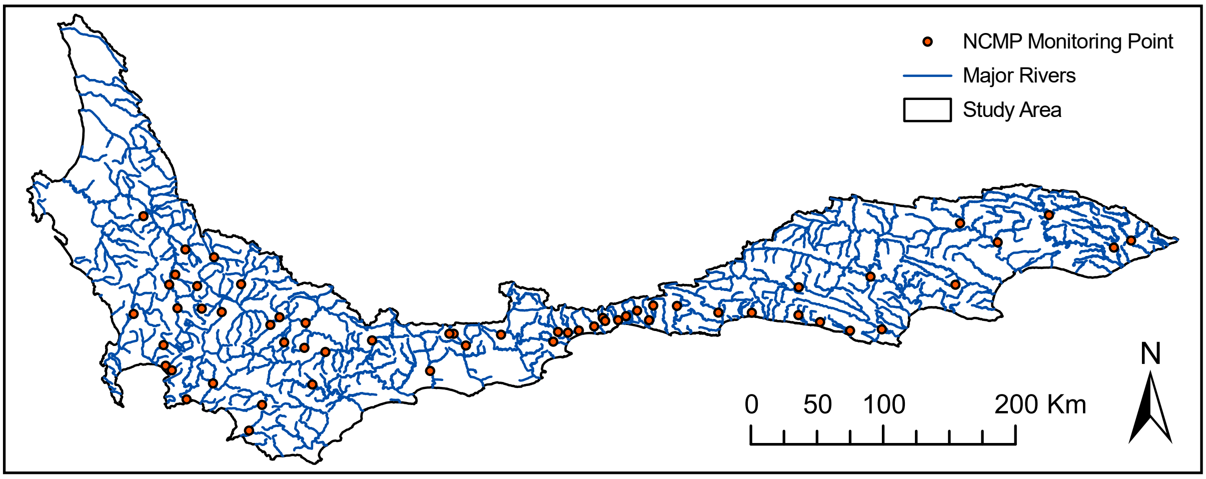


Figure 22. Map showing the locations of the 58 selected NCMP monitoring points that made up the cross-sectional sample for this study. Major rivers, based on a 1:500,000 stream network, are also shown. Each site represented a location for which adequate water quality data were available for the period of interest and for which an independent sub-catchment could be delineated. Geospatial data obtained from DWS (2017d).

Water Quality Analysis

Water Quality Indices

As the primary aim of the study was to develop statistical models of the relationship between water quality and natural vegetation in the chosen study area (from which thresholds of natural vegetation

[48] As far as possible, sites were chosen such that water quality samples spanned both wet and dry seasons so that the measurements taken at each site would be representative of average conditions across both seasons (thus minimising the influence of intra-annual seasonal differences in precipitation and discharge on measured concentrations; see below under "Potentially Confounding Factors" on pp. 139f).
[49] In two instances, where an insufficient number of water quality samples were available for these years, records from 2015–2016 were also considered.
[50] The choice of these parameters is discussed later.

could be estimated) it was necessary to adopt a suitable metric by which to measure the former. However, water quality, when considered holistically, is a complex function of innumerable physical, chemical, and biological variables, each of which may be measured against specific standards according to the intended use of the water (Weiner, 2013; Boyd, 2020). For this reason, no single water quality parameter can provide a sufficiently comprehensive measure of overall water quality (Sutadian et al., 2016; Mladenović-Ranisavljević et al., 2018; Gossweiler et al., 2019; Kachroud et al., 2019). This is particularly relevant when considering the impacts of LULC on water quality, where different classes of land cover, and the various land use processes with which they are associated, generate runoff containing a wide range of contaminants (Rhodes et al., 2001; Tsegaye et al., 2006; Schiff & Benoit, 2007).

In view of the foregoing, rather than modelling the statistical response of one or more individual water quality parameters against metrics of natural vegetation, a composite physiochemical water quality index (WQI) was used in the present study to estimate the cumulative impact of LULC on water quality. WQIs have a long history of development dating back to the mid-twentieth century, and the acceptance of such indices as tools for the assessment of water quality has continued to grow in recent decades (Sutadian et al., 2016; Aziz et al., 2021; Lee et al., 2022a; Chemeri et al., 2023; Lukhabi et al., 2023). A number of helpful publications review the history and development of several of the more commonly used WQIs, including their various advantages and limitations (see, for instance, Fernández et al., 2004; Lumb et al., 2011; Abbasi & Abbasi, 2012; Sutadian et al., 2016; Banda & Kumarasamy, 2020c; Uddin et al., 2021; Chidiac et al., 2023; Lukhabi et al., 2023). The use of WQIs has been argued for, and subsequently demonstrated, in several similar studies.[51]

The principal advantage of these indices is their ability to translate the observed measurements of several individual parameters into a single unitless score of overall water quality, which is intuitively understandable and thus easy to communicate to the public, local stakeholders, planners, and policymakers (Gitau et al., 2016; Mladenović-Ranisavljević et al., 2018; Namugize & Jewitt, 2018; Banda & Kumarasamy, 2020b; Uddin et al., 2021; Benkov et al., 2023; Gikas et al., 2023). WQIs achieve this by converting the observed measurements of the relevant parameters into standardised sub-index scores, and then combining these individual sub-index scores into an overall score using an aggregation function (Abbasi & Abbasi, 2012; Chemeri et al., 2023; Lukhabi et al., 2023). The ability to synthesise large and potentially unwieldy sets of multivariate water quality data into an easy-to-understand, yet technically robust, measurement of overall water quality offers significant practical and scientific utility (Ladson, 2000; Abbasi & Abbasi, 2012; Gitau et al., 2016; Sutadian et al., 2016; Banda

[51] These include, for example, Tsegaye et al. (2006), Schiff and Benoit (2007), Firdaus and Nakagoshi (2013), Yu et al. (2013), Rodríguez-Romero et al. (2018), Shukla et al. (2018), Wang and Zhang (2018), Gossweiler et al. (2019), Kim et al. (2020), Sutjiningsih (2017), Karakuş (2020), Hanna et al. (2021), Molekoa et al. (2021), Senbore and Oke (2021), Umwali et al. (2021), Paná et al. (2022), Zhang et al. (2022a), Pandey et al. (2023), Gani et al. (2023), Wang et al. (2023b), and Zhang et al. (2023b).

& Kumarasamy, 2020c; Lee et al., 2022a; Gikas et al., 2023; Lupi et al., 2023). Namugize and Jewitt (2018, p. 525) have therefore concluded that, despite any shortcomings, WQIs are "useful supporting tools to summarise large water quality datasets and provide information understandable by scientists, water suppliers, planners, policy makers and the general public."

Nemerow's Pollution Index (NPI)

WQIs typically score water quality on an ascending scale, according to which higher index scores indicate better water quality. Conversely, pollution indices use an inverted scale, by which higher index scores reflect greater levels of impairment/contamination. An important limitation of most WQIs is that the index scoring scale effectively "bottoms out" at zero. Due to this, in situations where water quality standards have been exceeded for one or more parameter, the index can only indicate this non-compliance with a score of zero. However, the index score will not reflect the magnitude of impairment (i.e., the degree of exceedance) beyond permissible limits. By contrast, the scale of a pollution index can, theoretically speaking, extend infinitely as the degree of contamination increases, thus allowing the index score to reflect the degree of impairment beyond stipulated guideline values. When comparing the degree to which the quality of different water bodies is impaired (one of the objectives of this study) this is an important consideration.

This study utilised Nemerow's Pollution Index (NPI) to assess the degree to which water quality in each of the 58 sub-catchments had been impacted by, among other potential sources of contamination, surrounding LULC. The index was originally proposed for use by the United States Environmental Protection Agency (USEPA) and subsequently recommended for more general use (Nemerow & Sumitomo, 1970; Nemerow, 1991). The NPI offers a relatively simple, intuitive, and robust method for quantifying the aggregate influence of multiple parameters on overall water quality. Nemerow's index has thus been used in several studies to assess water and/or sediment contamination (e.g., Xu et al., 2010; Wu et al., 2014; Brady et al., 2015; Effendi, 2016; Gevorgyan et al., 2016; Wang et al., 2017; Rahmatillah & Ramli, 2021; Sarhat et al., 2022; Su et al., 2022). As with most composite indices, a standardised sub-index score is first calculated for each of the chosen water quality parameters. To do this, the NPI uses a relative-concentration function by which the *observed value* of each water quality parameter is evaluated against the relevant *guideline value* (i.e., the maximum permissible concentration for that parameter according to the relevant water quality standards).

Adapted slightly from Nemerow (1991), the general sub-index function is given below in Equation 1:

$$SI_i = \frac{C_i}{L_i^{max}} \tag{1}$$

where SI_i is the standardised sub-index score of the ith parameter, C_i is the observed concentration of the ith parameter, and L_i^{max} is the maximum permissible (i.e., guideline) value of the ith parameter.

For parameters such as dissolved oxygen, where water quality impairment increases as the concentration of the parameter decreases, the following sub-index function (Equation 2) is used:

$$SI_i = \frac{C_i^{max} - C_i}{C_i^{max} - L_i^{min}} \tag{2}$$

where L_i^{min} is the minimum guideline value of the parameter in question and C_i^{max} is the maximum possible value that C_i can attain (such as maximum saturation in the case of dissolved oxygen).

In cases where the parameter has maximum *and* minimum guideline values (e.g., pH) the following sub-index function (Equation 3) is used:

$$SI_i = \frac{C_i - \left[\frac{L_i^{max} - L_i^{min}}{2}\right]}{L_i^{max}\ or\ L_i^{min}\ [whichever\ is\ closest\ to\ C_i] - \left[\frac{L_i^{max} - L_i^{min}}{2}\right]} \tag{3}$$

where L_i^{max} and L_i^{min} are the maximum and minimum guideline values, respectively, of the ith parameter.

The final index score is calculated using a modified root mean square (RMS) function, as shown in Equation 4:

$$NPI = \sqrt{\frac{(SI_{max})^2 + (SI_{mean})^2}{2}} \tag{4}$$

where NPI is the aggregate index score, SI_{max} is the maximum of the sub-index scores, and SI_{mean} is the arithmetic mean of the sub-index scores of all included water quality parameters.

Different WQIs have employed a variety of mathematical functions, including various additive and multiplicative functions, to aggregate individual sub-index scores into a final index score (see Abbasi & Abbasi, 2012; Banda & Kumarasamy, 2020a; Uddin et al., 2021). Each of the established aggregation functions is subject to certain limitations and work is therefore ongoing to develop improved methods for combining individual sub-index scores into a final index score (Briciu et al., 2020). Most recently, for example, fuzzy logic and artificial intelligence have been applied to the aggregation of sub-indices (Banda & Kumarasamy, 2020a; Chidiac et al., 2023; Tabassum et al., 2023). While a full treatment of this discussion is beyond the scope of this study, the relatively simple and intuitive aggregation function of the NPI, while subject to certain caveats (discussed below), provided a suitably accurate indication of the overall degree to which water quality was impaired at the locations sampled in this study. More specifically, by incorporating site-specific water quality guidelines (the determination of which is discussed below) the index was able to indicate whether the degree of overall impairment could be declared ecologically unacceptable. This latter consideration was important in order to provide water quality benchmarks on which minimum thresholds of natural vegetation could be based.

By using the modified RMS aggregation function above (Equation 4), the final score is intentionally biased towards the highest-scoring sub-index score, thus reducing the effect of eclipsing (Nemerow, 1991; Abbasi & Abbasi, 2012). Eclipsing affects all composite WQIs and is due to the limitations of some of the aggregation functions used to combine individual sub-index scores. It occurs when the aggregate index score falsely indicates compliance even though one or more of the constituent sub-index scores are non-compliant. However, the NPI's modified RMS aggregation function has the benefit of making the overall index score especially sensitive to the highest-scoring water quality parameter, thereby reducing the eclipsing effect. By factoring in the mean of the other sub-index scores, the aggregate index score also maintains a degree of compensation. Compensation refers to the resistance of the aggregation function to undue influence by extreme sub-index scores. Ideally, an aggregation function will "compensate" for any extreme sub-index scores by also reflecting the more moderate values of the other sub-indices (the purpose of a composite index is, after all, to evaluate water quality holistically by reflecting the combined influence of multiple parameters). While an index should, up to a point, demonstrate compensation, if the observed measurements of one or more parameters exceed the relevant water quality guideline values, this non-compliance should be reflected in the final index score. Where this does not occur, the result is an ambiguous index score from which it is difficult to determine whether the water resource is in fact polluted beyond acceptable limits (i.e., non-compliant). The need for the index to offer compensation, and the need to avoid eclipsing, are thus somewhat in tension (fuller treatments of eclipsing, compensation, and ambiguity can be found in Ott, 1978; Wepener et al., 1992; Lumb et al., 2011; Abbasi & Abbasi, 2012; Uddin et al., 2021; Chidiac et al., 2023; Lukhabi et al., 2023).

By virtue of the RMS function used, any aggregate NPI score below 0.7 indicates that the observed concentrations of all parameters are, without any doubt, within acceptable levels. By contrast, an aggregate index score ≥ 1.0 indicates definite non-compliance (i.e., the observed value of at least one of the included parameters would have exceeded the relevant guideline value). However, due to eclipsing, there is a small region of ambiguity between aggregate index scores of 0.7 and 1.0 (a score between these index values indicates that there is a possibility that at least one of the parameters is non-compliant). Nevertheless, for all practical intents and purposes, and according to the original design of the index, the critical aggregate index score is usually taken as 1.0 (Nemerow, 1991). This score unambiguously indicates that pollution levels have exceeded acceptable limits and that the water is unfit for its intended use. However, in accordance with the precautionary principal, a more conservative score of 0.7 may also be adopted (cf. the NPI score classification scale used by Gevorgyan et al., 2016). These two scores thus provided convenient criteria by which to estimate tiered regulatory thresholds of natural vegetation: the lower value (NPI = 0.7) was used as the water quality benchmark on which to base precautionary thresholds of natural vegetation, while the higher value (NPI = 1.0) was used as the benchmark by which target natural vegetation thresholds were estimated (see the earlier discussion regarding tiered regulatory thresholds on pp. 76f).

Application of Nemerow's Pollution Index

Parameter Selection

Nemerow's Pollution Index is flexible in that, theoretically speaking, the measurements of any number and combination of water quality parameters can be aggregated to calculate the final index score. However, Abbasi and Abbasi (2012, p. 11) have cautioned that whereas parameter selection is "crucial to the usefulness of any index," it is also "fraught with uncertainty and subjectivity," and therefore urge that "enormous care, attention, experience, and consensus-gathering skills are required to ensure the most representative parameters are included." In particular, the inclusion of redundant and/or strongly correlated variables should be avoided (Sutadian et al., 2016). The aim is thus to select a combination of parameters which, when taken together, are fully representative of the water quality concerns pertinent to the intended application of the index (Kachroud et al., 2019; Uddin et al., 2021; Lukhabi et al., 2023).

From a preliminary perusal of the NCMP database, it was determined that six water quality parameters were routinely measured across the majority of sampling sites located within the study area, namely, electrical conductivity (EC), nitrite-and-nitrate nitrogen (NO_2+NO_3-N), ammonium nitrogen (NH_4-N), orthophosphate (PO_4), sulphate (SO_4), and pH. Although several additional water quality parameters are nominally available, not all of these parameters are regularly measured across the NCMP network. Notwithstanding these restrictions, it was accepted that the measurement of these six parameters would provide an indication of some of the more common water quality problems typically associated with land use related activities (see Chapter 3 and Appendix 1).[52] In addition, as limiting the number of parameters included in the composite index has the advantage of reducing the effect of eclipsing when aggregate index scores are calculated, it was also decided to take the sum of the concentrations of nitrite-and-nitrate nitrogen (NO_2+NO_3-N) and ammonium nitrogen (NH_4-N) to represent total inorganic nitrogen (TIN) concentrations (as per USEPA, 2023). Thus, in view of the above, the following five parameters were used to calculate aggregate NPI scores:

- Electrical conductivity (EC)
- Total inorganic nitrogen (NO_2+NO_3-N + NH_4-N = TIN)
- Orthophosphate (PO_4)

[52] A more detailed discussion on parameter selection is provided in the following chapter.

- Sulphate (SO_4)
- pH

Determining Observed Values

Of principal interest in this study was the statistical relationship between long-term water quality conditions and proportions of natural vegetation at different spatial scales across the sample of 58 sub-catchments. Thus, as per the latest water quality assessment guidelines published for Australia and New Zealand (ANZG, 2018; published online), the "observed value" of each water quality parameter was estimated using the median value of the measurements taken at each of the monitoring sites over a 24-month sampling period, covering both wet and dry seasons (see also Nde & Mathuthu, 2018; Duan et al., 2019; Huynh & Hobbs, 2019; Nde et al., 2021). Due to the fact that water quality data are frequently skewed, the median provides a better estimate of the typical long-term conditions at a given site than the arithmetic mean (McBride, 2005; ANZG, 2018; Helsel et al., 2020). In addition, because of temporal fluctuations in water chemistry—due, for instance, to natural seasonal variations in precipitation, runoff, and discharge—once-off spot samples are unreliable and, at best, only provide a "snapshot" of water quality at a given location at the time of sampling (Bate et al., 2004). Therefore, the median value of measurements taken over a 24-month period reflects the typical conditions at each sampling site over the relevant period, irrespective of natural seasonal variation.

Determining Site-Specific Water Quality Guideline Values Using Local Reference Data

According to D'Arcy et al. (2022a, p. 11), determining the pollution levels of a given water body is typically achieved by evaluating the observed measurements of a chosen set of water quality parameters against "threshold concentrations of indicator parameters, below which it is hoped there would be no adverse impacts." In other words, the observed value (see above) of each parameter is compared with the agreed "guideline value" for that parameter. The guideline value typically represents the maximum (or minimum, where applicable) permissible value of that parameter for a given water use. In the present study, rather than using generic water quality standards (e.g., those published by a national authority) to define the relevant water quality guideline values, the observed values of each of the selected water quality parameters were compared against site-specific guideline values derived from an analysis of local reference conditions. McDowell et al. (2013, p. 3) have defined reference conditions as "the chemical, physical or biological conditions that can be expected in streams and rivers with minimal or no anthropogenic influence." Rosemond et al. (2009, p. 224) have thus described site-specific water quality guideline values derived from reference condition data as numerical limits developed to support and protect water at a specified location by intentionally taking natural conditions into consideration. The main advantage of the reference condition approach is that it allows researchers to take local conditions and other "geogenic" factors into account when setting environmental standards, thereby providing important context for the interpretation of observed water quality measurements (Schneider et al., 2017). This is particularly relevant when naturally-occurring background concentrations at a particular location may be higher than generic water quality guidelines, or in areas of high ecological importance where generic standards may not offer sufficient protection (McDowell et al., 2013; van Dam et al., 2014; van Dam et al., 2019). Therefore, according to Agboola et al. (2020, p. 1), “the use of reference conditions is essential to the monitoring and management of aquatic ecosystems.”

Deriving guidelines using reference data is typically achieved using a percentile approach. While the choice of the critical percentile is essentially arbitrary, it is usual for the upper guideline value of each parameter to be defined according to either the 75th or 80th percentile of the reference data (see, for example, USEPA, 2000; CCME, 2016; ANZG, 2018). However, in situations where a less conservative guideline limit is more appropriate, the 90th percentile has also been used (see, for instance, Khan et al., 2005; Lumb et al., 2006; Rosemond et al., 2009; Maine DEP, 2021). These percentiles are intended to represent the extremes of local variation in the absence of anthropogenic disturbance, and thus provide a contextually specific ecological benchmark against which observed water quality measurements can be evaluated. If the observed concentrations at a given site exceed the maxima or minima of the normal ranges of natural variation (defined by the chosen percentiles of the reference data) this is deemed to be an “ecologically meaningful” deviation and the water quality at this site may be declared unfit for the protection of aquatic ecosystems (i.e., unacceptably polluted or “non-compliant”) (Chambers et al., 2012b, p. 11 ; D'Arcy et al., 2022a, p. 11). In other words, the reference condition approach allows for the extremes of natural variation at specific locations to be estimated using data from undisturbed sites, thus enabling researchers to determine “the degree of deviation from [these] natural conditions” (Agboola et al., 2020, p. 2). This is illustrated graphically in Figure 23 below.

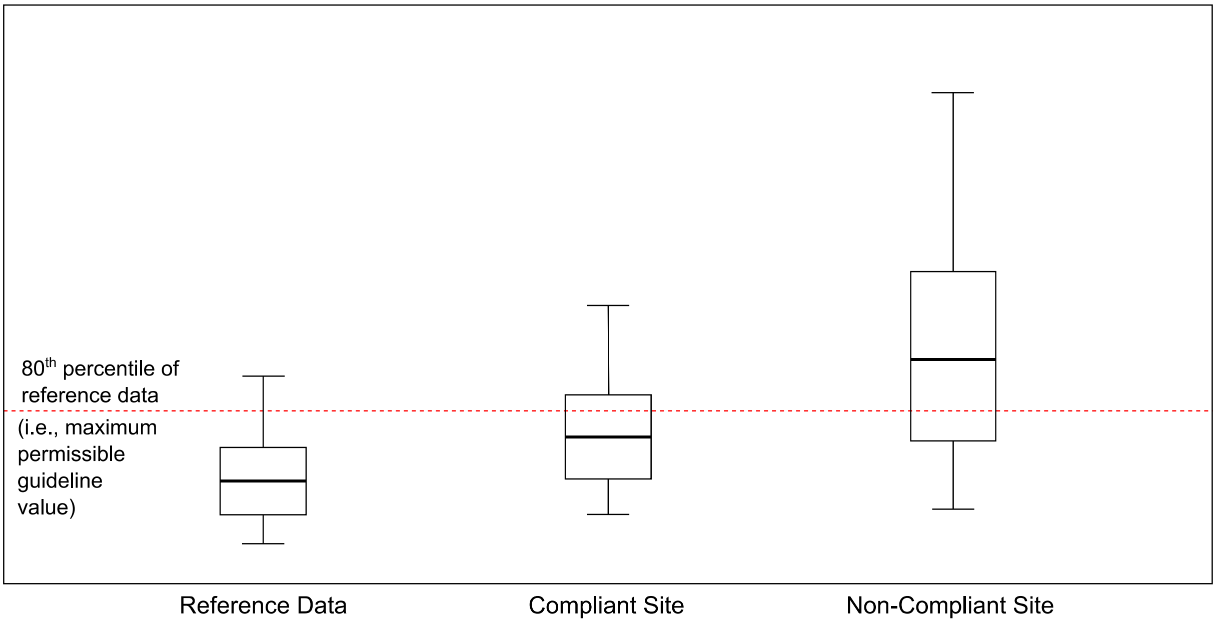


Figure 23. Boxplots comparing three hypothetical water quality datasets: reference data from a sample of undisturbed sites, a compliant sample from a moderately impacted site, and a non-compliant sample from a

severely disturbed site. The 80th percentile of the reference data is used in this instance to define the maximum guideline value against which the median of the other samples is compared.

The illustration above shows boxplots of three hypothetical datasets: reference data collected from an appropriate selection of undisturbed sites, data from a moderately impacted but compliant site, and data from a severely contaminated and thus non-compliant sample site. As shown by the dashed red line, the 80th percentile of the reference data defines the maximum permissible guideline value for the water quality parameter in question. As described above, the median of the data from the two sampled sites is compared with this guideline value. In the case of the compliant site, the median is approaching but has not yet exceeded the guideline value, suggesting a moderate (but ecologically acceptable) degree of contamination. At the non-compliant site, the median value has significantly exceeded the guideline value, indicating that typical conditions at that site fall beyond the range deemed acceptable based on the reference data. The magnitude of non-compliance (i.e., the severity of water quality impairment) is indicated by the degree to which the median value of the observed measurements exceeds the guideline value (i.e., the relative difference between the two values). It is in this manner, using the relative-concentration function described above (see Equation 1), that the NPI calculates the sub-index scores for each parameter.

According to the Australian and New Zealand guidelines cited above, ideal reference sites are "similar to assessment sites… but are minimally impacted, have limited exposure to anthropogenic drivers, and have sufficient historical data to characterise water quality condition and variability" (ANZG, 2018). Reference sites should therefore be analogous to the sample sites (in terms of ecology, climate, topography, and geology) while also being representative of the full range of these conditions within the region of interest (Stein & Yoon, 2007). McDowell et al. (2013) further suggested that reference sites should be defined as those in which no more than five percent of the total catchment area has been modified by human activity. In addition, flow regimes at these sites should not be significantly altered, and there should be no significant point-source discharges upstream of the sampling point (Huynh & Hobbs, 2019). Moreover, determining reference conditions accurately requires a sampling period of no less than 24-months, coupled with a sampling regime of sufficient frequency to account for intra-annual seasonal variation in the system (DWAF, 1996; van Dam et al., 2014; ANZG, 2018; Huynh & Hobbs, 2019).

Therefore, in addition to the 58 sample sites selected above, the same systematic review identified 18 NCMP monitoring points to be used as reference sites in the study area. The land area draining each of these sites was estimated by means of a catchment-delineation procedure in ArcGIS Pro 3.1.2 (Esri, 2023) with 30 m Shuttle Radar Topography Mission (SRTM) digital elevation data downloaded from the USGS Earth Explorer platform (USGS, 2023). By consulting national land cover datasets and, where available, high-resolution satellite imagery for the relevant period via Google Earth, it was confirmed that each of these sites contained negligible anthropogenic activity and that the catchments were dominated by apparently healthy vegetation. The distribution of the reference sites is shown in the map below (Figure 24), while details of each site are listed in Appendix 7.

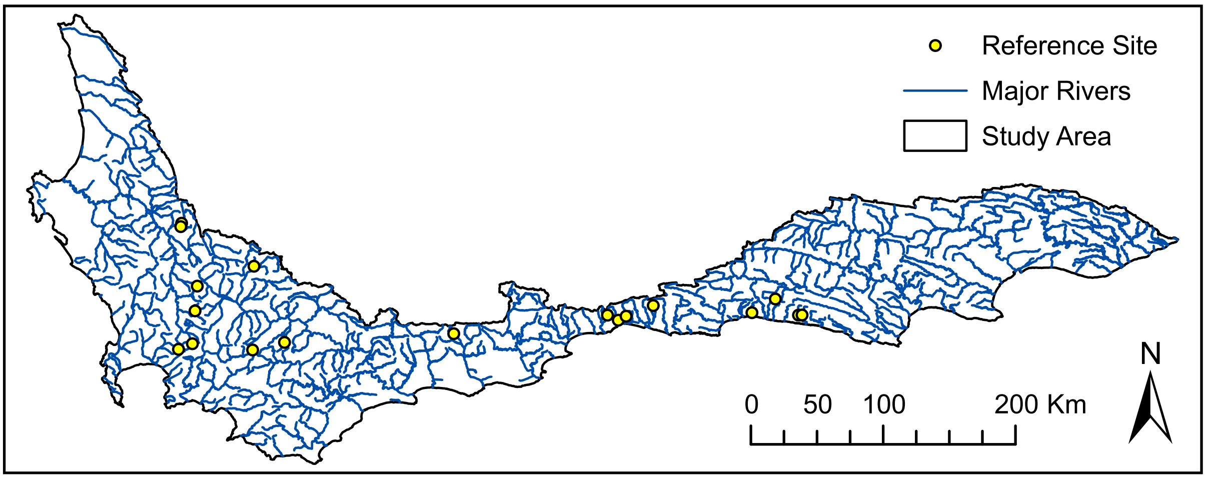


Figure 24. Map showing the locations of the 18 reference sites used in this study to determine guideline values. Geospatial data obtained from DWS (2017d, 2023).

Thirty-six months of historic monitoring data from each of these 18 reference catchments were used to determine site-specific guideline values for each water quality parameter (typically, the earliest reliable three-year sampling period for each site was used).[53, 54] The maximum guideline value for each parameter was estimated using the 90th percentile of the reference data collected from all 18 locations (the 10th percentile was additionally used to define the lower guideline value in the case of pH). These percentiles, as explained above, were taken to represent the upper and lower limits of the range of natural variation that should be expected for each parameter under undisturbed conditions in the study area. While lower percentiles are typically used elsewhere (see above), the 90th percentile was used in this study to account for the considerable natural variation apparent in parameter concentrations among the reference sites in the study area. This inherent variation is particularly evident in electrical conductivity and pH values (see the boxplots that follow).

Based on the relevant percentiles of the data obtained from the 18 reference sites, the maximum and minimum guideline values for each parameter are given in Table 3 below. Once again, these values are taken to represent the extremes of natural variation under natural conditions within the study area. Thus, for the purposes of the present study, any exceedance of these guideline values by an observed value

[53] The same caveat regarding anomalies in pH measurements recorded before 1990 applies here (see Ramjukadh et al., 2018).

[54] Water quality samples were typically taken once a month at most of the reference sites. However, in instances where multiple samples had been collected per month, only the first of the samples taken during each month was included in this analysis. This was done so that reference sites at which multiple water quality measurements were recorded per month did not bias the percentile estimation (i.e., by using only the first of multiple monthly samples, no single reference site contributed more than 36 measurements for each parameter to the total sample from which the percentiles were estimated).

(i.e., median) at any of the 58 selected monitoring sites was considered ecologically unacceptable (and thus non-compliant according to these guidelines).

Table 3. Maximum and minimum guideline values estimated from local reference data taken from 18 sites across the study area.

Guideline Value	EC (mS/m)	TIN (mg/l)	PO_4 (mg/l)	SO_4 (mg/l)	pH
Maximum (90th percentile of reference data)	16.90	0.22	0.06	13.30	7.05
Minimum (10th percentile of reference data)	N/A	N/A	N/A	N/A	3.85

The boxplots that follow (Figures 25–29) show the distributions of the data for each parameter from each of the 18 reference sites. Each plot also shows the position of the upper (and lower, where applicable) guideline value for the given parameter, based on the relevant percentile of the reference data. It is evident from the boxplots of electrical conductivity that two of the reference sites (102248 and 102252) had median conductivity values that exceeded the 90th percentile of the total reference sample. Similarly, the median pH values of catchments 102249 and 102276 were below the 10th percentile of the total reference sample. (For all other parameters, however, these four sites fell within the expected ranges). While the extremes in EC and pH at these sites may have been due to unidentified sources of pollution not immediately evident from the high-resolution satellite imagery consulted when screening the reference sites, it is also possible that they simply reflect natural variability in water chemistry characteristic of the study area. For this reason, a more conservative percentile (such as the 75th or 80th percentile) was deemed too strict for determining guideline values.

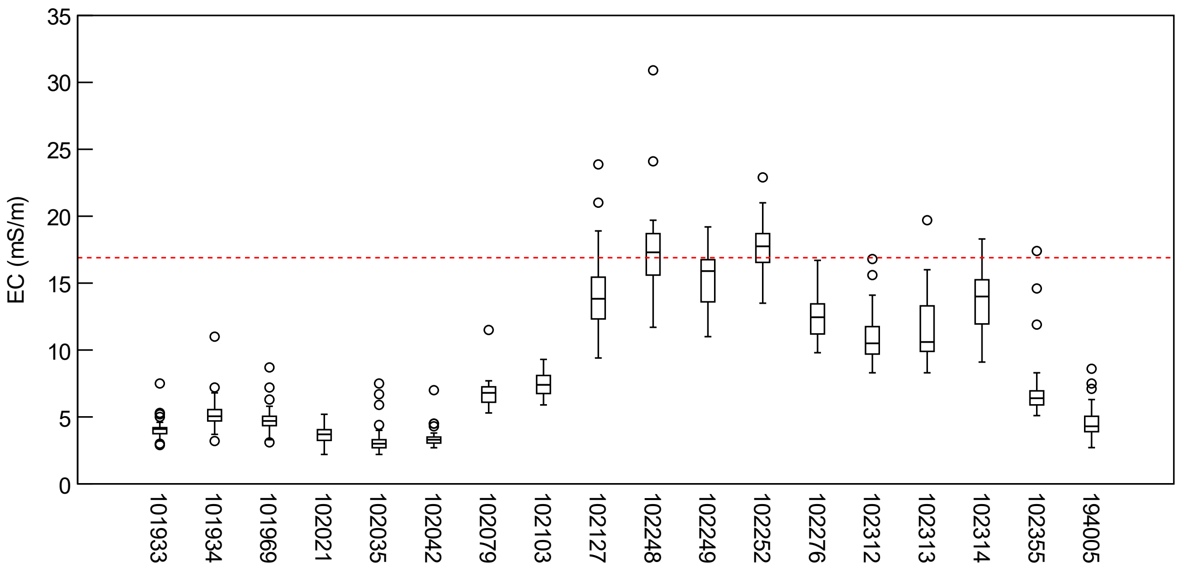


Figure 25. Boxplots of electrical conductivity (EC) reference data. The location of the maximum guideline value of 16.9 mS/m (i.e., the 90th percentile of the sample) is shown by the dashed horizontal line.

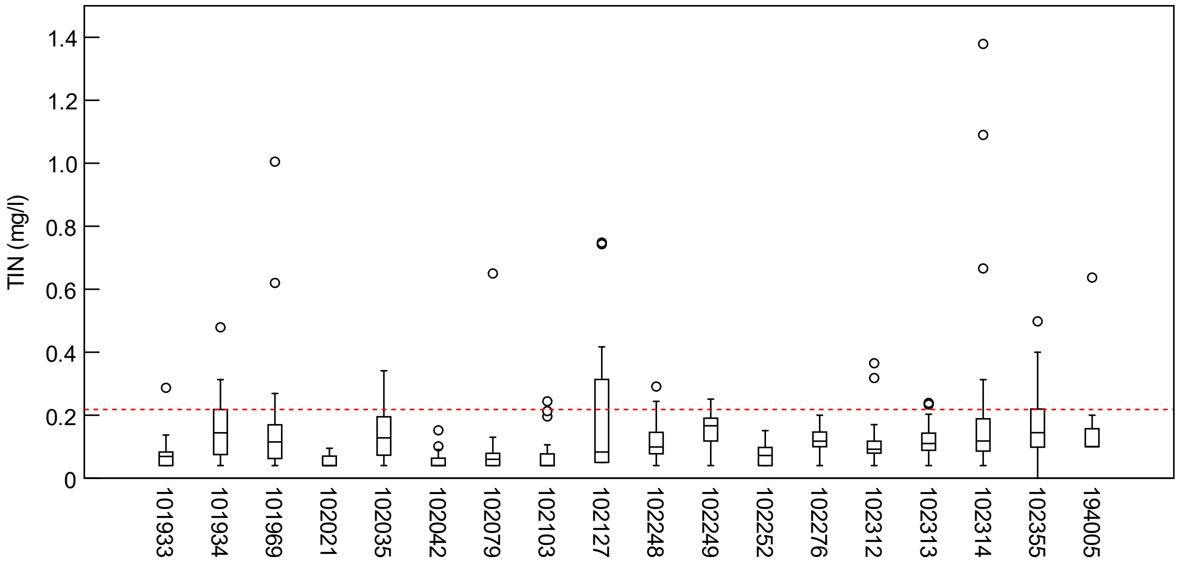


Figure 26. Boxplots of total inorganic nitrogen (TIN) reference data. The location of the maximum guideline value of 0.22 mg/l (i.e., the 90th percentile of the sample) is shown by the dashed horizontal line.

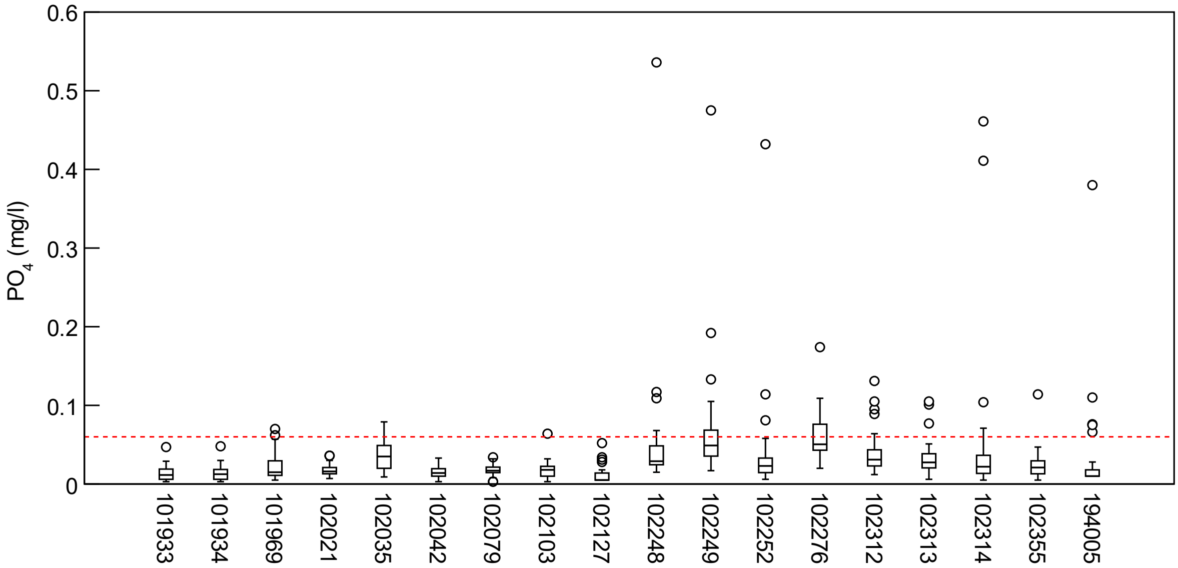


Figure 27. Boxplots of orthophosphate (PO_4) reference data. The location of the maximum guideline value of 0.06 mg/l (i.e., the 90th percentile of the sample) is shown by the dashed horizontal line.

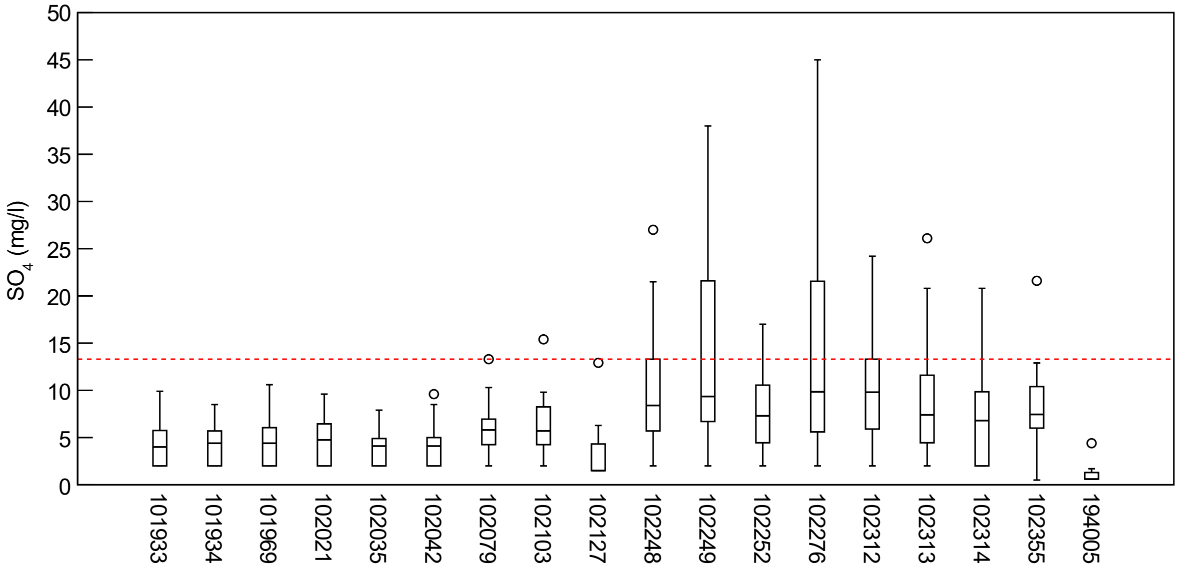


Figure 28. Boxplots of sulphate (SO_4) reference data. The location of the maximum guideline value of 13.3 mg/l (i.e., the 90th percentile of the sample) is shown by the dashed horizontal line.

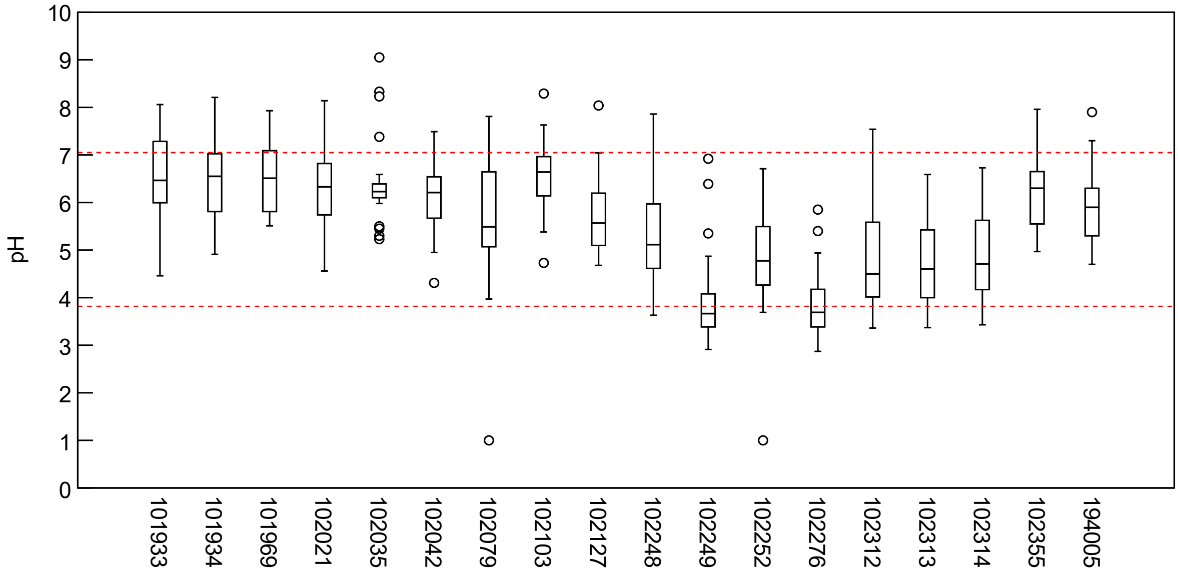


Figure 29. Boxplots of pH reference data. The location of the minimum and maximum guideline values of 3.85 and 7.05 respectively (i.e., the 10th and 90th percentiles of the sample) are shown by the dashed horizontal line.

Calculating and Interpreting Aggregate Index Scores

Using the maximum and minimum guideline values derived from the reference data (see above), aggregate NPI scores were calculated for each of the 58 sub-catchments. Table 4 below lists the sub-catchments, the 24-month period of water quality data used to calculate the index scores, the sub-index scores for each parameter, and the aggregate NPI scores. The catchments are listed in ascending order according to their respective aggregate pollution index scores.

Table 4. Aggregate NPI scores of the 58 sub-catchments located within the study area. Sub-index scores ≥ 1 indicate that the observed measurements of the parameter in question exceeded the guideline values derived from the reference data.

Catchment ID	Sampling Period	No. of Samples	Sub-Index Scores					Aggregate NPI Score
			EC	TIN	PO_4	SO_4	pH	
102021	2013/14	22	0.25	0.41	0.17	0.11	0.10	0.33
102079	2013/14	23	0.47	0.35	0.17	0.11	0.20	0.38
102312	2013/14	24	0.57	0.37	0.17	0.11	0.46	0.47
102313	2013/14	25	0.52	0.46	0.17	0.11	0.56	0.47
87219	2013/14	23	0.63	0.36	0.17	0.11	0.32	0.50
102132	2013/14	20	0.64	0.47	0.17	0.11	0.27	0.51
102097	2013/14	20	0.70	0.35	0.17	0.11	0.58	0.57
102127	2013/14	22	0.74	0.51	0.17	0.11	0.28	0.58
102276	2013/14	24	0.69	0.41	0.22	0.11	0.73	0.60
102293	2013/14	23	0.86	0.49	0.17	0.11	0.05	0.65
102029	2013/14	23	0.26	0.46	0.18	0.11	0.87	0.67
102248	2013/14	24	0.96	0.31	0.17	0.11	0.33	0.73
102252	2013/14	24	1.01	0.30	0.12	0.11	0.09	0.75
102202	2013/14	24	1.04	0.40	0.12	0.11	0.92	0.82
102358	2013/14	26	0.90	0.47	0.17	0.11	1.14	0.91
102121	2013/14	21	1.17	0.46	0.17	0.11	1.12	0.93
102277	2013/14	23	1.34	0.46	0.17	0.11	0.61	1.03
102251	2013/14	23	0.84	1.51	0.25	0.11	0.21	1.14
101998	2013/14	23	0.86	1.48	0.17	0.11	1.02	1.16
102023	2013/14	18	0.45	1.56	0.17	0.13	0.76	1.18
102317	2013/14	25	1.58	0.98	0.35	0.11	0.22	1.22
102241	2013/14	22	1.63	0.32	0.08	0.11	1.13	1.24
101917	2013/14	23	1.18	1.54	0.22	0.46	1.35	1.28
101944	2013/14	22	1.59	0.59	0.17	0.82	1.33	1.29
102353	2013/14	38	1.63	0.43	0.17	0.11	1.41	1.31
102275	2013/14	17	1.74	0.42	0.17	0.11	0.61	1.33
102207	2013/14	22	1.74	0.46	0.17	0.11	1.23	1.37
102254	2013/14	20	1.88	0.46	0.33	0.11	1.11	1.44
101986	2013/14	17	0.94	1.93	0.17	0.32	1.27	1.51
102107	2013/14	22	2.01	0.90	0.17	0.84	1.26	1.60
101979	2013/14	19	1.70	1.98	0.48	0.73	1.42	1.66
102206	2013/14	23	2.20	0.46	0.08	0.11	1.25	1.69
102130	2013/14	20	2.48	0.32	0.17	0.11	1.31	1.92
101987	2013/14	20	1.78	2.42	0.42	0.85	1.33	1.97
102002	2013/14	22	2.55	2.22	1.30	1.35	1.15	2.17
102368	2013/14	26	2.89	0.46	0.17	0.11	1.29	2.22
101929	2013/14	23	0.63	3.20	0.36	0.39	1.16	2.40
102043	2013/14	19	0.75	3.26	0.17	0.78	1.07	2.46
102320	2013/14	25	3.39	0.46	0.17	0.11	1.48	2.61
187987	2015/16	17	3.56	0.46	0.17	0.11	1.25	2.69
102250	2013/14	23	3.73	0.46	0.17	0.11	1.06	2.76
102019	2013/14	20	2.14	3.57	0.90	1.59	1.47	2.87
102316	2013/14	26	3.92	1.49	0.71	0.11	1.14	3.01
102423	2013/14	15	3.89	0.46	0.95	0.11	1.85	3.13
102217	2013/14	24	5.59	0.62	0.17	0.11	1.33	4.22
102123	2013/14	19	6.08	0.46	0.56	0.11	1.50	4.62
101997	2013/14	22	7.02	1.32	0.17	3.46	1.42	5.31
86712	2013/14	17	13.29	9.29	9.27	7.55	1.63	11.04
102438	2013/14	24	15.08	1.60	1.87	0.11	1.85	11.39
102063	2013/14	23	14.96	4.60	1.30	12.38	1.85	11.69
102430	2013/14	25	15.72	0.46	0.17	0.11	1.84	11.72
101942	2013/14	15	16.26	13.69	2.28	11.66	1.70	13.18
102083	2013/14	17	17.83	0.46	0.17	12.03	1.89	13.41
102435	2013/14	24	28.20	7.78	0.17	0.11	1.72	21.09
102082	2013/14	19	29.11	1.05	0.17	25.78	1.83	22.16
101937	2013/14	16	45.44	2.04	6.64	22.20	1.83	33.98
102427	2013/14	25	46.83	5.04	0.35	0.11	1.82	35.68
102017	2013/14/15	21	53.79	1.07	0.75	24.06	1.84	39.74

Sixteen of the sub-catchments (approximately 28% of the sample) had NPI scores below the target value of 1.0. Eleven of these 16 locations had NPI scores below the precautionary score of 0.7. The remaining 42 sub-catchments (approximately 72% of the sample) were, to a greater or lesser degree, non-compliant. Eleven of the sub-catchments had NPI scores ≥ 10 (indicating severe contamination). The boxplot to the right (Figure 30) shows the distribution of NPI scores across the sample of 58 sub-catchments.

Among the 42 non-compliant sub-catchments, the principal contributing parameter appeared to have been electrical conductivity. Sub-index scores for EC and the aggregate NPI scores show almost perfect linear correlation (Pearson's r = 0.999; $p < 0.001$) throughout the sample, as shown in Figure 31 below. Thirty-nine of the 58 sub-catchments (more than two-thirds of the sample) had non-compliant EC sub-index scores (i.e., SI ≥ 1).

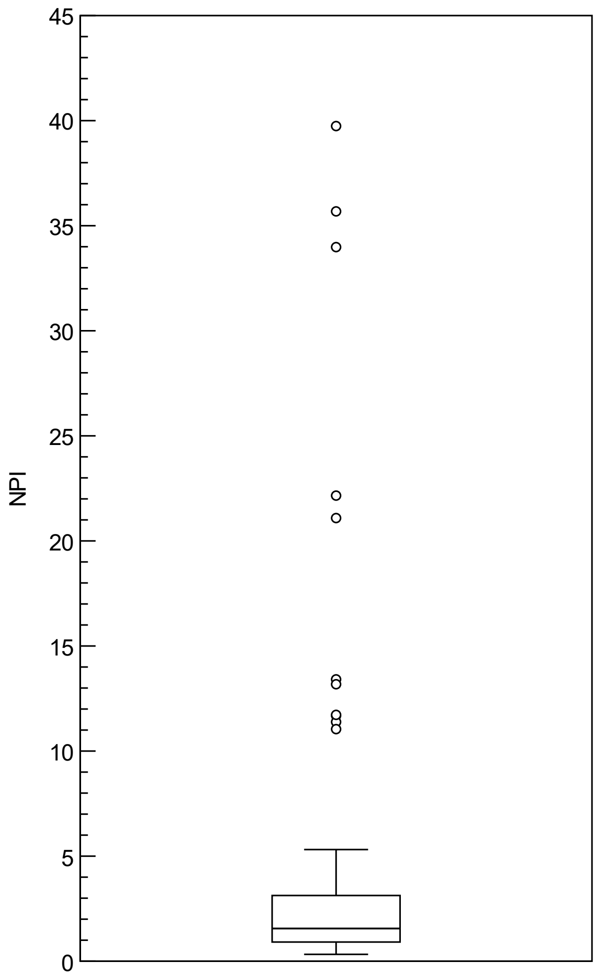


Figure 30. Boxplot of aggregate pollution index scores from across the sample of 58 sub-catchments. Only 16 catchments (approximately 28% of the sample) had NPI scores < 1.0. Most of the locations were, to varying degrees, non-compliant. The boxplot also shows several extreme scores ≥ 10.

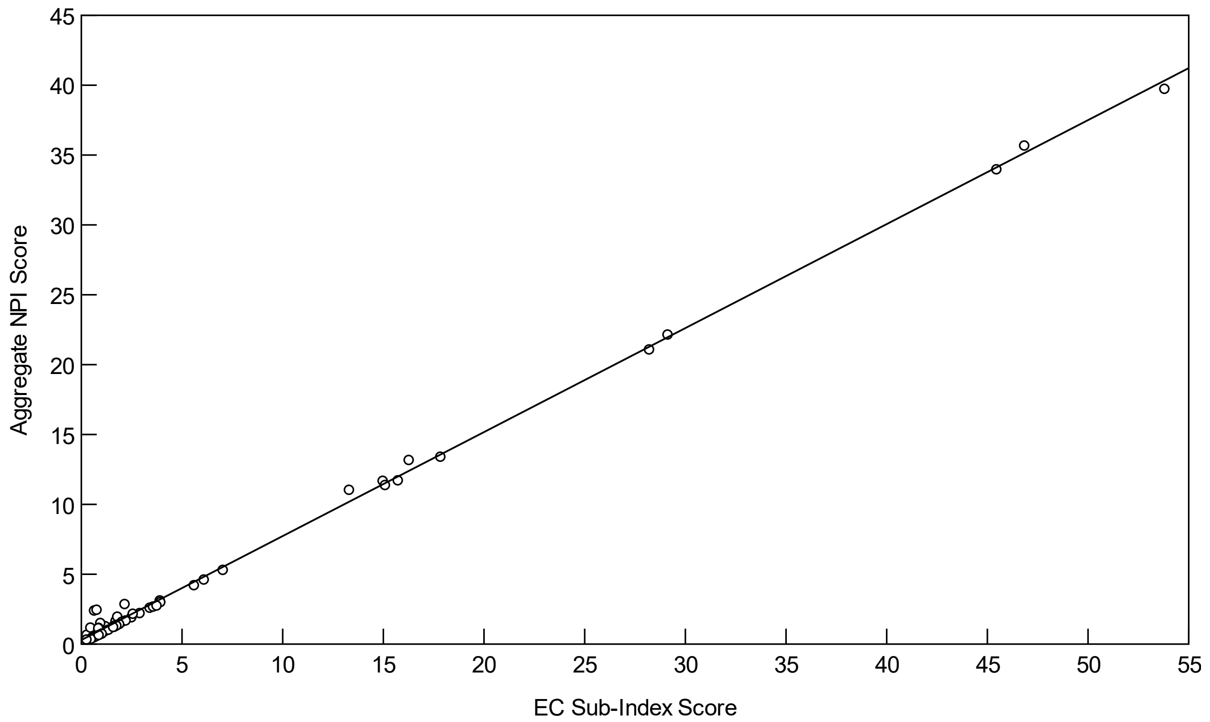


Figure 31. Scatterplot showing a strong correlation (Pearson's $r = 0.999$; $p < 0.001$) between aggregate NPI scores and EC sub-index scores. This suggests that NPI scores largely reflect elevated electrical conductivity measurements.

Some sub-catchments also showed elevated nutrient levels, indicating various degrees of eutrophication. Twenty-two of the 58 sub-catchments had total inorganic nitrogen (TIN) sub-index scores ≥ 1.0. Six of the 58 sub-catchments also had non-compliant orthophosphate (PO_4) sub-index scores. Of the 58 sub-catchments, approximately two-thirds had non-compliant pH sub-index scores. However, as can be seen from Table 4, the magnitude of exceedance for pH was, in general, relatively minor.

In four of the 58 sub-catchments (namely, 102252, 102202, 102358, and 102121), the effect of eclipsing and the potential ambiguity of the NPI scores were also evident (see Table 4). In these four instances, while at least one of the sub-index scores was non-compliant (i.e., ≥ 1.0), the aggregate NPI score was less than 1.0 (suggesting compliance). As argued above, it is for this reason that an additional precautionary threshold of 0.7 was also considered.[55]

Land Cover and Landscape Analysis

Catchment and Riparian Buffer Zone Delineation

In order to model the relationship between water quality and natural vegetation across a statistical sample of sub-catchments in the study area—and having quantified pollution levels at each of the 58

[55] The especially observant reader will note that one of these catchments (namely 102252) was also used as a reference catchment, and that the high electrical conductivity measurement at this site resulted in a sub-index score of 1.01 for EC (see Table 4). The low sub-index scores for all other parameters, however, compensate for this, resulting in an aggregate NPI score for this site of 0.75.

NCMP monitoring points using the NPI—it was next necessary to estimate proportions of natural vegetation in each sub-catchment at various scales. Sub-catchments were thus delineated for each of the 58 NCMP monitoring points using ArcGIS Pro 3.1.2 (Esri, 2023). To do this, a void-filled Digital Elevation Model (DEM) mosaic was created for the study area using Shuttle Radar Topography Mission (STRM) digital elevation data downloaded from the USGS Earth Explorer website (USGS, 2023). The DEM mosaic was subsequently used to develop flow direction and accumulation models for the region, which were in turn used to calculate the contributing area for each of the 58 NCMP monitoring points using the Watershed tool in ArcGIS Pro (see Bajjali, 2018). As the NCMP monitoring sites were used as "pour points" for catchment delineation, it was necessary in some cases to adjust the location of the monitoring point to ensure agreement with the flow accumulation model. In each instance where this was done, a 1:50,000 stream network layer (obtained from DWS, 2023) was used to confirm that the relocated monitoring point was correctly positioned based on the locational metadata for each point.

To ensure that the sub-catchments had been delineated correctly, each was inspected in turn and evaluated for accuracy with reference to the aforementioned 1:50,000 stream network and a high-resolution hillshade layer to identify any discrepancies or incongruities.[56] A few minor corrections to the boundaries of the sub-catchments were made where necessary. Overall, however, the accuracy with which the catchments were delineated appeared to be very high. The spatial distribution of 58 sub-catchments is shown in Figure 32.

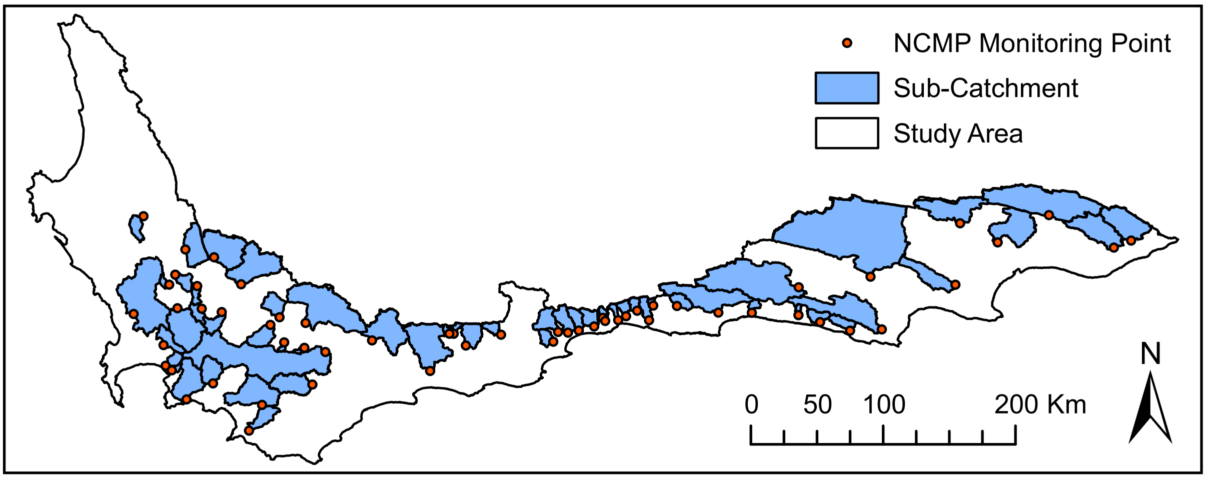


Figure 32. Map showing the sub-catchments delineated for each of the 58 NCMP monitoring sites. Pollution index scores calculated for each of these sites, based on water quality data collected between 2013 and 2014, were regressed against land cover data for each of these catchments for the same period to create statistical models from which minimum thresholds of natural vegetation were estimated. Geospatial data obtained from DWS (2017d).

The delineated sub-catchments varied significantly in size, ranging from a minimum of 6.35 km^2 to a maximum of 3,663.03 km^2, with a standard deviation of 614.80 km^2. Using historical bioclimatic data from Fick and Hijmans (2017), the mean annual precipitation (MAP) of the sub-catchments was

[56] This was done using the 5 metre Stellenbosch University Digital Elevation Model (SUDEM5), currently distributed by GeoSmart (https://geosmart.space). The SUDEM5 is reportedly the highest resolution elevation model covering South Africa (van Niekerk, 2016; GeoSmart, 2023).

calculated using the Zonal Statistics tool in ArcGIS Pro. Thus estimated, MAP across the sample of sub-catchments ranged from 356 mm to 811 mm, with a mean of 563 mm across all sub-catchments (see Appendix 6).

One aspect of the third objective of this study (see the Introduction) was to investigate which scale(s) of analysis would be most appropriate for modelling and threshold estimation. To evaluate the relationship between water quality and natural vegetation metrics at different scales, riparian buffer zones (RBZs) were also delineated for the major rivers and tributaries in each of the 58 sub-catchments. The Pairwise Buffer tool in ArcGIS Pro was used to delineate RBZs of 200, 400, and 800 m. These buffers were delineated for a 1:500,000 stream network GIS layer, which contains only higher order "mainstems" and their tributaries (DWAF, 2006; DWS, 2017d). Having undergone several updates and consistency checks, this stream network layer is now considered "stable" and was used previously in the identification of freshwater ecosystem priority areas in South Africa (Nel et al., 2011b; van Deventer et al., 2018).

The RBZs, once delineated, were subsequently clipped to the sub-catchment boundaries. When choosing buffer widths, consideration was given to (1) the buffer widths regularly used in previous studies (see Chapter 4) and (2) the spatial resolution of the land cover data available for the present study (30 m per pixel). The more detailed 1:50,000 stream network (which includes additional lower-order tributaries) was not used for buffer delineation as the greater density of streams in this GIS layer would mean that the land area occupied by the delineated riparian buffer zones in each catchment would not differ significantly from the total area of the catchment itself. This would render comparisons between these scales largely meaningless (refer to the earlier discussion on p. 67). However, where necessary, minor adjustments were made to the 1:500,000 stream network using the 1:50,000 network and high-resolution satellite imagery as guides. Modifications to the stream network were mainly required to circumscribe large bodies of water, such as dams/lakes, so that riparian buffer zones, when delineated, would occur along the edges (rather than through the middle of) such features. Additional modifications were made in instances where important tributaries had been obviously omitted from the 1:500,000 stream network layer. This latter procedure was admittedly subjective, but a visual inspection of the catchments, using high-resolution satellite imagery and the high-resolution SUDEM5, confirmed that the modified stream network layer had captured the major rivers and tributaries located in each sub-catchment.[57]

[57] Although considered in several other studies, LULC within a "local contributing area" (i.e., a circular buffer of specified radius, extending from the sampling point and clipped to the boundaries of the catchment; see Figure 7 on p. 65) was not considered here due to the large variation in catchment size across the sample of 58 sub-catchments. As argued earlier (see the discussion and Figure 9 on pp. 67–68) the relative proportion of a catchment's total area occupied by an LCA will depend not only on the radius of the LCA, but also on the size and shape of the catchment. Therefore, across a sample of sub-catchments that vary in size and shape (as is the case in this study) the proportional area represented by LCAs of the same radius will likewise vary, making comparisons with other analytical scales inconsistent.

Classifying Natural Vegetation

Of principal interest in this study was the relationship between water quality and natural vegetation, and whether statistical models of this relationship could be used to estimate minimum thresholds of the latter for the management and protection of the former. While water quality was evaluated using Nemerow's Pollution Index, a metric by which natural vegetation could be appropriately classified was also required. In the present study, this involved identifying which of the individual vegetative land cover classes identified in the SANLC 2013/14 map (viz. indigenous forests, thickets, woodlands, commercial forestry plantations, shrubland, grassland, and wetlands) might be combined into a single aggregate land cover class that would thereafter provide an appropriate representation of natural vegetation cover in the region of interest (with particular regard to its ability to offer water resources protection from diffuse pollution). Whereas it might be reasonable to assume that an aggregate classification of natural vegetation would, by default, include *all* types of locally occurring indigenous vegetation (and thus exclude all types of non-indigenous or cultivated vegetation), previous research has shown that some classes of indigenous vegetation (e.g., grassland) are not always associated with improved water quality, while some classes of planted vegetation (e.g., commercial forestry) may in fact have a positive influence on water quality (refer to the earlier discussion on pp. 58ff). Therefore, as the aim of the study was to estimate minimum thresholds of natural vegetation *for the management and protection of water quality*, the process of determining a suitable metric by which to classify natural vegetation was performed with specific reference to the association of the latter with improved water quality. To simplify this process, the 17 original land cover classes identified in the 2013/14 SANLC map were reclassified according to the following scheme:

Table 5. Scheme used for the reclassification of the 2013/14 SANLC map.

Original Class	**Reclassified Class**
1. Indigenous Forest	1. Indigenous Woody Vegetation
2. Thicket/Dense Bush	
3. Woodland/Open Bush	
4. Low Shrubland	
5. Forest Plantations/Woodlots	2. Forestry Plantations
6. Cultivated Commercial Annuals (rainfed/non-pivot)	3. Agriculture
7. Cultivated Commercial Annuals (pivot)	
8. Cultivated Commercial Permanent (Orchards)	
9. Cultivated Commercial Permanent (Vines)	
10. Cultivated Subsistence	
11. Settlements/Built-up	4. Urban
12. Wetlands	5. Wetlands
13. Grassland	6. Grasslands
14. Waterbodies	7. Water
15. Bare Ground	8. Bare/Degraded
16. Degraded	
17. Mines	9. Mines

While not strictly based on any established land cover classification system, the scheme shown in Table 5 was intended to group individual land cover classes that, for the purposes of this investigation, were presumed to have similar impacts on water quality based on previous research (see Chapter 3). Relatively simple classification schemes such as this are typical of the studies reviewed, as is the reclassification/generalisation of existing land cover datasets into simpler categories.[58] Thus, in the present study, all classes of cultivated land (which tend to be sources of dissolved salts, nutrients, pesticides, and bacteriological contamination) were grouped together as "agriculture". In addition, while the four classes of indigenous woody vegetation found in the study area (to wit, indigenous forest, thickets, woodlands, and shrubland) were grouped together as such, commercial forestry plantations and grassland (which previous research has indicated may have atypical impacts on water quality) were maintained as separate classes. Moreover, the technical report released with the 2013/14 SANLC map reveals that classification confusion between the base natural vegetation classes (especially indigenous forest, thickets, woodlands, and shrubland) was common (Geoterra Image, 2015). Therefore, merging these individual classes into a single combined class representing indigenous woody vegetation (distinguishable from planted forests and herbaceous vegetation) was not unreasonable. By requiring the evaluation of fewer possible class combinations, this simplified classification scheme made it easier to determine which of the individual vegetative classes might reasonably be aggregated into a single natural vegetation land cover class.

Figure 33 below shows land cover data from the 2013/14 SANLC map reclassified according to the scheme above.

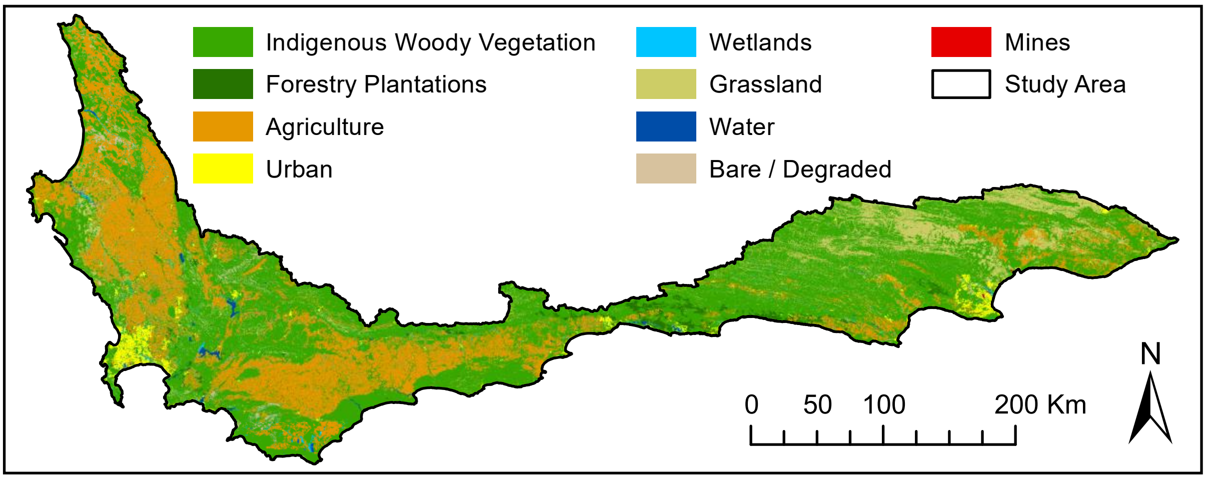


Figure 33. Land cover map of the study area, based on data from the 2013/14 SANLC map, but reclassified according to the scheme shown in Table 5. Geospatial and land cover data obtained from DWS (2017d); DFFE (2023).

[58] See, for example, Ahearn et al. (2005), Uuemaa et al. (2007), Lee et al. (2009), Rothenberger et al. (2009), Bu et al. (2014), Iñiguez-Armijos et al. (2014), Clément et al. (2017), Slaughter and Mantel (2017), Namugize et al. (2018), Palma et al. (2020), Barnard et al. (2021), Aalipour et al. (2022), and Aalipour et al. (2023).

The subsequent step was to determine which of these land cover classes, when combined into a single aggregate class and measured as a proportion of the area under analysis, showed the strongest *negative* correlation with pollution scores (and thus a positive association with improved water quality). The four re-classified land cover classes that were considered for inclusion in this aggregate natural vegetation class were as follows:

1. Indigenous Woody Vegetation (IWV)
2. Forestry Plantations (FP)
3. Wetlands (WET)
4. Grasslands (GRSS)

To further simplify the analysis, IWV was taken as a base class. All possible combinations of the three other classes (to wit, FP, WET, and GRSS) with IWV were therefore considered as "candidate" aggregate classes by which natural vegetation might thereafter be classified. The aggregate class that demonstrated the strongest negative correlation with NPI scores was selected as the metric by which natural vegetation was classified for all subsequent analyses (it being presumed that this classification of natural vegetation would therefore offer water resources the best protection from diffuse pollution).

First, for each of the 58 sub-catchments, the area occupied by each of the nine re-classified land cover classes was calculated using Fragstats 4.2 (McGarigal & Ene, 2023) at the following scales:

- Whole catchment
- 200 m Riparian Buffer Zone
- 400 m Riparian Buffer Zone
- 800 m Riparian Buffer Zone

Fragstats software has become the de facto standard for landscape analyses (Fuller et al., 2011; Hagen-Zanker, 2016; Uuemaa & Oja, 2017) and has been used in several similar studies.[59] Figure 34 illustrates the different scales of analysis, using one of the 58 sub-catchments (namely 102247) as an example.

[59] Including, most recently, Shen et al. (2015), Ding et al. (2016), Clément et al. (2017), Wang and Zhang (2018), Zhang et al. (2019), Liu et al. (2021), Wang et al. (2021), Li et al. (2022a), Deng et al. (2023), Wang et al. (2023a), Yao et al. (2023), and Zhang et al. (2023b).

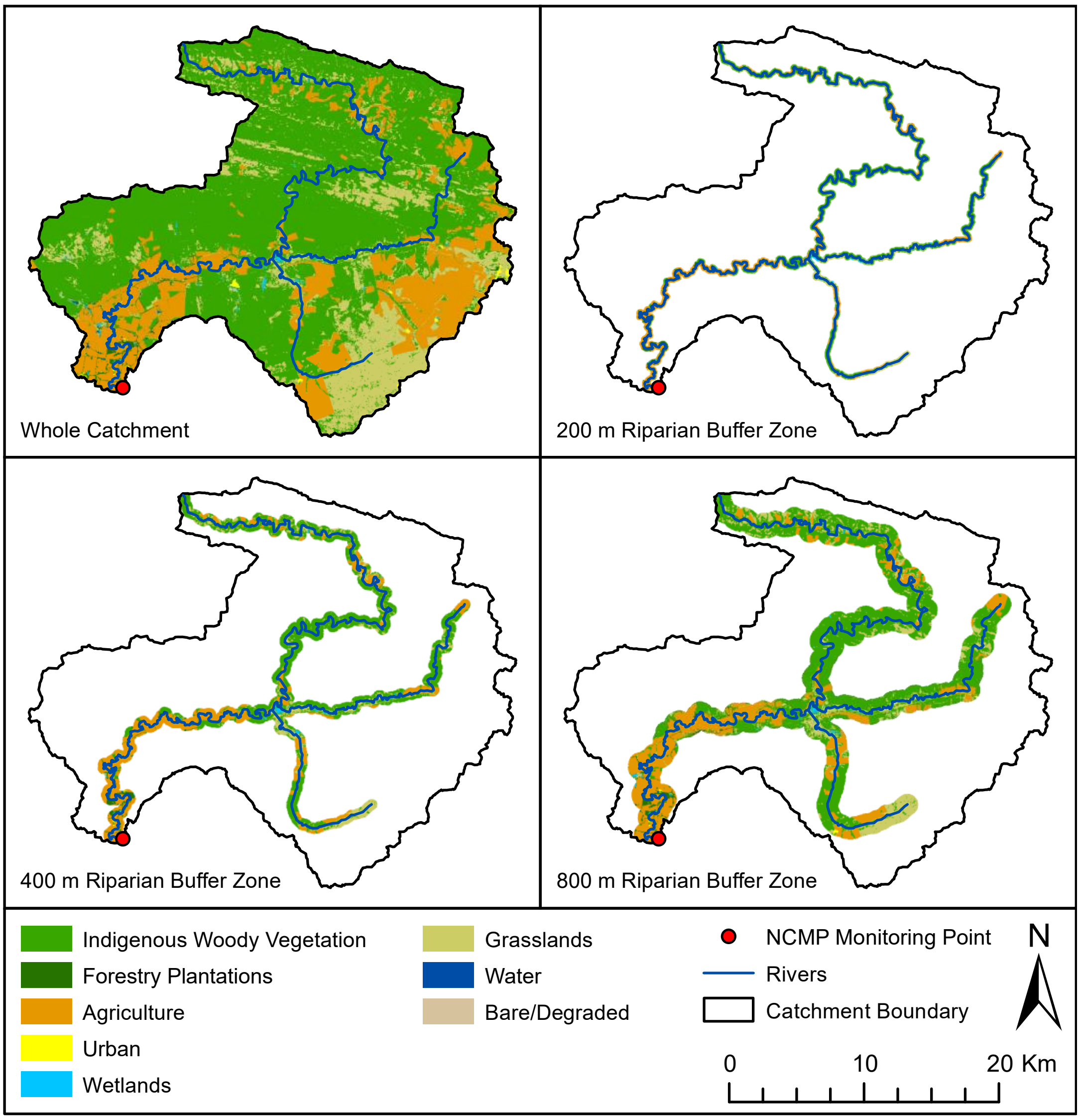


Figure 34. Illustration of the different scales of analysis at which proportions of natural vegetation were estimated. It is often assumed that riparian land use is likely to have a greater influence on water quality than land use further afield.

For each of the 58 sub-catchments, and at each of the above analytical scales, the area occupied by each of the land cover classes listed in Table 5 was used to calculate the proportion of the landscape occupied by each of the candidate aggregate classes of natural vegetation using the following equation:

$$P_i = \frac{A_i}{T - W} \tag{5}$$

where P_i is the proportion of the landscape occupied by the ith land cover class, A_i is the area occupied by the ith land cover class at the same scale, T is the total area of the landscape under analysis, and W is the area occupied by water at the same scale.[60] Thus, the proportion of the landscape occupied by

[60] Reducing the total area of the landscape (T) by subtracting the area occupied by water bodies (W) is important as it provides a more reasonable estimate of the area of the landscape *available* for natural vegetation (T–W), which in turn provides a more sensible estimate of the proportion of the landscape occupied by natural vegetation (which could not reasonably be expected to occupy areas of the landscape already occupied by water bodies). This

each of the candidate aggregate classes of natural vegetation (i.e., all possible combinations of IWV with FP, WET, and GRSS) was calculated for each of the 58 sub-catchments at each scale of analysis. This metric is very similar to Tiner's (2004, p. 232) Natural Cover Index, except that Equation 5 above intentionally takes into account the area of the catchment occupied by water bodies (which is thus unavailable for natural vegetation).

Spearman's rank correlation analysis was then used to determine the strength and direction of the relationship between the candidate aggregate classes of natural vegetation and pollution index scores, as well as the spatial scale(s) at which these correlations were strongest. Spearman's rank correlation, being a robust non-parametric measure, was favoured in this study due to the possibility of a nonlinear relationship between NPI scores and proportions of natural vegetation (Fernandes et al., 2021). Table 6 shows the results of the correlation analysis conducted using the candidate aggregate classes with results ordered according to the strength of the correlation. All results were statistically significant at $p < 0.01$.

is especially true if there are large bodies of water present in the catchment, such as dams or lakes, which may occupy significant proportions of the landscape (thus making those areas *unavailable* for natural vegetation). If the area occupied by water is not accounted for in this manner, the proportion of the landscape occupied by natural vegetation will be improperly underestimated in these instances. To the best of the author's knowledge, this is not an issue that has been given due consideration in the literature reviewed. The fact that water may occupy a significant proportion of the landscape, especially at smaller analytical scales, was hinted at in Wang et al. (2023c, p. 6), but the potential significance of this was not discussed by the authors.

Table 6. Results of Spearman's rank correlation analysis between candidate aggregate classes of natural vegetation and NPI scores across the sample of 58 sub-catchments. All results were statistically significant at $p < 0.01$. RBZ = Riparian Buffer Zone.

Scale of Analysis	Combined Vegetation Classes	Correlation with NPI Scores (Spearman's ρ)
RBZ (200 m)	Indigenous Woody Vegetation; Forestry Plantations; Wetlands	–0.735
Catchment	Indigenous Woody Vegetation; Forestry Plantations; Wetlands	–0.729
RBZ (400 m)	Indigenous Woody Vegetation; Forestry Plantations; Wetlands	–0.726
Catchment	Indigenous Woody Vegetation; Forestry Plantations	–0.714
RBZ (200 m)	Indigenous Woody Vegetation; Forestry Plantations; Wetlands; Grasslands	–0.711
RBZ (800 m)	Indigenous Woody Vegetation; Forestry Plantations; Wetlands	–0.696
RBZ (400 m)	Indigenous Woody Vegetation; Forestry Plantations	–0.689
RBZ (800 m)	Indigenous Woody Vegetation; Forestry Plantations	–0.677
RBZ (200 m)	Indigenous Woody Vegetation; Forestry Plantations	–0.675
RBZ (400 m)	Indigenous Woody Vegetation; Forestry Plantations; Wetlands; Grasslands	–0.670
RBZ (200 m)	Indigenous Woody Vegetation; Forestry Plantations; Grasslands	–0.640
RBZ (400 m)	Indigenous Woody Vegetation; Forestry Plantations; Grasslands	–0.630
RBZ (200 m)	Indigenous Woody Vegetation; Wetlands	–0.625
RBZ (800 m)	Indigenous Woody Vegetation; Forestry Plantations; Wetlands; Grasslands	–0.622
Catchment	Indigenous Woody Vegetation; Forestry Plantations; Wetlands; Grasslands	–0.611
RBZ (400 m)	Indigenous Woody Vegetation; Wetlands	–0.593
Catchment	Indigenous Woody Vegetation; Forestry Plantations; Grasslands	–0.592
RBZ (800 m)	Indigenous Woody Vegetation; Forestry Plantations; Grasslands	–0.589
RBZ (200 m)	Indigenous Woody Vegetation	–0.585
Catchment	Indigenous Woody Vegetation; Wetlands	–0.582
RBZ (400 m)	Indigenous Woody Vegetation	–0.581
Catchment	Indigenous Woody Vegetation	–0.580
RBZ (200 m)	Indigenous Woody Vegetation; Wetlands; Grasslands	–0.550
RBZ (800 m)	Indigenous Woody Vegetation; Wetlands	–0.538
RBZ (800 m)	Indigenous Woody Vegetation	–0.519
RBZ (200 m)	Indigenous Woody Vegetation; Grasslands	–0.516
RBZ (400 m)	Indigenous Woody Vegetation; Wetlands; Grasslands	–0.474
RBZ (400 m)	Indigenous Woody Vegetation; Grasslands	–0.460
Catchment	Indigenous Woody Vegetation; Grasslands	–0.412
Catchment	Indigenous Woody Vegetation; Wetlands; Grasslands	–0.411
RBZ (800 m)	Indigenous Woody Vegetation; Wetlands; Grasslands	–0.410
RBZ (800 m)	Indigenous Woody Vegetation; Grasslands	–0.391

The results of this analysis reveal that, when calculated as a proportion of the landscape under analysis (i.e., at each of the relevant scales using Equation 5 above) the aggregate class of natural vegetation which showed the strongest negative correlation with pollution levels was that which combined Indigenous Woody Vegetation (IWV), Forestry Plantations (FP), and Wetlands (WET). This result was consistent across all scales. Figure 35 below shows the distribution of natural vegetation according to this aggregate classification within the study area.

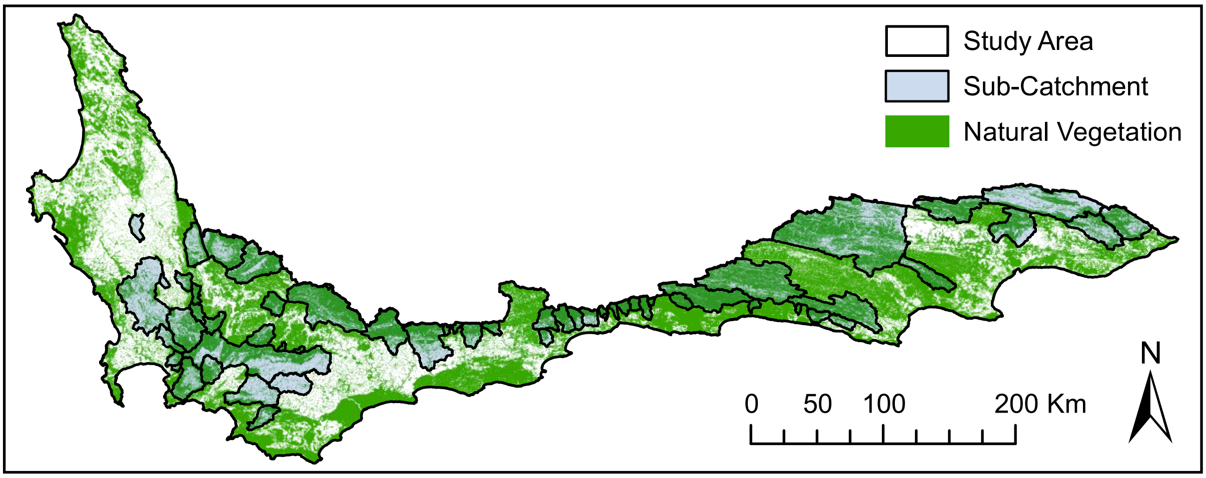


Figure 35. Map showing the distribution of natural vegetation in the study area, with the former defined as the combination of Indigenous Woody Vegetation (IWV), Forestry Plantations (FP), and Wetlands (WET). Also shown are the 58 sub-catchments which made up the statistical sample for this study.

Furthermore, as the results above reveal, correlations between NPI scores and proportions of natural vegetation (when the latter was classified as the combination of IWV, WET, and FP) were strongest when measured at the 200 m riparian buffer zone scale (Spearman's ρ = –0.735) and at the whole-catchment scale (Spearman's ρ = –0.729). The difference between these two correlation coefficients was statistically insignificant, suggesting that LULC at both scales had a meaningful influence on water quality.

Across the sample of 58 sub-catchments, proportions of natural vegetation cover, when thus classified and calculated at the whole-catchment scale, ranged from a minimum of 0.11 to a maximum of 0.99. Within 200 m riparian buffer zones, proportions of natural vegetation ranged from a minimum of 0.29 to a maximum of 0.99. The sample of sub-catchments was thus representative of a wide range of land cover conditions, ranging from essentially undisturbed catchments to extensively modified catchments. However, the distributions of the samples in both cases were not truly gaussian; the majority of the catchments had proportions of natural vegetation ≥ 0.5 (i.e., more than 50%). The histograms below (Figure 36) show the distribution of proportions of natural vegetation across the sample of 58 sub-catchments at both scales.

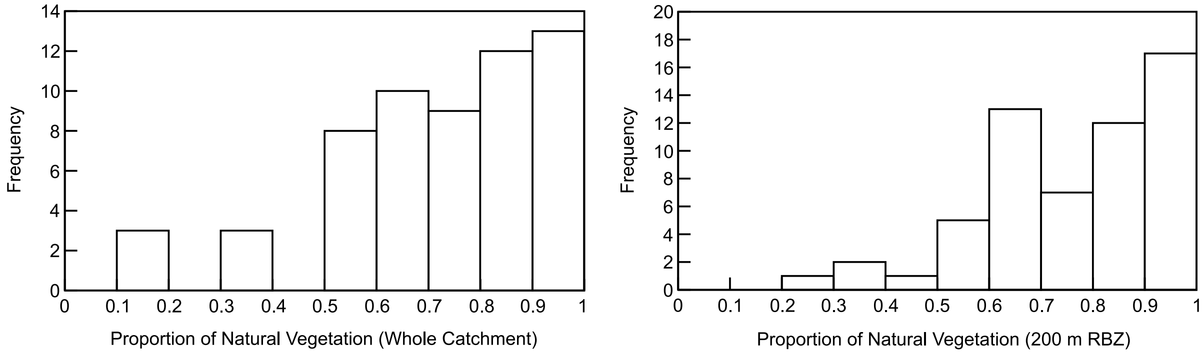


Figure 36. Histograms showing the distribution of natural vegetation across the sample of 58 sub-catchments when measured as a proportion of the landscape at the whole-catchment scale (left) and within the 200 m riparian buffer zone (right).

Moreover, in terms of the distribution and extent of anthropogenic disturbance, the dominant land use across the sample of sub-catchments was agriculture. Proportions of agricultural land use ranged from zero (which was the case in seven of the 58 sub-catchments) to approximately 0.89. In terms of urban land, proportions were typically much smaller across the sample. Of the 58 sub-catchments, 23 contained no urban land use, whereas the maximum extent of urban land cover was approximately 0.37. The comparative distributions of natural vegetation, agricultural, and urban land cover, when measured as a proportion of the whole catchment across the sample of sub-catchments, are shown in Figure 37 below.

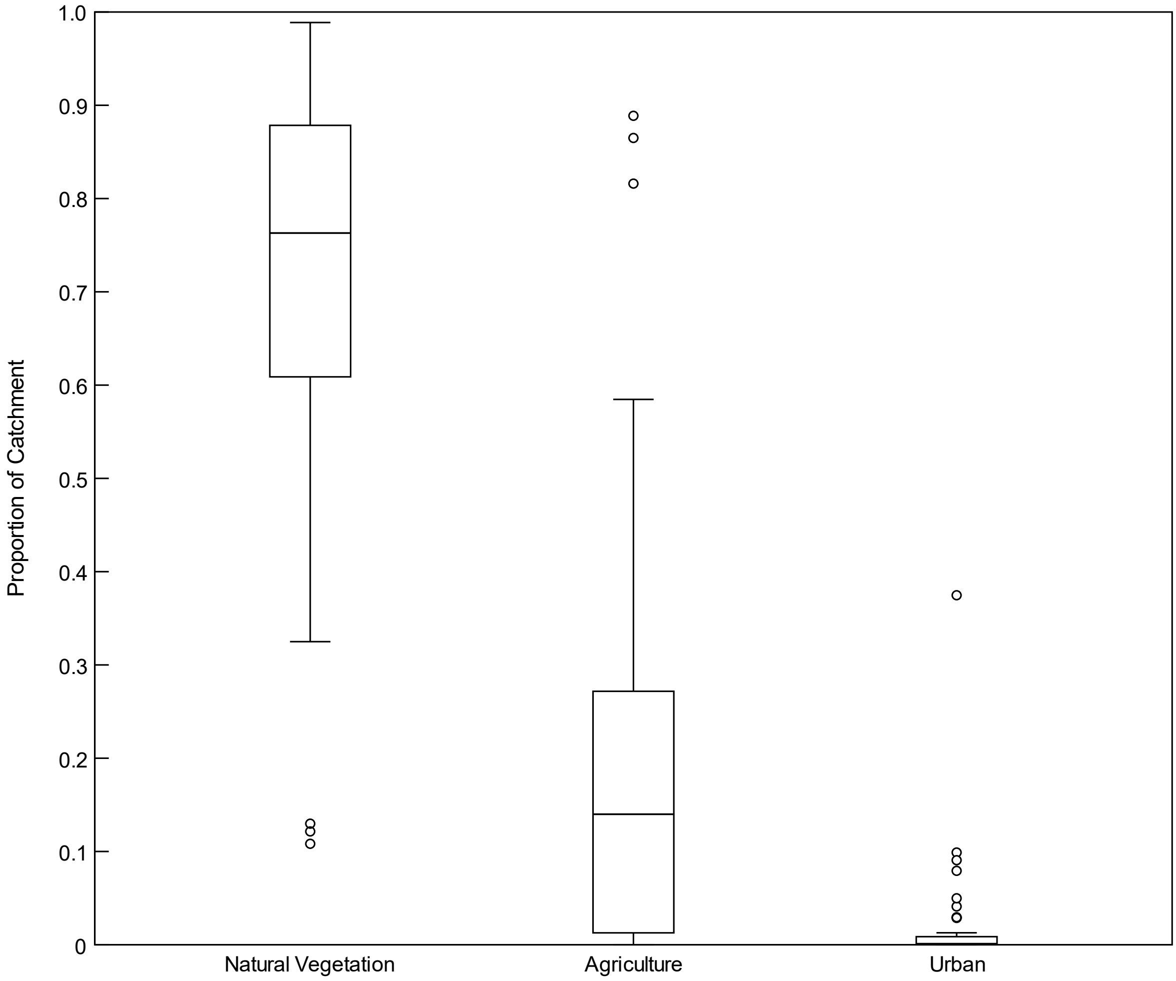


Figure 37. Boxplots of proportions of natural vegetation, agriculture, and urban land cover, measured at the whole-catchment scale, across the sample of 58 sub-catchments.

Normalised Difference Vegetation Index (NDVI)

Although the combination of IWV, FP, and WET provided a satisfactory aggregate classification of natural vegetation that was strongly and negatively correlated with NPI scores, previous research has suggested that the Normalised Difference Vegetation Index (NDVI) may also provide a possible means by which the health and extent of natural vegetation cover in a landscape could be evaluated (e.g., Griffith et al., 2002a, 2002b; Chu et al., 2013; Masocha et al., 2017; Chen et al., 2021; Senbore & Oke, 2021; Wang et al., 2021; Torres-Bejarano et al., 2022; Pandey et al., 2023). NDVI is a widely used spectral index for assessments of vegetation using remotely-sensed satellite data and takes advantage of the fact that while vegetation tends to reflect light in the near-infrared (NIR) band, the chlorophyll pigment in leaves readily absorbs light in the red (R) band (Huang et al., 2021). NDVI values, which range from –1.0 to 1.0, therefore provide an indication of plant productivity and health (Jump et al., 2010). The NDVI is calculated as follows (Equation 6):

$$NDVI = \frac{NIR - R}{NIR + R} \tag{6}$$

Landsat 8 (OLI) scenes, acquired by the sensor during 2014, were downloaded from the Earth Explorer platform (USGS, 2023). Fifteen scenes of Level 2 “analysis-ready” surface reflectance data were used to create a mosaic that covered the study area (see Table 7 below). Where possible, and as far as the presence of obstructive cloud cover allowed, scenes that had been captured during the wet season were preferred so that natural vegetation would be in leaf (Waturu et al., 2023). While the majority of the Landsat scenes had negligible cloud cover, ordering and overlap were resolved to minimise the occlusive effect of cloud-related artefacts.

Table 7. Landsat 8 OLI scenes used to create a mosaic of the study area.

Acquisition Date	Cloud Cover (%)	WRS Path	WRS Row
2014/08/12 08:04:22	2.31	170	83
2014/07/18 08:10:22	0.64	171	83
2014/08/03 08:10:53	2.23	171	84
2014/06/23 08:16:23	0.04	172	83
2014/09/11 08:16:49	3.47	172	83
2014/06/23 08:16:47	11.17	172	84
2014/09/02 08:22:58	0.01	173	83
2014/09/02 08:23:22	0.01	173	84
2014/08/24 08:29:07	0.03	174	83
2014/08/24 08:29:31	0.04	174	84
2014/08/31 08:34:55	0.01	175	82
2014/08/31 08:35:19	0.22	175	83
2014/08/31 08:35:42	0.01	175	84
2014/07/21 08:40:52	0.01	176	82
2014/07/21 08:41:16	0.01	176	83

The final Landsat 8 mosaic is shown in Figure 38 below.

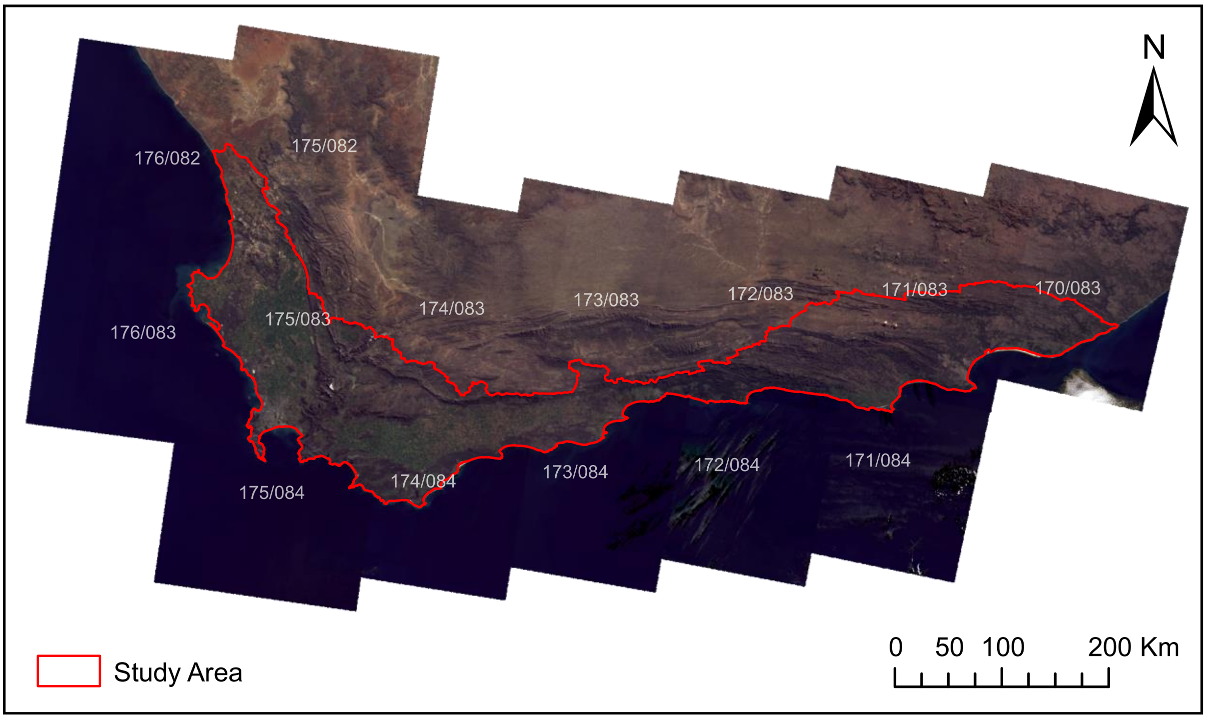


Figure 38. Mosaic of Landsat 8 (OLI) scenes used to calculate mean NDVI values for the sample of 58 sub-catchments. Landsat data obtained from USGS (2023).

This mosaic of Landsat scenes was then used to compute per-pixel NDVI values for 2014 using ArcGIS Pro, as shown below in Figure 39. Mean NDVI values for each of the 58 sub-catchments were then calculated using the Zonal Statistics tool.

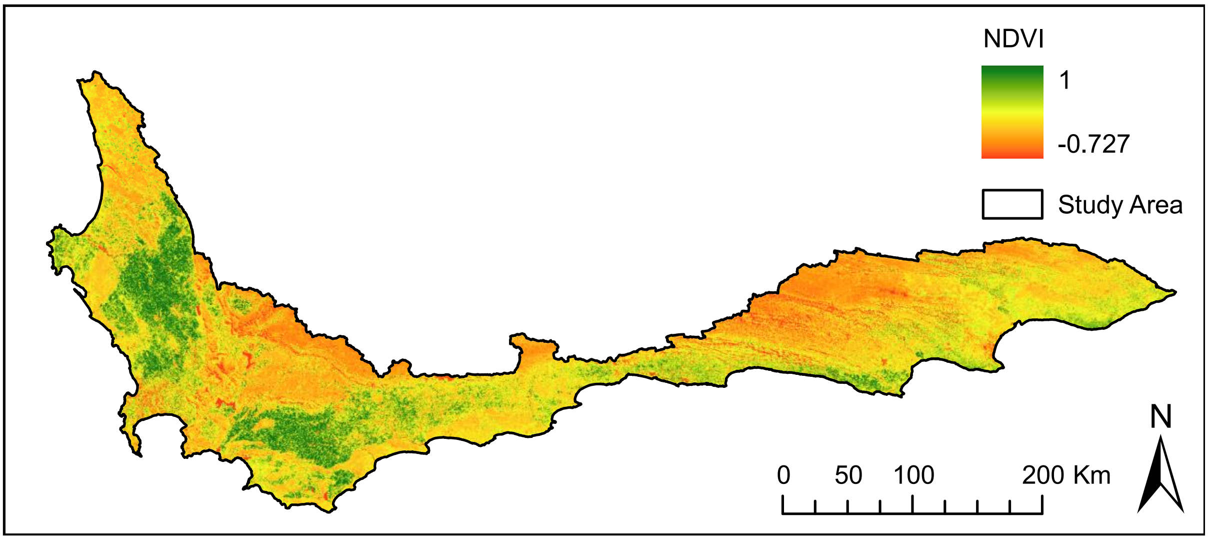


Figure 39. Colourised NDVI map of the study area, computed from Landsat 8 (OLI) scenes acquired in 2014.

When assessed using Spearman's rank correlation analysis, NDVI values showed a statistically significant positive correlation of moderate strength with NPI scores across the sample of sub-catchments (Spearman's ρ = 0.340; p < 0.01). Further investigation revealed that mean NDVI values were strongly correlated (Spearman's ρ = 0.752, p < 0.01) with the proportion of agriculture in the catchment (the latter was also calculated using Equation 5 above). The strong positive linear relationship between mean NDVI values and the proportion of agricultural land cover is shown below in Figure 40.

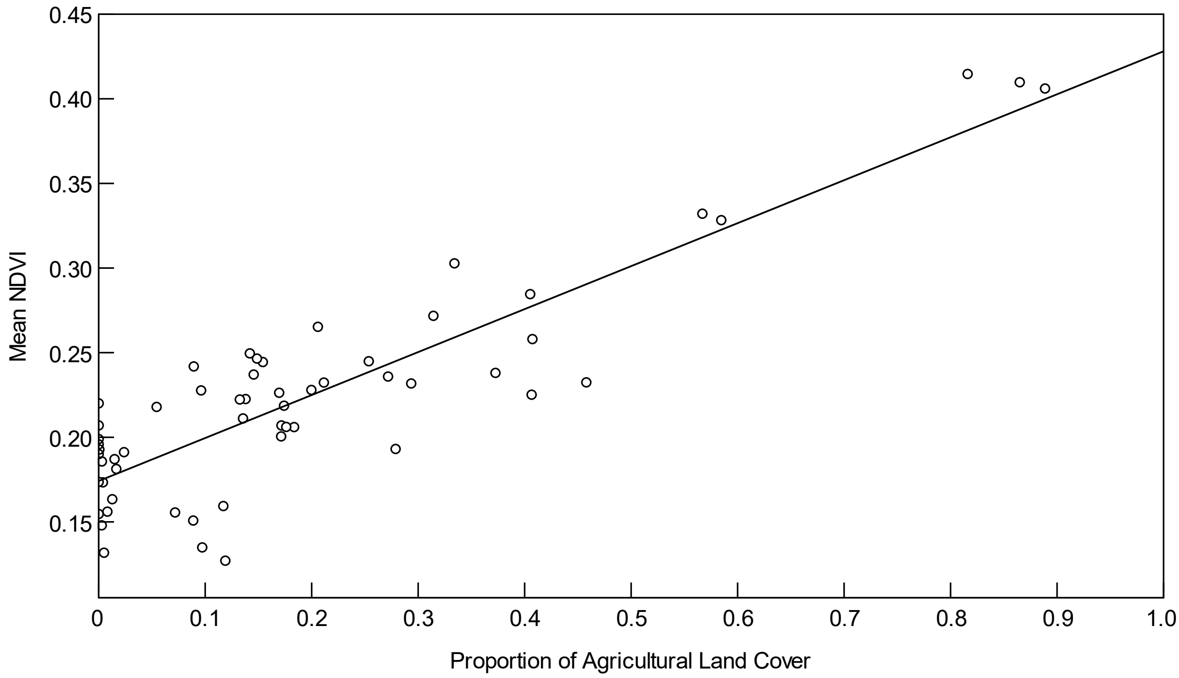


Figure 40. Plot showing the positive correlation (Spearman's $\rho = 0.752$; $p < 0.01$) between mean NDVI values and proportions of agricultural land cover across the sample of 58 sub-catchments.

Comparing the NVDI map above (Figure 39) with the reclassified 2013/14 land cover map (Figure 33) confirms that areas with high NDVI values correspond to areas containing agricultural land cover. It was therefore concluded that, in the context of this study, NDVI values were an inappropriate metric for natural vegetation. Thus, for the purposes of all subsequent statistical analyses (including regression modelling and threshold estimation), natural vegetation was classified as the area of the landscape occupied by the combination of Indigenous Woody Vegetation, Forestry Plantations, and Wetlands (i.e., IWV+FP+WET). Moreover, considering that this combination was equally significant at both the whole-catchment and 200 m riparian buffer zone scales, regression analysis and subsequent threshold estimation procedures were conducted using data at both scales.

Accounting for Fragmentation with the Natural Vegetation Integrity Index (NVII)

The third objective of this study, as outlined in the Introduction, was to assess the influence and/or significance of the location and fragmentation of natural vegetation within a landscape (questions of scale and landscape configuration, respectively). Previous research has suggested that in addition to the composition of LULC within a catchment, the configuration of the landscape may also have a significant influence on its relationship with water quality. Pertinent to this study was the supposition that the degree to which natural vegetation is fragmented may have an effect (generally assumed to be negative) on its ability to serve as a sink and protect water resources from diffuse pollution. It is often assumed, for example, that more contiguous patches of natural vegetation would offer improved buffering against diffuse pollution, while more fragmented patches would be less efficacious in this regard. Moreover, based on existing research, it has been asserted that taking both composition and configuration into account when modelling relationships between LULC and water quality is likely to improve the explanatory power of the models (Uuemaa et al., 2007; Lee et al., 2009; Yu et al., 2013; Qiu & Turner, 2015; Song et al., 2021). To test this supposition, and in order to account for the potential significance of fragmentation when performing regression analysis and estimating minimum thresholds of natural vegetation, a land cover metric that incorporated some measure of fragmentation was required. As argued by Shen et al. (2015, p. 97), "to fully understand the effect of the surrounding landscape on water quality, it is necessary to consider *both the composition and the spatial configuration of the landscape*" (emphasis added). To this end, the current study proposed and tested a new landscape index (namely the Natural Vegetation Integrity Index, or NVII):

$$NVII = \left(\frac{V}{T - W}\right)F \tag{7}$$

The NVII is a unitless metric, ranging from 0 to 1, that reflects both the amount of natural vegetation within the landscape and the degree to which that vegetation is fragmented. In Equation 7 above, V is the area of the landscape occupied by patches of natural vegetation, T is the total area of the landscape, W is the area of the landscape occupied by water, and F is a standardised class-level measure of the degree to which patches of natural vegetation are fragmented (adjusted, if necessary, so that it ranges from between 0 and 1, such that a lower score indicates a greater degree of fragmentation). The NVII is thus a straightforward metric that adjusts the proportion of the landscape occupied by natural vegetation (as per Equation 5) by the degree to which patches of that self-same vegetation are fragmented. The index scores are therefore reflective of the degree to which a landscape has been disturbed by anthropogenic activity—such as urban or agricultural expansion—which would not only reduce the amount of natural vegetation in the landscape, but also result in the remaining patches of natural vegetation being more fragmented (see Tiner, 2004, p. 232). The NVII is thus designed to integrate and reflect both consequences of ecological disturbance.

Several Landscape Pattern Metrics (LPMs) have been developed to measure, amongst other landscape characteristics, class-level fragmentation (Wei et al., 2017; Ene & McGarigal, 2023d). In order to test the proposed NVII, two common class-level fragmentation metrics—the Patch Cohesion Index (Schumaker, 1996) and the Aggregation Index (He et al., 2000)—were considered. Both LPMs have been widely used to measure landscape configuration and its influence on water quality.[61]

[61] See, for instance, Lee et al. (2009), Uuemaa et al. (2009), Bu et al. (2014), Ding et al. (2016), Shi et al. (2017), Liu and Yang (2018), Wang and Zhang (2018), Mirzaei et al. (2020), Song et al. (2020), Chiang et al. (2021), Liu et al. (2021), Wang et al. (2021), Aalipour et al. (2022), Li et al. (2022a), Zhang et al. (2022a), Zhong et al. (2022), Zhou et al. (2022), and Zhang et al. (2023b).

The Patch Cohesion Index (COHESION) measures the physical connectedness of the land cover class of interest. The index approaches zero as the proportion of the landscape comprised of the focal class decreases, becomes increasingly subdivided, and is less physically connected. It increases monotonically as the patch type becomes more aggregated until an asymptote is reached (Ene & McGarigal, 2023b). This occurs when the proportion of the total landscape occupied by the focal class reaches a critical "percolation threshold" (which itself depends on whether neighbouring pixels must share common edges, or only corners, in order to be defined as a patch) (Gustafson, 1998; Ene & McGarigal, 2023b). Above this threshold, COHESION becomes relatively insensitive to fragmentation.

The Aggregation Index (AI), as the name suggests, reflects the degree to which patches of the class of interest are aggregated. This is computed for the focal class by calculating the actual number of shared edges relative to the maximum possible number of shared edges (achieved when the class is maximally clumped into a single compact patch). The index thus equals zero when the focal patch type is maximally disaggregated (i.e., when there are no shared edges). The index score increases as the focal patch type is increasingly aggregated and equals 1 when the patch type is maximally aggregated into a single compact patch (which is not necessarily a square) (Rutledge, 2003; Ene & McGarigal, 2023a).

Another metric, namely Patch Density (PD), while also widely used, is not standardised and thus not suitable for calculating the proposed NVII. Furthermore, it conveys no information about the size and spatial distribution of patches (Ene & McGarigal, 2023c). In any case, PD and AI are highly correlated, making the former redundant (Wei et al., 2017).

Across the entire sample of 58 sub-catchments, Fragstats 4.2 (McGarigal & Ene, 2023) was used to compute both AI and COHESION scores at the whole-catchment scale for the aggregate natural vegetation class identified in the previous section. Patches were defined using the 8-cell neighbourhood rule (i.e., pixels of the same land cover class sharing either adjacent edges *or* corners were defined as a patch). This is the default setting in Fragstats and was deemed an appropriate patch definition rule considering the spatial resolution of the land cover data.

However, when an 8-cell neighbourhood rule is used to calculate COHESION, the percolation threshold mentioned above is approximately 0.41 (see Gustafson, 1998). This means that the index is relatively insensitive to fragmentation when the proportion of the landscape occupied by the land cover class of interest is above 41%. As such, across the sample of sub-catchments (in which the proportion of natural vegetation was, on average, well above this threshold), COHESION was not a very sensitive measure of fragmentation and showed very little variation across the sample. COHESION index scores were thus discounted. The Aggregation Index, by contrast, offered a more sensitive measure of fragmentation. AI scores were thus used to calculate NVII scores for each of the 58 sub-catchments, as per Equation 7 above. The results are shown in Table 8 below, with catchments ordered according to the proportion of the landscape occupied by natural vegetation.

Table 8. Composition and configuration of natural vegetation at the whole-catchment scale across the sample of 58 sub-catchments.

Catchment	Proportion of Natural Vegetation Cover (IWV+FP+WET)	Aggregation Index (AI) Score	Natural Vegetation Integrity Index (NVII) Score
102017	0.1083	0.7035	0.0762
101942	0.1215	0.6941	0.0843
101937	0.1298	0.7219	0.0937
86712	0.3250	0.8425	0.2738
102430	0.3889	0.8796	0.3421
101997	0.3903	0.9031	0.3525
102123	0.5205	0.9293	0.4837
101917	0.5458	0.9019	0.4922
102107	0.5620	0.9326	0.5242
102435	0.5625	0.9099	0.5119
102250	0.5638	0.9226	0.5201
101979	0.5735	0.8931	0.5122
102217	0.5831	0.9273	0.5407
102254	0.5967	0.9350	0.5579
101944	0.6088	0.9142	0.5566
102316	0.6225	0.9393	0.5847
102427	0.6399	0.9444	0.6044
102438	0.6517	0.9433	0.6147
102353	0.6547	0.8926	0.5844
101987	0.6586	0.9069	0.5973
101986	0.6623	0.9092	0.6022
102019	0.6650	0.9330	0.6204
101929	0.6871	0.9042	0.6213
187987	0.6916	0.9167	0.6340
102130	0.7071	0.9442	0.6677
102002	0.7107	0.9552	0.6789
101998	0.7268	0.9227	0.6706
102043	0.7350	0.9312	0.6845
102423	0.7519	0.9340	0.7022
102206	0.7742	0.9566	0.7406
102241	0.7749	0.9641	0.7471
102358	0.7889	0.9361	0.7385
102121	0.7990	0.9645	0.7707
102320	0.8028	0.9567	0.7680
102202	0.8090	0.9633	0.7793
102063	0.8120	0.9455	0.7677
102082	0.8216	0.9513	0.7816
102317	0.8281	0.9723	0.8051
102207	0.8350	0.9681	0.8084
102132	0.8370	0.9577	0.8016
102023	0.8531	0.9347	0.7974
102029	0.8592	0.9363	0.8045
102368	0.8667	0.9724	0.8428
102083	0.8785	0.9628	0.8458
102275	0.8837	0.9790	0.8651
102127	0.9147	0.9743	0.8912
102251	0.9169	0.9730	0.8921
87219	0.9314	0.9742	0.9074
102097	0.9499	0.9749	0.9260
102313	0.9537	0.9720	0.9270
102079	0.9599	0.9719	0.9329
102021	0.9618	0.9743	0.9371
102312	0.9619	0.9814	0.9440
102248	0.9676	0.9808	0.9490
102252	0.9702	0.9827	0.9534
102293	0.9748	0.9890	0.9640
102276	0.9844	0.9896	0.9742
102277	0.9887	0.9917	0.9805

Calculated at the whole-catchment scale, AI scores ranged from a minimum of 0.69 to a maximum of 0.99, with a mean of 0.93 and a standard deviation of only 0.06. Owing to this low variance in fragmentation, the metrics of composition and configuration at this scale demonstrated strong multicollinearity across the sample of sub-catchments (see Table 9 below).

Table 9. Correlation matrix (Spearman's ρ) of metrics of natural vegetation assessed at the whole-catchment scale (all correlations significant at $p < 0.01$).

Spearman's Rho (ρ)	**Proportion of Natural Vegetation Cover**	**Aggregation Index (AI) Score**	**Natural Vegetation Integrity Index (NVII) Score**	**NPI Scores**
Proportion of Natural Vegetation Cover		0.911	0.997	–0.729
Aggregation Index (AI) Score	0.911		0.933	–0.646
Natural Vegetation Integrity Index (NVII) Score	0.997	0.933		–0.721
NPI Scores	–0.729	–0.646	–0.721	

The proportion of natural vegetation cover at the whole-catchment scale, for instance, was very strongly correlated with the degree to which that vegetation was fragmented (Spearman's ρ = 0.911; $p < 0.01$). Thus, as the proportion of the catchment occupied by natural vegetation decreased, the degree to which patches of that vegetation were fragmented also increased. Moreover, the proportion of natural vegetation cover in the catchment showed a near-perfect correlation with NVII scores (Spearman's ρ = 0.997; $p < 0.01$), suggesting that, in this particular sample of sub-catchments, NVII scores were largely a function of the proportion of natural vegetation in the landscape and were not significantly modified by measures of fragmentation (i.e., due to the generally low degree of fragmentation across the sample, it was not a particularly influential factor in the calculation of the NVII scores).

Furthermore, across the sample of sub-catchments, NVII scores showed a strong negative correlation with NPI scores (Spearman's ρ = –0.721; $p < 0.01$). However, the correlation between pollution levels and the degree to which natural vegetation was fragmented, while also negative, was significantly weaker (Spearman's ρ = –0.646; $p < 0.01$). Moreover, when both of these correlation coefficients were compared with the strength of the correlation already noted between pollution levels and the proportion of natural vegetation cover in the catchment (Spearman's ρ = –0.729; $p < 0.01$), there was no apparent advantage offered by including a measure of fragmentation in the analysis. The foregoing thus demonstrated that in the present study, and when using these particular metrics at this scale of analysis, the degree to which natural vegetation was fragmented was unlikely, from a statistical perspective, to offer any additional explanatory power. Rather, a simple compositional metric (i.e., proportions of natural vegetation cover estimated at the whole-catchment scale) was deemed sufficient for subsequent regression analysis. The results of the same analysis conducted at the 200 m riparian buffer zone scale are shown in Table 10 below.

Table 10. Composition and configuration of natural vegetation at the 200 m riparian buffer zone scale across the sample of 58 sub-catchments.

Catchment	Proportion of Natural Vegetation Cover (IWV+FP+WET)	Aggregation Index (AI) Score	Natural Vegetation Integrity Index (NVII) Score
101942	0.2887	0.7912	0.2284
101937	0.3260	0.7787	0.2539
102017	0.3452	0.8093	0.2794
102430	0.4023	0.7980	0.3211
102353	0.5490	0.7742	0.4250
86712	0.5736	0.8553	0.4906
101917	0.5860	0.8650	0.5069
101997	0.5870	0.8810	0.5172
102019	0.6000	0.8552	0.5131
101987	0.6050	0.8480	0.5130
102427	0.6097	0.8732	0.5324
102123	0.6260	0.8791	0.5503
102043	0.6264	0.8805	0.5515
101986	0.6396	0.8739	0.5590
102254	0.6504	0.9360	0.6088
102217	0.6566	0.8890	0.5837
101929	0.6604	0.8346	0.5512
101944	0.6686	0.8797	0.5881
102083	0.6781	0.9043	0.6132
102063	0.6814	0.8623	0.5875
102082	0.6869	0.9051	0.6217
102107	0.6975	0.8913	0.6217
102121	0.7011	0.8982	0.6297
102423	0.7191	0.8573	0.6165
101979	0.7407	0.8922	0.6608
102358	0.7473	0.8751	0.6540
102002	0.7509	0.8880	0.6668
101998	0.7567	0.8755	0.6624
102435	0.7729	0.8984	0.6943
102250	0.8061	0.9324	0.7516
102320	0.8113	0.8954	0.7264
102368	0.8251	0.9155	0.7554
102316	0.8295	0.9344	0.7750
102438	0.8425	0.9324	0.7856
187987	0.8488	0.9286	0.7882
102130	0.8514	0.9352	0.7962
102202	0.8532	0.9304	0.7939
102206	0.8625	0.9305	0.8026
102251	0.8902	0.9419	0.8384
102317	0.8912	0.9510	0.8475
102029	0.8977	0.9137	0.8202
102132	0.9040	0.9251	0.8363
102097	0.9130	0.9136	0.8341
87219	0.9298	0.9288	0.8635
102023	0.9337	0.9319	0.8700
102207	0.9423	0.9460	0.8914
102079	0.9594	0.9398	0.9016
102275	0.9621	0.9406	0.9049
102021	0.9672	0.9421	0.9111
102241	0.9691	0.9391	0.9101
102313	0.9706	0.9541	0.9260
102276	0.9718	0.9545	0.9277
102248	0.9764	0.9511	0.9287
102312	0.9818	0.9509	0.9336
102252	0.9870	0.9540	0.9416
102293	0.9870	0.9552	0.9427
102277	0.9901	0.9609	0.9514
102127	0.9914	0.9615	0.9533

AI scores at this scale ranged from a minimum of 0.77 to a maximum of 0.96, with a mean of 0.90 and a standard deviation of only 0.05. As with the catchment-scale metrics, the generally low degree of fragmentation across the sample meant that including a measure fragmentation at 200 m RBZ scale did not appear to offer any increased explanatory power. The correlation matrix below (Table 11) confirms that Aggregation Index (AI) scores, when calculated for natural vegetation patches within a 200 m RBZ across the sample of 58 sub-catchments, were highly correlated to proportions of natural vegetation and did not significantly modify NVII scores. Therefore, as with the catchment-scale analyses, simple estimates of the proportion of the landscape occupied by natural vegetation at this scale were preferred for the regression models.

Table 11. Correlation matrix (Spearman's ρ) of metrics of natural vegetation measured within a 200 m riparian buffer zone (all correlations significant at $p < 0.01$).

Spearman's Rho (ρ)	**Proportion of Natural Vegetation Cover**	**Aggregation Index (AI) Score**	**Natural Vegetation Integrity Index (NVII) Score**	**NPI Scores**
Proportion of Natural Vegetation Cover		0.908	0.997	–0.735
Aggregation Index (AI) Score	0.908		0.933	–0.618
Natural Vegetation Integrity Index (NVII) Score	0.997	0.933		–0.732
NPI Scores	–0.735	–0.618	–0.732	

Correlation with Agricultural and Urban Land

It is also worth mentioning that, in the current study, proportions of natural vegetation showed a significantly stronger correlation with NPI scores than proportions of either urban or agricultural land cover (when all were measured at the whole-catchment scale using Equation 5 above). As is evident from Table 12 below, while both urban and agricultural land cover had statistically significant relationships with pollution levels (which, as expected, were positive) neither were as strongly correlated with water quality as proportions of natural vegetation measured at the same scale. Simple compositional metrics of natural vegetation (classified, in this study, as the aggregation of IWV, FP, and WET) were therefore used for the development of regression models and in the estimation of thresholds at both whole-catchment and 200 m riparian buffer zone scales.

Table 12. Correlation between NPI scores and natural vegetation, agriculture, and urban land cover, when the latter were measured as a proportion of the catchment.

Land Cover Class	Correlation with NPI Scores	
	Spearman's Rho (ρ)	**Significance Level**
Natural Vegetation	–0.729	$p < 0.01$
Agriculture	0.621	$p < 0.05$
Urban	0.333	$p < 0.01$

Moreover, as expected, proportions of natural vegetation, agricultural, and urban land cover were significantly correlated across the sample of sub-catchments (i.e., the multicollinearity that Tu, 2011a, and others have cautioned may confound statistical analyses). This is shown in Table 13 below. Notably, there was a strong negative correlation (Spearman's ρ = –0.808; $p < 0.01$). between proportions of natural vegetation and agricultural land cover.

Table 13. Correlation matrix (Spearman's ρ) of selected land cover metrics across the sample of sub-catchments.

	Natural Vegetation	Agriculture	Urban
Natural Vegetation		–0.808**	–0.484**
Agriculture	–0.808**		0.331*
Urban	–0.484**	0.331*	

* Significant at $p < 0.05$; ** Significant at $p < 0.01$

Modelling

The primary aim of this study, as outlined in the Introduction, was to estimate statistical models of the relationship between water quality and natural vegetation in the chosen study area, from which thresholds of natural vegetation could be estimated for the protection and maintenance of water quality. Therefore, having evaluated water quality across the sample of sub-catchments using the NPI, and having confirmed, through correlation analysis, that there was a strong and statistically significant relationship between metrics of natural vegetation and water quality at both the whole-catchment and 200 m RBZ scales, simple ordinary least-squares (OLS) linear regression analysis was used to model the relationship between these two variables at both analytical scales. Unless otherwise stated, all analyses were performed using SPSS (IBM, 2022).

As per Barnett (2004) and Helsel et al. (2020), before any further statistical analyses were performed scatterplots of the data were inspected (Figure 41). Loess smooth curves were fitted to the scatterplots to assist in the identification and interpretation of any trends or patterns. This initial visual assessment revealed several important issues.

Firstly, as emphasised by the loess smooth curves, it is readily apparent that a negative and nonlinear relationship exists between proportions of natural vegetation and NPI scores at both scales. This accounts for the strength and significance of the correlation previously noted between these two variables (Spearman's ρ = –0.735 and –0.729 at the 200 m RBZ and whole-catchment scales, respectively). It is evident from the scatter plots (and the loess smooth curves) that as proportions of vegetation decrease, the severity of water pollution increases. Put differently, lower proportions of natural vegetation are clearly associated with poorer water quality.

However, notwithstanding the patent correlation between the two variables, the scatter plots also reveal at least six "anomalous" datapoints that do not appear to fit the pattern of the rest of the sample. It is readily apparent at the whole-catchment scale, for example, that compared to other sub-catchments with similar proportions of natural vegetation, these six observations have disproportionately high NPI scores. They appear, in this sense, discordant from the rest of the sample. The same six observations remain atypical when considered at the 200 m RBZ scale.

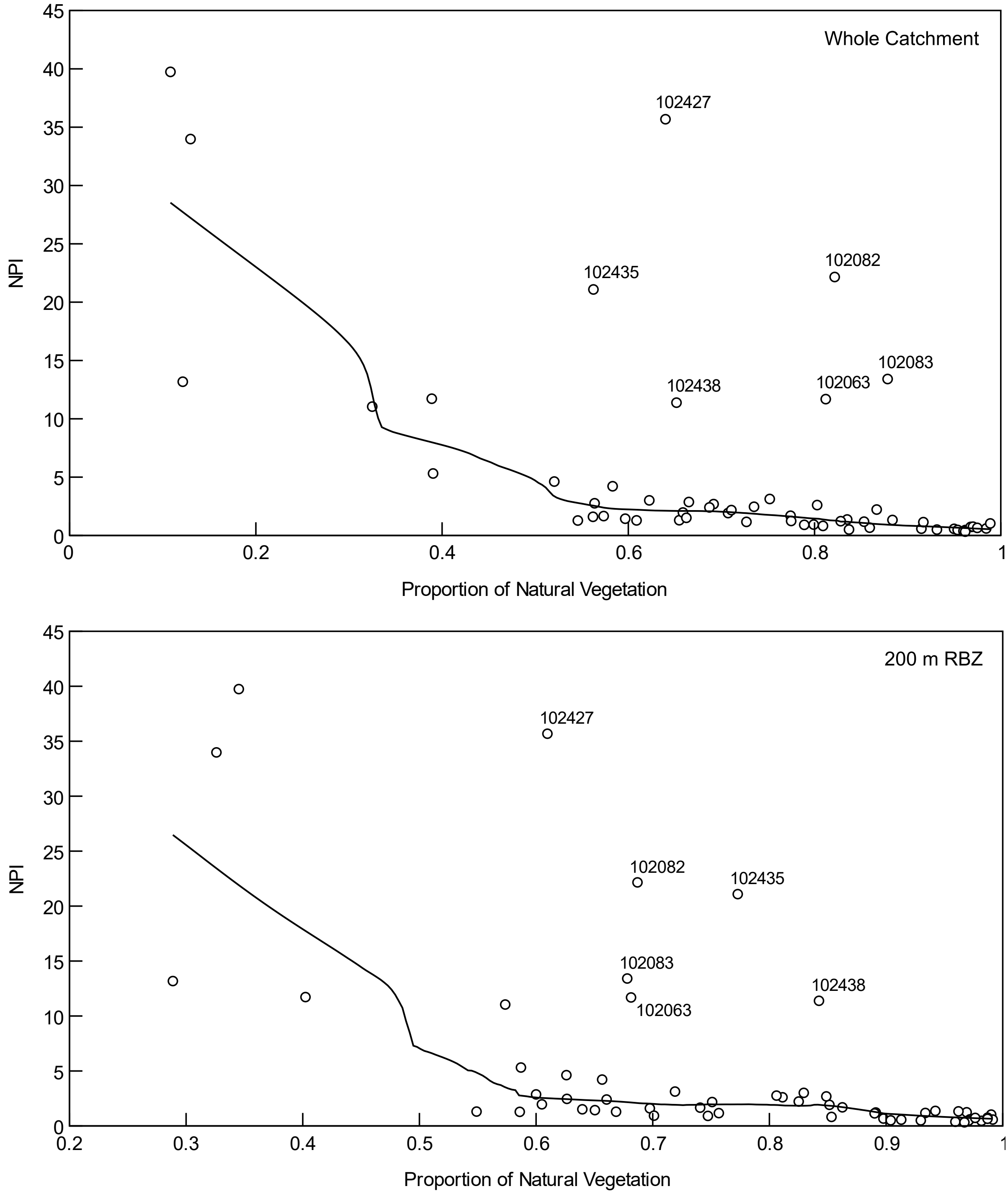


Figure 41. Scatterplots of NPI scores against proportions of natural vegetation cover at the whole-catchment scale (above) and 200 m RBZ scale (below) with loess smooth curves (solid line) fitted to the data. The six discordant observations are labelled with their respective NCMP identification numbers.

Identification and Investigation of Outliers

As the name suggests, one of the underlying assumptions of simple linear regression is that the relationship between the two variables is linear. This being the case, NPI scores were log transformed to achieve linearity. Log transformations are a common means of satisfying this requirement, especially in water resources data (Fox, 2016; Darlington & Hayes, 2017; Helsel et al., 2020). A scatterplot of the thus linearised data, using catchment-scale observations as an example, is shown in Figure 42 below.

As can be seen from the scatterplot, the data follow a much more linear pattern once transformed. Nevertheless, the discordance of the six anomalous catchments is still clearly apparent.

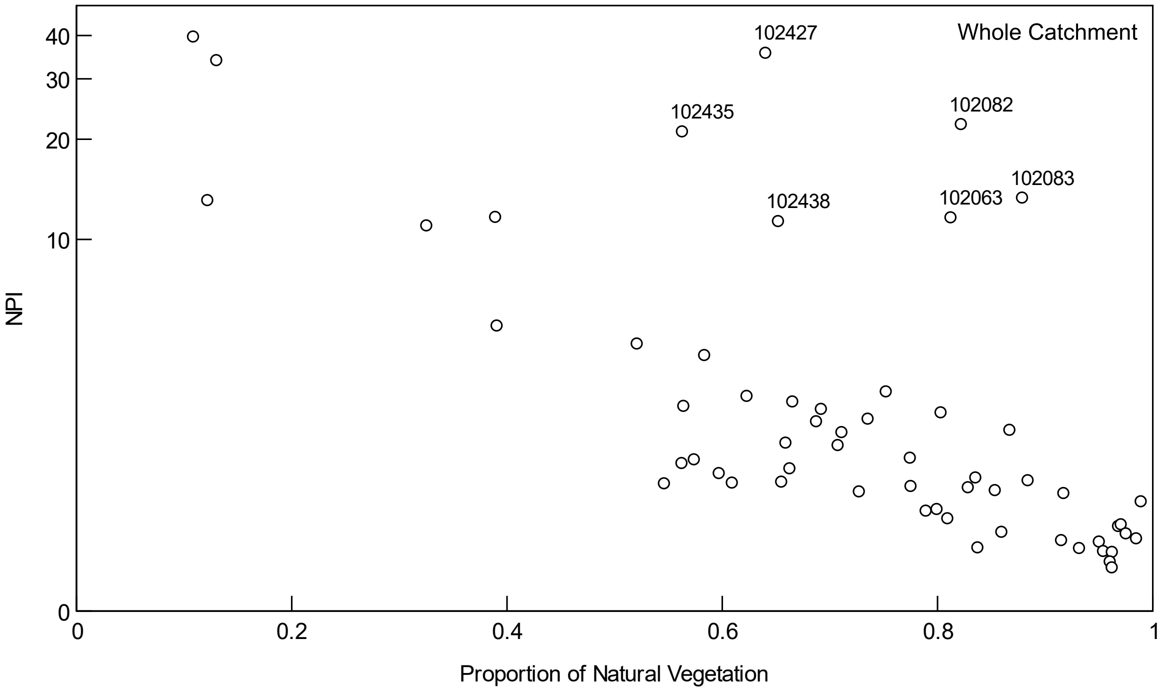


Figure 42. Scatterplot of proportions of natural vegetation against NPI scores at the whole-catchment scale, suitably linearised by a log transformation of the latter. The six outliers are labelled.

Outliers are common in environmental samples, and perhaps especially so in water resources data (Barnett, 2004; Helsel et al., 2020). Moreover, in the case of regression analysis, outliers may not necessarily be extreme values of either variable. Instead, outliers may be datapoints that do not fit the overall pattern of the rest of the sample and may therefore exert an improper influence on the estimated model (Barnett & Lewis, 1994; Barnett, 2004; Osborne & Overbay, 2004). While the temptation may be to reject apparent outliers in favour of a “tidier” sample, anomalous points should not be automatically deleted as they may in fact represent legitimate (albeit unusual) cases, and so reveal important insights about, or limitations for, the applicability of the model (Osborne & Overbay, 2004; Chatterjee & Hadi, 2012; Helsel et al., 2020). According to most texts (e.g., Barnett & Lewis, 1994; Helsel et al., 2020), suspected outliers should therefore be subjected to the following:

1. Further examination to determine whether they are due to sampling, transcription, or analytical errors, or if they instead represent legitimate (although atypical) cases.
2. Formal discordancy tests to determine whether they are true outliers in the statistical sense.

In cases where outliers result from sampling or analytical errors, and if these errors cannot be corrected, these observations may be justifiably removed from the sample (Judd et al., 2017; Helsel et al., 2020). However, in instances where outliers are not due to any obvious analytical or recording errors, the appropriate procedures for handling them are somewhat contentious (Osborne & Overbay, 2004; Yang & Berdine, 2016; Judd et al., 2017). In such instances, Osborne and Overbay (2004, p. 8) have argued that researchers "must use their training, intuition, reasoned argument, and thoughtful consideration" when taking decisions regarding whether outliers should be retained or rejected.

In the present study, further investigation revealed that in four of the six anomalous catchments there was significant anthropogenic disturbance directly upstream of, or adjacent to, the NCMP sampling points and/or along stretches of the main tributaries. Land cover maps of these four catchments (namely, 102063, 102082, 102083, and 102427) are shown below in Figure 43. As the maps show, the catchments contain relatively high proportions of natural vegetation cover. However, the presence of agriculture directly upstream of the NCMP points in these four catchments may account for the higher-than-expected pollution index scores. This finding is significant in and of itself and has important implications for the applicability of the thresholds estimated from the regression models.

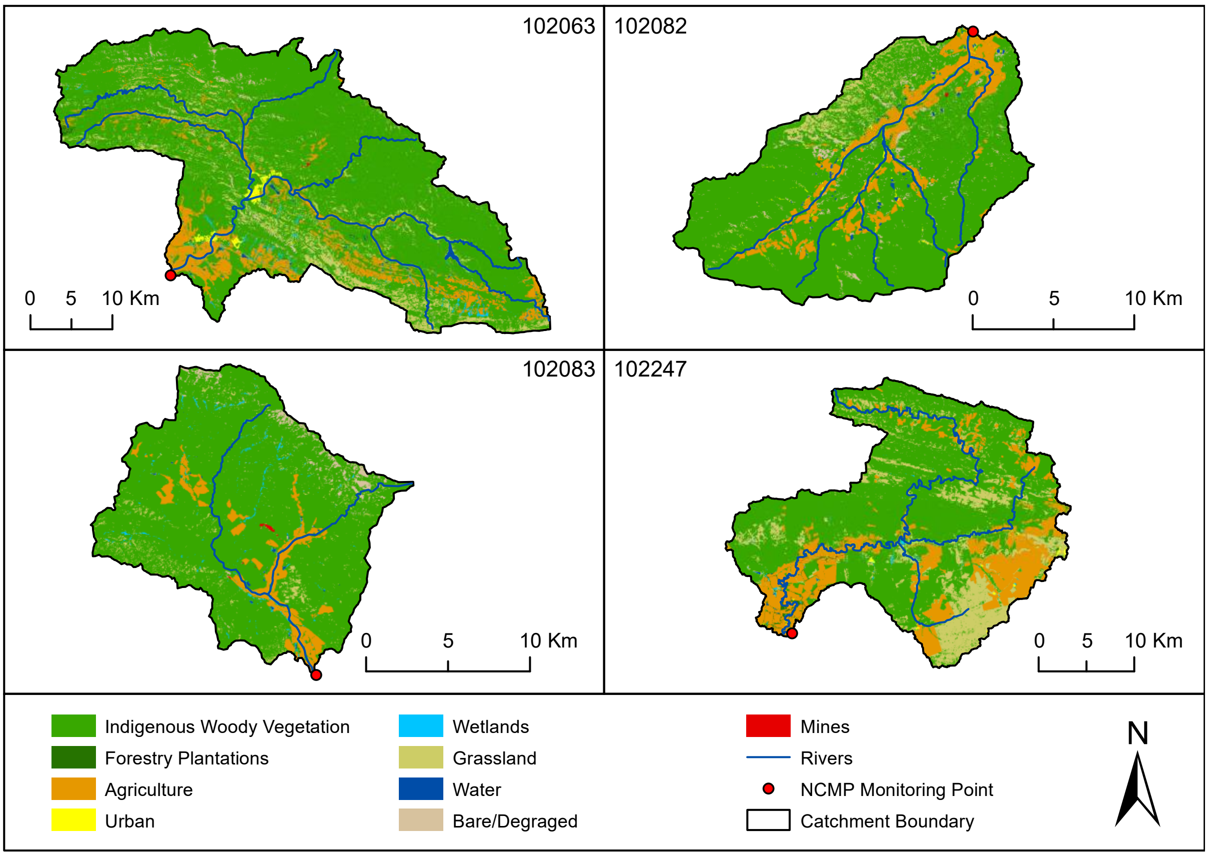


Figure 43. Maps showing the composition and arrangement of land cover in four of the six anomalous catchments (102063, 102082, 102083, and 102427).

The other two anomalous catchments (namely, 102435 and 102438, which neighbour one another in the eastern-most part of the study area) are admittedly more difficult to account for. As with the majority of the other non-compliant sub-catchments, the NPI sub-index scores of these two catchments show that elevated electrical conductivity levels are the primary water quality issue, with non-compliant nitrogen levels and slightly elevated pH measurements also common to both catchments (refer to Table 4). As can be seen from Figure 44 below, there is nothing immediately evident from the land cover maps that would account for the higher-than-expected NPI scores relative to the amount of natural vegetation cover in these two catchments. While both catchments contain patches of agriculture (and, in the case of 102438, some urban land), the size and location of these land cover patches is unlikely to account for the unusually high NPI scores calculated for each. Moreover, when considering the ancillary data available, neither catchment is particularly distinct from the rest of the sample in terms of geology, ecology, topography, or climate. It is conceivable—although there is admittedly no direct evidence to support this—that some point-source of contamination at or near the sampling points in these two catchments is the cause of the high NPI scores. Therefore, based on the available evidence, these two cases are, to quote Barnett and Lewis (1994, p. 33), “inexplicable.”

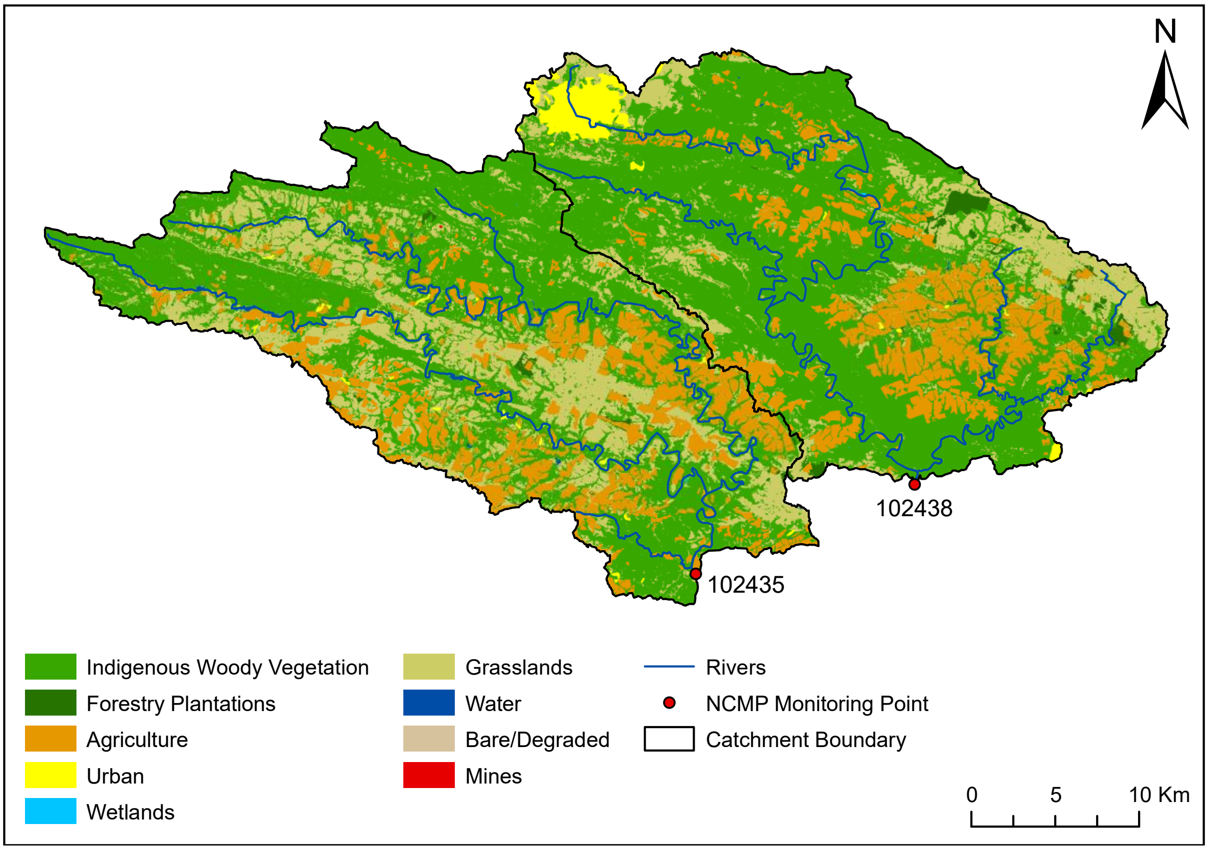


Figure 44. Map showing the composition and arrangement of land cover in two of the six anomalous catchments (102435 and 102438).

These findings notwithstanding, it remained to be determined whether these six catchments were "statistically unreasonable" using formal discordancy tests (Barnett, 2004, p. 57). Such tests typically consider either the magnitude of the residual error associated with suspected outliers (i.e., how far they deviate from the regression line fitted to the sample), or the amount of leverage/influence that suspected outliers exert on the model (i.e., the degree to which the exclusion of these points might affect the slope of the fitted regression line). However, the statistical tests generally used for identifying anomalous points may lack power in the presence of multiple outliers owing to issues of masking and swamping (Barnett, 2004). The first of these two terms (i.e., "masking") describes the combined influence of multiple outliers, which, by "pulling" the regression line towards themselves, can reduce their own apparent discordance (the residual error of these points is reduced as the regression line is drawn towards them). In doing so, multiple outliers can also falsely inflate the residual error of non-outliers in the same region of the model, making these points appear discordant as the regression line is pulled away from them (this effect is termed "swamping") (Chatterjee & Simonoff, 2013).

In an attempt to overcome the problem of masking, an iterative sequence of discordancy tests was conducted, involving an examination of the studentised deleted residual (SDR) error of each observation. While no precedent for this iterative procedure could be found in the literature, it was able to overcome issues of masking and flag statistically discordant observations.

Typically, observations which have SDR values greater than ±3 are confirmed as outliers (as, according to the Empirical Rule, 99.7% of the sample should fall within ±3 standard deviations of the sample mean) (Graybill & Iyer, 1994; Osborne & Overbay, 2004; Blatná, 2006; Chatterjee & Simonoff, 2013; Fox, 2016; Judd et al., 2017). However, owing to the masking effect described above, it was foreseen that the presence of multiple outliers in the sample would reduce the residual error associated with true outliers. For this reason, a more conservative critical SDR value of ±2.5 was selected to identify statistically discordant points (as per Chatterjee & Simonoff, 2013, p. 56, who note that less than 1% of the sample is expected to fall outside ±2.5 standardised residuals). The iterative process involved the following steps:

1. Performing a preliminary regression analysis on the original, uncensored sample.
2. Computing the SDR error of each of the observations in the sample.
3. Removing observations with SDR error ≥ ±2.5.
4. Re-running the regression analysis with the new sample to identify previously masked outliers and repeating the cycle until all outliers had been revealed (i.e., until none of the remaining observations in the sample had SDR error of ≥ ±2.5).

With each iteration, as the confirmed outliers were removed and their influence on the model eliminated, the residual error of other discordant points (which had hitherto been reduced due to the presence of other outliers in the same region pulling the regression line towards themselves) now exceeded the threshold of 2.5 SDRs. Figuratively speaking, this iterative technique "peeled away" successive layers of outliers and, with each run of the analysis, previously hidden outliers were thus "unmasked" and shown to be statistically discordant. This exercise illustrated how multiple outliers can reduce the power of traditional discordancy tests through masking, and how the iterative removal of these observations allowed the true discordancy of other observations to be revealed.

Using catchment-scale data, two runs of this procedure were sufficient to confirm that all six of the initially identified catchments were in fact unreasonably discordant (in a statistical sense) from the rest of the sample. The remaining 52 observations had SDR values of less than ±2.5. The same iterative process was then applied to confirm whether these six points remained statistically discordant at the 200 m RBZ scale. Within four iterations of the procedure described above, the six observations were again confirmed as outliers and statistically uncharacteristic of the rest of the sample.

With these six observations declared as genuine outliers, and with the causes of their discordance investigated, further thought could be given to the most appropriate way to handle them in subsequent analyses (i.e., whether to retain or exclude them from the samples used to estimate regression models). However, before continuing with the modelling procedures, it was also important to consider the potential influence of other factors and variables which might confound the analyses.

Potentially Confounding Factors

The relationship between LULC and water quality is influenced by a variety of site-specific environmental variables—including local geology, ecology, topography, and climate—which can make it difficult to attribute changes in water quality to differences in LULC with confidence. As such, the potential significance of these factors should not be discounted. For the particular purpose of statistical modelling, however, their influence may be minimised, controlled, or otherwise accounted for so as to highlight the specific impacts of LULC. Therefore, the fourth objective of the present study was to minimise the potentially confounding influence of additional/extraneous variables so as to isolate the impacts of LULC on water quality.

Geology, Ecology, and Climate

While the study area comprises several major geological groups (see Figure 19 in Chapter 5), actual lithological variation, when assessed across the sample of 58 sub-catchments, was minor. The catchments themselves are dominated by the sandstones, shales, and mudstones that characterise the Cape Supergroup (which was estimated to account for over 76% of the total area occupied by the sample of sub-catchments). The remaining area of the 58 sub-catchments is occupied by relatively small and isolated zones of the other geological formations found in the study area. This being the case, lithological variation across the sample of sub-catchments was not deemed to be significant enough to warrant the inclusion of catchment geology as an additional variable in multivariate analyses. Moreover, as outlined in the preceding chapter, the different ecoregions that characterise the study area—namely, the southern folded mountains and the southern, south-western and south-eastern coastal belts—are all fairly similar in terms of their ecological characteristics (see Table 2 on p. 91).

In addition, using data from Fick and Hijmans (2017) the mean annual precipitation (MAP) received in each of the 58 sub-catchments was estimated using the Zonal Statistics tool in ArcGIS Pro (see Appendix 6). Somewhat surprisingly, despite the fact that MAP varies spatially across the study area, no significant relationship was found between NPI scores and MAP estimates across the sample of sub-catchments (Spearman's $\rho = -0.162$; $p = 0.226$). Thus, the moderate variation in precipitation across the study area, which would in turn influence runoff and discharge rates in each of the sub-catchments, did not appear to have a significant influence on water quality.

Seasonality

Several studies have noted that relationships between LULC and water quality often vary according to season, being influenced by intra-annual variations in precipitation, runoff, and discharge. However, as the principal objective of this study was to observe the impact of land use on long-term water quality conditions in the study area—with a view to informing integrated land and water management strategies, for which natural seasonal variation is relatively unimportant—the question of seasonality was not deemed relevant. Thus, by averaging water quality measurements over a 24-month sampling period (with a minimum of 15 monthly samples collected at each location during both wet and dry seasons over this period) the potential influence of intra-annual seasonal variation was, by design, excluded from this study (see Nde & Mathuthu, 2018, p. 4; Nde et al., 2021, p. 7).

Catchment Size

The total area, estimated in hectares, of each of the 58 sub-catchments in the sample was calculated using ArcGIS Pro (see Appendix 6 for details). Subsequent correlation analysis revealed a moderate and statistically significant positive relationship between NPI scores and catchment size (Spearman's ρ = 0.513; p < 0.01). This warranted further investigation as part of the modelling procedure (see below).

Regression Analysis

While most statistical texts caution against excluding outliers from a sample, there are circumstances in which a robust argument can be made for the exclusion of discordant observations if they are likely to adversely influence the analysis. In the particular case of regression analysis, the inclusion of genuine outliers can have deleterious effects on model estimation by increasing error variance and reducing the power of the regression procedure to detect statistically significant relationships between variables (Osborne & Overbay, 2004; Yang & Berdine, 2016). Moreover, because the principal aim of regression analysis is to model relationships inherent in the bulk of the data, the inclusion of outliers (which, by definition, are irregular observations and thus uncharacteristic of the majority of the sample) is argued to be counterproductive. Chatterjee and Simonoff (2013, pp. 54–56), for example, reason that the widely proclaimed censure against outlier removal is a "fundamentally incorrect attitude as it ignores the key goal of any statistical model which is to describe as accurately as possible the underlying process driving the bulk of the data." The authors go on to conclude that, "For this reason, the least squares fit with unusual observations omitted should always be examined… as it is likely to be a better representation of the underlying relationship." Judd et al. (2017, p. 326ff) have similarly argued that the inclusion of clearly outlying observations that have a strong statistical influence on the regression model is methodologically unethical as conclusions based on this model are likely to misrepresent the sample under analysis. Both conclude that a sample containing outlying observations should be analysed twice—once with the anomalous observations retained and once without them—and the resultant models compared. Furthermore, Judd et al. (2017) suggested that the underlying reasons for the occurrence of unusual observations should be investigated as these particular cases are likely to provide important caveats or limitations for the applicability of the models.

In the present study, the causality presumed in the relationship between land use and water quality suggests that natural vegetation should assume the role of the independent variable (as shown in Figures 41 and 42 above). However, in the case of regression analysis, regardless of any assumed causality, the variable being predicted should always be assigned the role of the dependent variable (Helsel et al., 2020).[62] Therefore, since the models were to be used to estimate proportions of natural vegetation cover associated with critical pollution index scores, the variables were switched such that the natural vegetation became the dependent (i.e., predicted) variable. A scatter plot of the transposed catchment-scale data is shown below in Figure 45 for illustrative purposes. Once again, while the bulk of the sample shows a clear linear pattern, the discordance of the six outliers is patent.

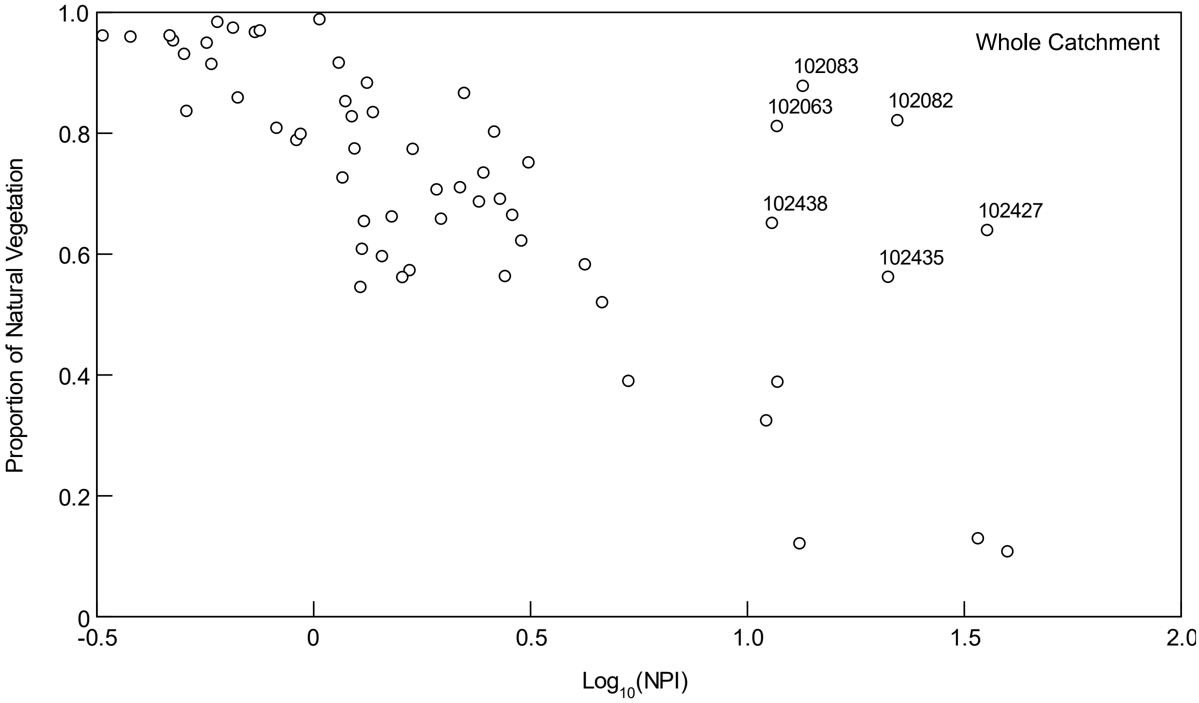


Figure 45. Transposed scatterplot of natural vegetation and log-transformed NPI scores at the whole-catchment scale. The discordance of the six outliers (labelled) is clearly visible.

To confirm the earlier findings regarding these anomalous points, the same iterative procedure for identifying outliers described above was once again conducted on the transposed data. Consistent with the earlier outlier tests, the six suspected observations were confirmed as statistically discordant within three iterations of the procedure.[63]

Therefore, with the variables duly transposed, and the outliers once again confirmed as statistically discordant using formal tests, regression analysis was performed twice at both scales: once on the sample containing the outliers (the "uncensored" sample), and once with the outliers excluded from the

[62] This is because one of the theoretical assumptions of OLS regression analysis is that the independent variable has been measured without error; the regression procedure thus seeks to minimise residual error along the axis of the dependent variable only (McBride, 2005). Consequently, the resultant regression equation will differ depending on which variable is set as the explanatory variable (Helsel et al., 2020).

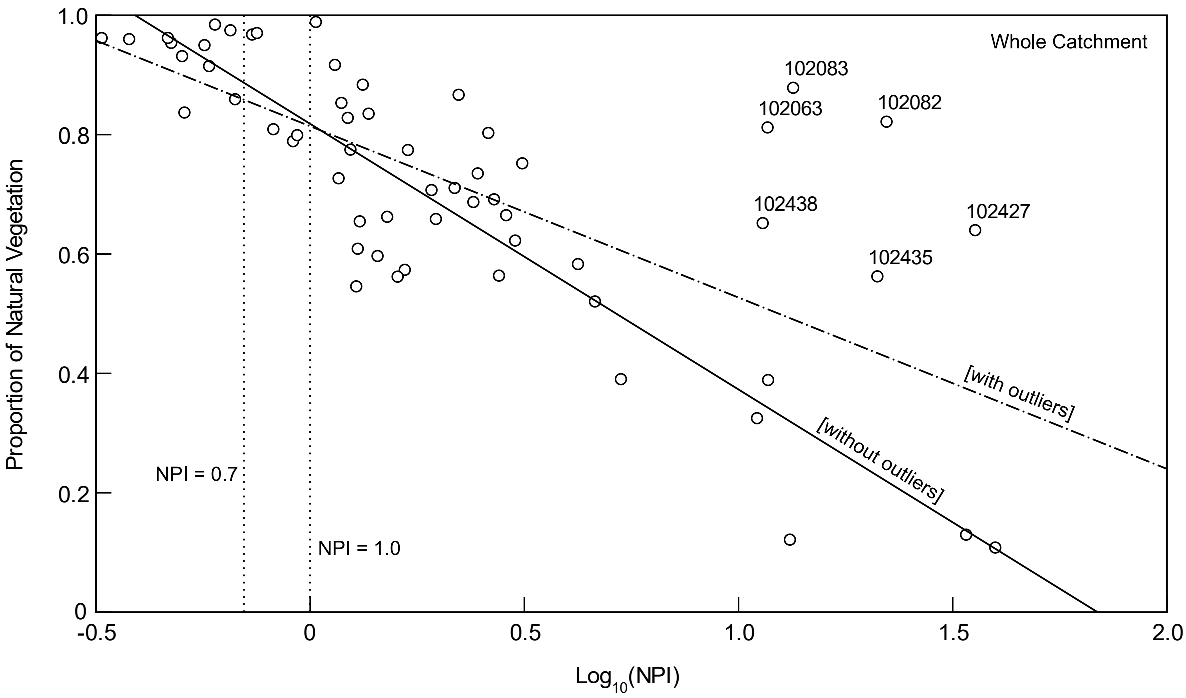
[63] Interestingly, when evaluating the SDRs of the observations with the sample thus transposed, the six outliers appeared to exert even greater influence on the model with the result that three other observations were incorrectly labelled as discordant. This occurred because the six genuinely discordant observations exerted enough influence on the model to "pull" the regression line towards themselves, thereby falsely inflating the SDRs of the non-discordant observations (an almost textbook example of the phenomenon known as swamping described earlier). Nevertheless, with the six discordant points confirmed and accordingly removed from the sample, the residuals of all remaining observations (including the three that had been falsely flagged as outliers) were well within tolerable limits.

sample (the "censored" sample). The models were then compared and evaluated. Overall fit and precision were assessed with reference to the coefficient of determination (R^2) and standard error (SE) of the models. Appropriate diagnostics were also used to evaluate whether the models met the assumptions necessary for regression analysis (i.e., normally distributed, unbiased, and homoscedastic residuals) (Barnett, 2004; Gelman & Hill, 2006; Chatterjee & Hadi, 2012). The normality of the residuals was assessed visually using normal probability plots and histograms, in addition to formal Shapiro-Wilk tests on the standardised residuals. The homoscedasticity of the residuals was also assessed visually from a plot of standardised residuals versus predicted values and subsequently confirmed by performing an auxiliary regression of the squared residuals on fitted values (essentially a Breusch-Pagan test; see Helsel et al., 2020, p. 424). The coefficients of the respective regression equations were also compared to assess the influence of the outliers on the fitted models. The results of the regression analysis are shown in Table 14 below. Plots of the different regression lines were also assessed to evaluate, visually, how much of an influence the six outliers exerted on the model at both scales (see Figure 46 below). Of particular interest was the difference between the regression lines around the two critical NPI values on which precautionary and target thresholds of natural vegetation were later based (NPI = 0.7 and 1.0, respectively).

Parenthetically, owing to the significant relationship between catchment size and NPI scores noted above, a multiple regression model including catchment area as an additional variable was also tested. However, the inclusion of catchment area as an additional variable did not offer any significant improvement to the model and, as such, the simpler model was preferred.

Table 14. Comparison of the OLS regression models estimated with and without outliers at both spatial scales.

Scale	**Model**	R^2	**SE**	**Significance**	**Regression Equation**	**Residual Distribution**	**Residual Variance**
Whole Catchment	Outliers included	0.510	0.152	$p < 0.01$	$y = -0.287x + 0.814$	Normal	Heteroscedastic
	Outliers excluded	0.815	0.097	$p < 0.001$	$y = -0.445x + 0.818$	Normal	Homoscedastic
200 m RBZ	Outliers included	0.526	0.125	$p < 0.001$	$y = -0.243x + 0.846$	Normal	Heteroscedastic
	Outliers excluded	0.688	0.105	$p < 0.001$	$y = -0.342x + 0.849$	Normal	Homoscedastic



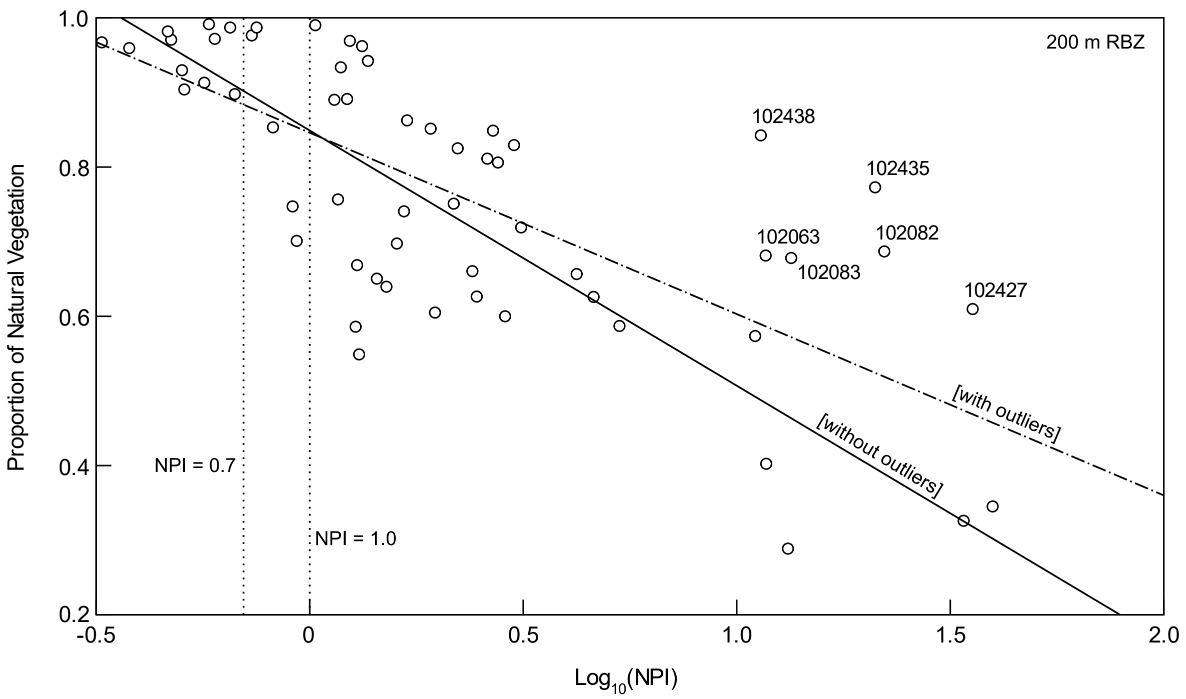


Figure 46. Comparison of regression models estimated with and without outliers (dashed and solid lines, respectively) at the whole-catchment scale (above) and 200 m RBZ scale (below). Also shown are the locations of the precautionary (0.7) and target (1.0) NPI scores used as water quality benchmarks for the estimation of regulatory thresholds of natural vegetation.

At both spatial scales, while all models were statistically significant ($p < 0.01$), the exclusion of the six confirmed outliers produced models that were preferable in several respects. Firstly, the percentage of variation that the models were able to account for (i.e., their predictive power) was significantly higher with the outliers removed (as indicated by the considerably higher R^2 values). Moreover, the error inherent in the models was also reduced when the outliers were excluded, allowing for more precise predictions to be made. The behaviour of the models' residuals also improved once the outliers were removed (showing more constant variance across the sample and thus satisfying the assumption of homoscedasticity). Furthermore, as is evident from the regression coefficients (see Table 14) and the plots (see Figure 46), the outliers also had a significant influence on the slopes of the regression lines. Nevertheless, at both scales, the two regression lines (i.e., those fitted with and without the outliers) appear to intersect around the target pollution index value (NPI = 1).[64]

When these two regression models were fitted to the untransformed data, the difference (and the improvement gained by excluding the outliers) remained evident (see Figure 47 below, in which the upward "pull" of the outliers on the regression line at the whole-catchment scale is clearly visible). Once again, the two regression lines can be seen to converge near the target NPI score of 1.0.

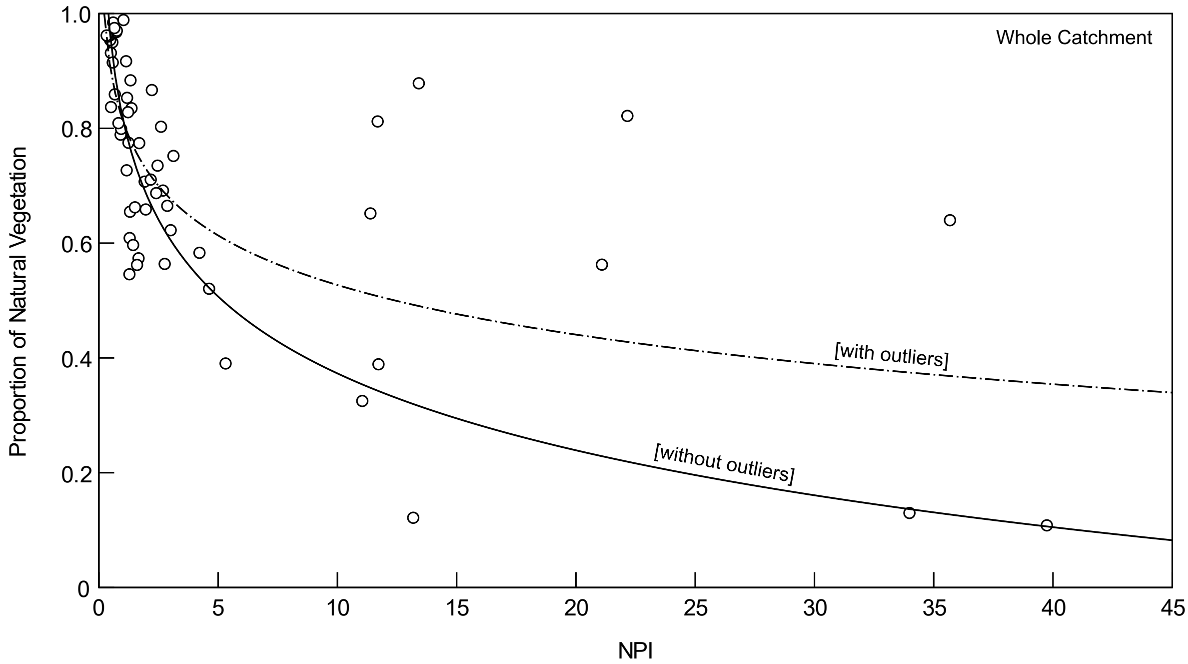
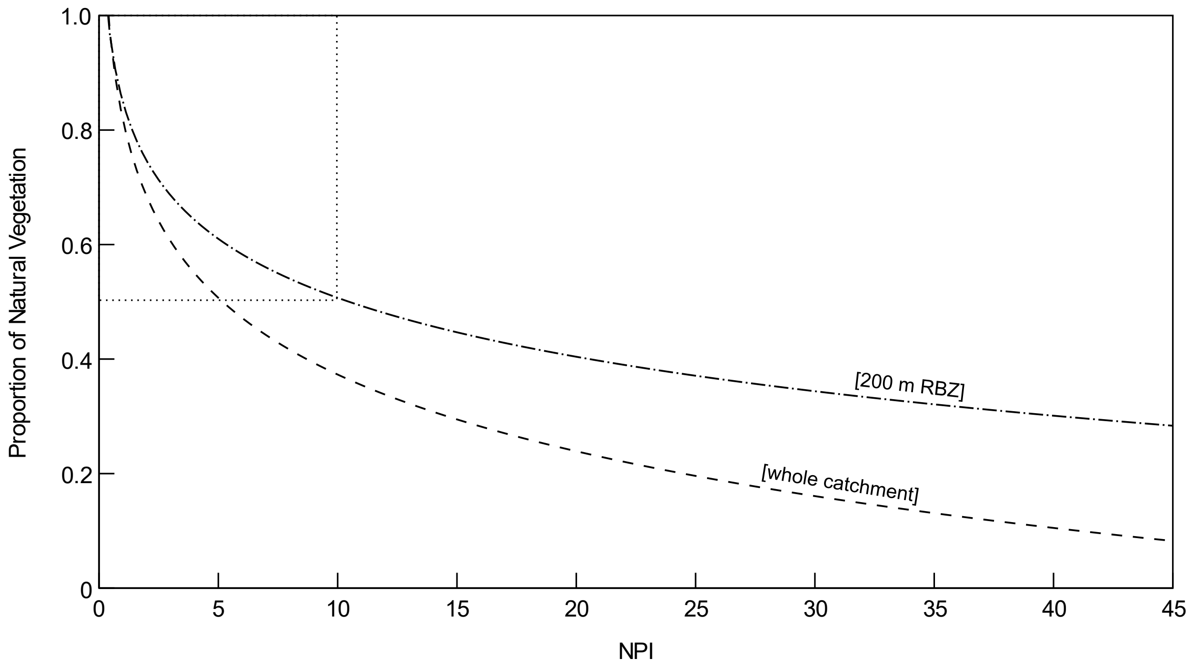


Figure 47. Regression models fitted to untransformed data at the whole-catchment scale, comparing models with and without outliers (dashed and solid lines, respectively). The upward "pull" of the outliers on the dashed line is evident.

In summary, excluding the six discordant observations at both scales produced models that were superior in several respects. In particular, predictions using these models were likely to be more precise based on the smaller standard error of the models and the homoscedasticity of the residuals. However, when compared to the regression models estimated at the whole-catchment scale, removing the outliers from the riparian-scale sample did not improve the regression model to as great an extent. Moreover, it was evident that, even with the outliers removed, the riparian model offered less explanatory power and had a greater standard error than the catchment-scale model. Nevertheless, both the whole-

[64] Conveniently, due to the log transformation applied to NPI scores, the proportion of natural vegetation associated with the target NPI score of 1.0 is simply equivalent to the constant term (i.e., the intercept) of the regression model.

catchment and riparian models were statistically significant and provided evidence of a clear relationship between water quality and natural vegetation at both analytical scales. When re-transformed back into their original units, the models estimated with the outliers excluded at both scales can be visually compared in Figure 48.



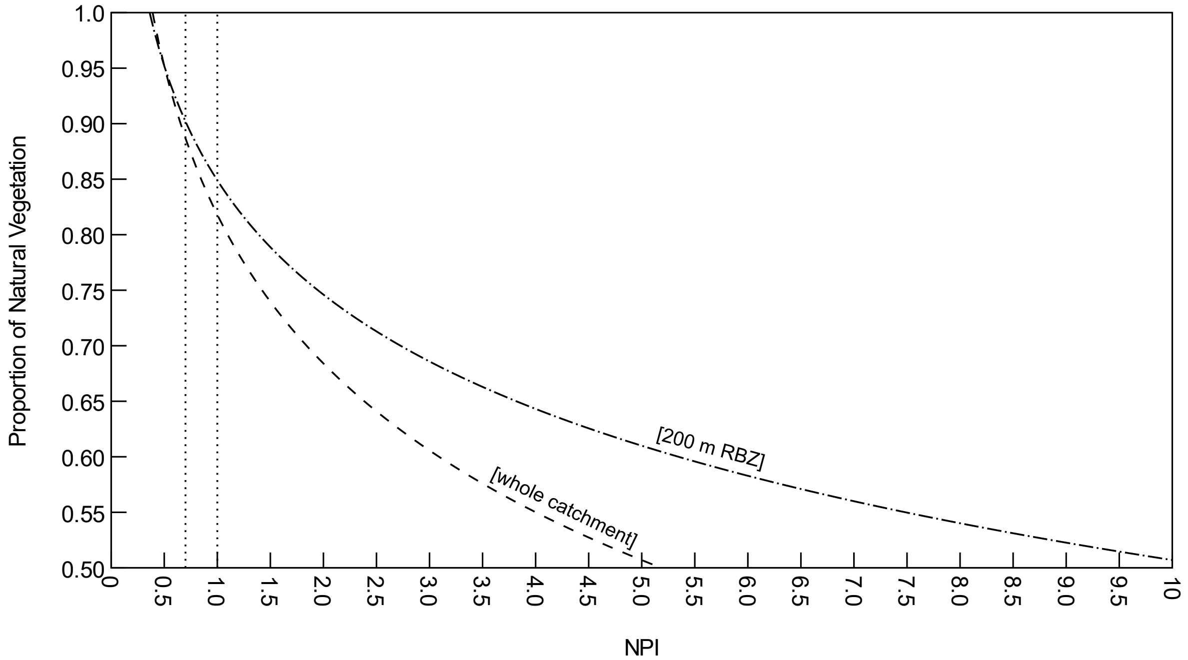


Figure 48. Comparison of the fitted models (with outliers removed from the sample) at the whole-catchment and 200 m RBZ scales. The lower plot shows the same models cropped to the scale indicated by the dotted rectangle in the upper plot. At this scale it is easier to compare the two regression models in the region of the response space where the regulatory thresholds were estimated (i.e., at the precautionary and target NPI scores of 0.7 and 1.0, represented by the two dashed vertical lines).

Quantile Regression

While OLS regression has been widely and effectively used when modelling the relationship between LULC and water quality, it is nevertheless very sensitive to the presence of outliers in the sample (as is readily apparent in the present study). Thus, in the interests of statistical and methodological rigour, quantile regression (QR) was additionally tested as an alternative modelling method. A seldom-used semi-parametric extension of linear regression, QR minimises the sum of the *absolute* residual error when fitting the model (rather than the sum of *squared* residual error, as in OLS) and thus has the advantage of being more robust—in most cases—to the presence of extreme observations (Davino et al., 2014; Koenker et al., 2018). A median QR model was thus fit to the data at the whole-catchment scale, both with and without outliers. The resultant QR models were compared with the results of the OLS regression procedure described above. From Table 15, an examination of the regression coefficients (which determine the slope of the respective regression line) reveals the magnitude of the difference between the models. The constant term (or intercept) represents the predicted value of the dependent variable when the independent variable equals zero. As noted above, owing to the log transformation applied to the NPI scores, the intercept is therefore associated with an NPI score of 1.0.

Table 15. Comparison of ordinary least squares (OLS) and median quantile regression (QR) model coefficients and constant terms, with and without outliers, using catchment-scale data.

Model	Regression Coefficient	Constant (Intercept)
OLS (with outliers)	–0.287	0.814
QR (with outliers)	–0.359	0.824
OLS (without outliers)	–0.445	0.818
QR (without outliers)	–0.442	0.815

OLS and QR models based on whole-catchment scale data are plotted below in Figure 49.

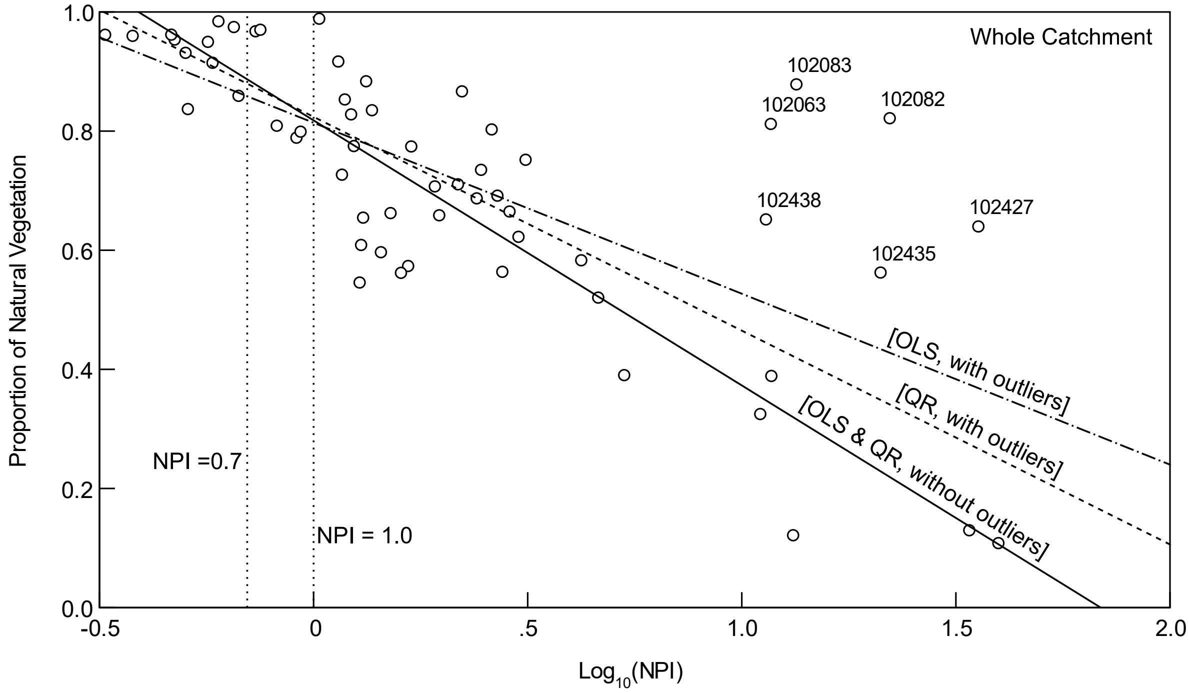


Figure 49. Graphic comparison of ordinary least squares (OLS) and median quantile regression (QR) models fit to catchment-scale data, with and without outliers.

With the outliers retained in the sample, the QR model was evidently more resistant to their influence than the OLS model. However, owing to the presence of *multiple* outliers, all of which were grouped in a similar region of the response space, the QR model was nevertheless "pulled" upwards in their direction. With the outliers removed from the sample, the QR model fell almost exactly over the OLS model. However, and perhaps most significantly, all four models appeared to converge near the target NPI value of 1.0. This is not only evident from the graph above but is also apparent from the values of the constant terms of the models, as shown in Table 15. In any case, considering the limited resistance of the QR procedure to the presence of multiple outliers, the OLS models estimated with the outliers excluded from the sample were preferred for threshold estimation.

Threshold Estimation

Regulatory Thresholds

The literature differentiates between nonlinear ecological thresholds and regulatory thresholds. Whereas nonlinear thresholds are characterised by abrupt "tipping points" in the condition of ecological systems, regulatory thresholds are based on some benchmark of "ecologically acceptable" disturbance (regardless of whether the system itself exhibits a nonlinear response to external perturbations). Moreover, regulatory thresholds can be tiered. Target thresholds, for instance, represent the point at which unwanted changes in the condition of an ecological system, driven by anthropogenic perturbations, become intolerable according to the benchmark of acceptability described above. Precautionary thresholds, which are more conservative by design, are intended to trigger management interventions before target thresholds or nonlinear tipping points are reached. Both types of regulatory threshold define a "safe operating space" in which anthropogenic development can occur without causing unacceptable or irreversible levels of environmental harm (see the discussion and Figures 12 and 13 on pp. 75-77). As noted earlier, the NPI allows for both precautionary and target thresholds to be estimated using the appropriate index scores as benchmarks on which to base thresholds of natural vegetation. Thus, with reference to the regression models, an NPI score of 0.7 was used as the more conservative benchmark by which to estimate precautionary thresholds of natural vegetation cover, while an index score of 1.0 was used as the benchmark by which target thresholds of natural vegetation cover were estimated. As described above, the precautionary NPI score of 0.7 represents the point at which unacceptable pollution levels become increasingly likely. By contrast, the target NPI score of 1.0 indicates that contamination levels have exceeded permissible limits for at least one of the selected water quality parameters. The principal question, therefore, was what proportions of natural vegetation cover were associated with each of these benchmark scores according to the regression models at both analytical scales?

As previously noted, the OLS regression models fit using samples from which the outliers had been removed were generally preferrable. It was therefore based on these "censored" samples that thresholds of natural vegetation cover were estimated. Significantly, however, as can be seen from Figure 46 above, at the target NPI score of 1.0 the models tend to converge regardless of whether the outliers are excluded from the sample or not. Thus, even with the outliers retained in the sample, the proportion of natural vegetation associated with an NPI score of 1.0 at the whole-catchment scale ranged very slightly from 0.814 to 0.818. Thus, using the censored sample from which the outliers had been deleted, the proportion of natural vegetation associated with the target NPI score of 1.0 at the whole-catchment scale was taken to be approximately 0.818 (roughly 82% of the catchment). Using the same censored sample at the whole-catchment scale, the proportion of natural vegetation associated with the more precautionary NPI score of 0.7 was approximately 0.887 (close to 89% of the catchment). Once again using the censored sample at the 200 m riparian buffer zone scale, the proportion of natural vegetation associated with the precautionary NPI score of 0.7 was approximately 0.902 (or 90%), while the proportion of natural vegetation associated with the target NPI score of 1.0 was approximately 0.849 (or 85%).

Nonlinear Thresholds

The scatterplots shown in Figure 41 above reveal clear nonlinearity in the relationship between proportions of natural vegetation cover and pollution index scores across the sample of sub-catchments at both spatial scales. This suggested the existence of additional nonlinear "tipping points" that might be estimated from these samples. One of the most frequently used methods for estimating nonlinear tipping points is piecewise regression analysis (also referred to in some texts as segmented or breakpoint regression) (Ficetola & Denoël, 2009; Dodds et al., 2010; Tran et al., 2010; Ye et al., 2014; Toms & Villard, 2015; D'Amario et al., 2019; Tomal & Ciborowski, 2020). Piecewise regression models are "broken-stick" models where two or more regression lines (or segments) with different slopes are joined at unknown points, called "knots" or "breakpoints" (Toms & Lesperance, 2003; Chen et al., 2011).

SegRegA software (Oosterbaan, 2021) was used to estimate the point at which there was a distinct increase in the rate at which pollution levels increased relative to decreasing proportions of natural vegetation cover across the sample of sub-catchments. SegRegA is a free tool developed specifically for the estimation of breakpoints using piecewise regression and has been used successfully in several similar studies for this purpose (see, for instance, Ye et al., 2014; Sayers et al., 2016; Tromboni & Dodds, 2017; D'Amario et al., 2019). Owing to the way the segmented regression lines are estimated, NPI scores once again assume the role of the dependent variable. The default SegRegA settings were used.

At the whole-catchment scale, SegRegA could not produce a statistically significant piecewise model from the uncensored sample. However, with the six outliers removed, the piecewise model was significant at $p < 0.05$, and the breakpoint was estimated as 0.4516 (i.e., approximately 45% natural vegetation cover). The fitted segments are shown below in Figure 50, where they can be compared to the loess smooth curve originally fitted to the scatterplot. As is evident from the scatterplot, the segmented model corresponds well with the loess smooth curve.[65]

It is also worth noting that, according to this model, the critical breakpoint of 0.452 is associated with an NPI score of approximately 3.12. Thus, based on this model, once the proportion of natural vegetation cover drops to approximately 45% of the catchment area, pollution levels, which at this point are expected to be approximately three times the acceptable limit, are likely to increase dramatically relative to further decreases in the proportion of natural vegetation cover.

[65] The anomalous points are included in the plots shown in Figures 50 and 51 only to illustrate the degree to which they appear discordant from the bulk of the sample. They were not, however, included in the sample from which the piecewise models were estimated.

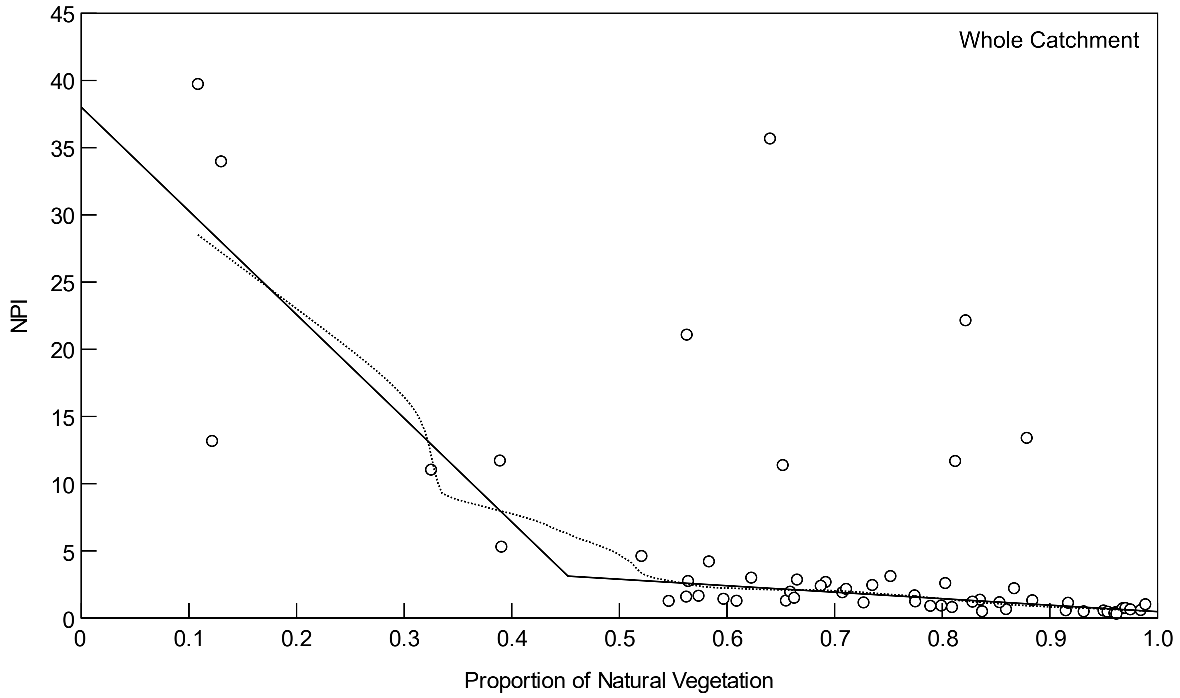


Figure 50. Results of piecewise regression analysis showing the fitted linear segments (solid lines) which join at the estimated breakpoint (0.452). Also shown is the original loess smooth curve (dotted line) fitted to the uncensored sample. Note that the six anomalous datapoints are included in the plot for illustrative purposes only (i.e., to show their discordance with the fitted models). They were however excluded from the sample that was used to estimate the piecewise model.

When SegRegA was used to estimate the breakpoint using data from the 200 m riparian buffer zone, the six outliers were once again removed from the sample to obtain a significant model. The breakpoint thus estimated at this scale was 0.6049 (approximately 60% natural vegetation cover). At this scale, when the proportion of natural vegetation reaches this level, it is estimated from the model that NPI scores will be approximately 2.7. The segments fitted by this piecewise model are shown below in Figure 51. As with the catchment-scale model, the segments corresponded well with the loess smooth curve. The discordance of the six outliers is, once again, apparent.

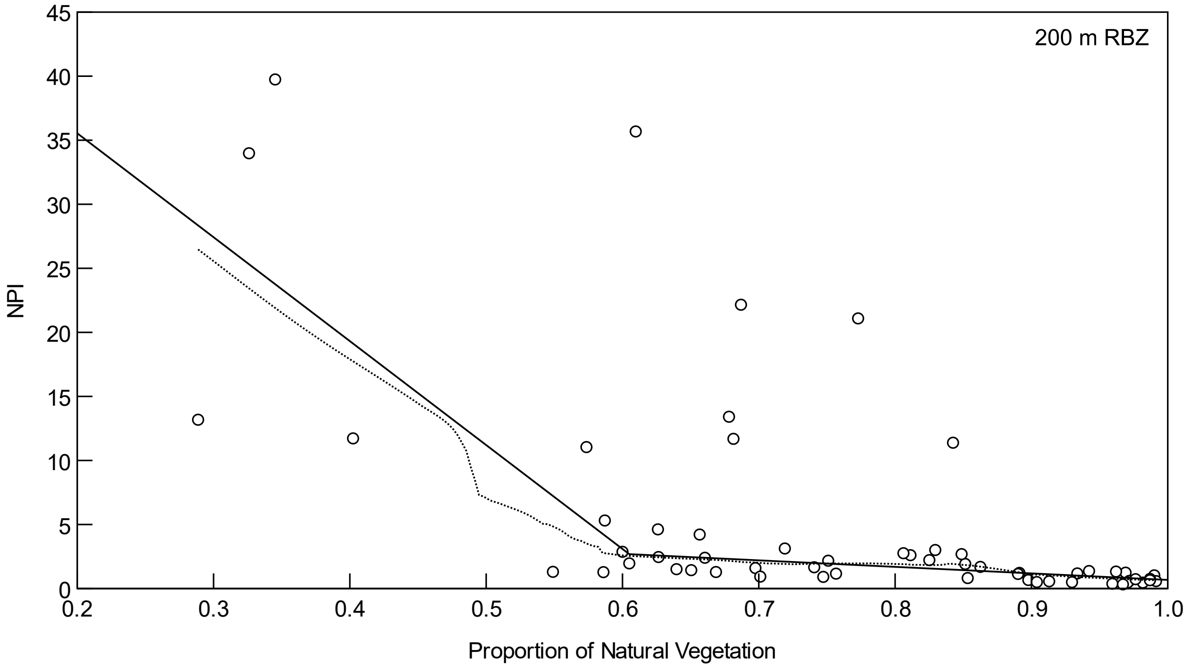


Figure 51. Piecewise regression segments (solid lines) fitted to data at the 200 m riparian buffer zone scale, which can be compared with the original loess smooth curve (dotted line) applied to the uncensored sample. The estimated breakpoint was approximately 0.6049. Note that the six outlying observations are included in the plot for illustrative purposes only (i.e., to show their discordance with the fitted models). They were however excluded from the sample used to estimate the piecewise model.

Application of Catchment-Scale Thresholds

In the preceding section, three catchment-scale thresholds of natural vegetation were estimated from the regression models: a precautionary threshold of approximately 89%, a target threshold of approximately 82%, and a nonlinear threshold of approximately 45%. Table 16 below offers an interpretation of each of these thresholds.

Table 16. Descriptions of each of the thresholds of natural vegetation cover estimated from the regression models.

Threshold Type	Description	Value (%)
Precautionary Threshold	An estimate of the proportion of natural vegetation cover (measured across the catchment) at which unacceptable levels of contamination become increasingly likely.	89
Target Threshold	An estimate of the proportion of natural vegetation cover (measured across the catchment) at which pollution is predicted to exceed permissible limits and put the health of aquatic ecosystems at risk. If proportions of natural vegetation at the catchment-scale are maintained above this level, water quality is likely to remain within acceptable levels.	82
Nonlinear Ecological Threshold or "Tipping Point"	An estimate of the proportion of natural vegetation cover (measured across the catchment) at which already non-compliant pollution levels are expected to increase dramatically.	45

To demonstrate how the thresholds may be applied to inform integrated land and water management strategies, proportions of natural vegetation in the 225 quaternary catchments that make up the study area were calculated based on land cover data from the 2020 SANLC map. These catchments range in size from approximately 53 km^2 to 2,004 km^2. Based on the results obtained above with respect to contextually appropriate aggregations of natural vegetation for the region in question, and with due regard given to the scheme by which land cover is classified in the 2020 SANLC map, forested land, shrubland, and wetlands were merged into a single land cover class considered to be representative of natural vegetation in terms of its ability to protect water resources from diffuse pollution.

Of the 225 quaternary catchments in the study area, only 12 had proportions of natural vegetation above the precautionary threshold of 89%. A further 19 of the quaternary catchments had proportions of natural vegetation above the target threshold of 82% natural vegetation cover. Thus, in total, only 14% of the quaternary catchments in the study area contained more natural vegetation than the 82% target threshold. The remainder (i.e., 194, or approximately 86% of the total) had less natural vegetation than the target threshold of 82% natural vegetation cover. Moreover, 55 catchments had less natural vegetation than the critical nonlinear threshold of 45%. These figures, and their expected water quality management implications, are summarised in Table 17 below.

Table 17. Breakdown of the population of quaternary catchments that make up the study area in terms of the proportion of the landscape occupied by natural vegetation and in respect of the thresholds estimated.

Proportion of Natural Vegetation (% of Catchment)	No. of Catchments	Percent of Total	Remarks
≤ 45	55	24.44	Water quality expected to be severely impaired. Urgent land use management interventions are likely to be necessary to restore water quality to acceptable levels.
$45 \leq 82$	139	61.78	Water quality likely to be significantly impaired, with pollution levels expected to have exceeded acceptable limits. Negative impacts on aquatic ecosystems likely. Restoration of natural vegetation required to improve water quality and prevent further degradation beyond critical levels.
$82 \leq 89$	19	8.44	Water quality is likely to be slightly impaired, with the possibility that at least one water quality parameter is non-compliant according to local guideline values. Close monitoring of conditions advised, with measures put in place to prevent further and/or unnecessary loss of natural vegetation.
$89 \leq 100$	12	5.33	Risk of impairment is low. Water expected to be of good (acceptable) quality and supportive of aquatic fauna and flora. Vegetated areas must be protected to maintain water quality.

The classification of the 225 quaternary catchments according to this scheme is shown in Figure 52 below. A comparison between the distribution of the classified catchments and the 2020 SANLC map shows that, as anticipated, catchments located within areas dominated by agricultural or urban land use are those in which, based on the estimated thresholds, severe water quality impacts can be expected (and in which management interventions are thus likely to be necessary).

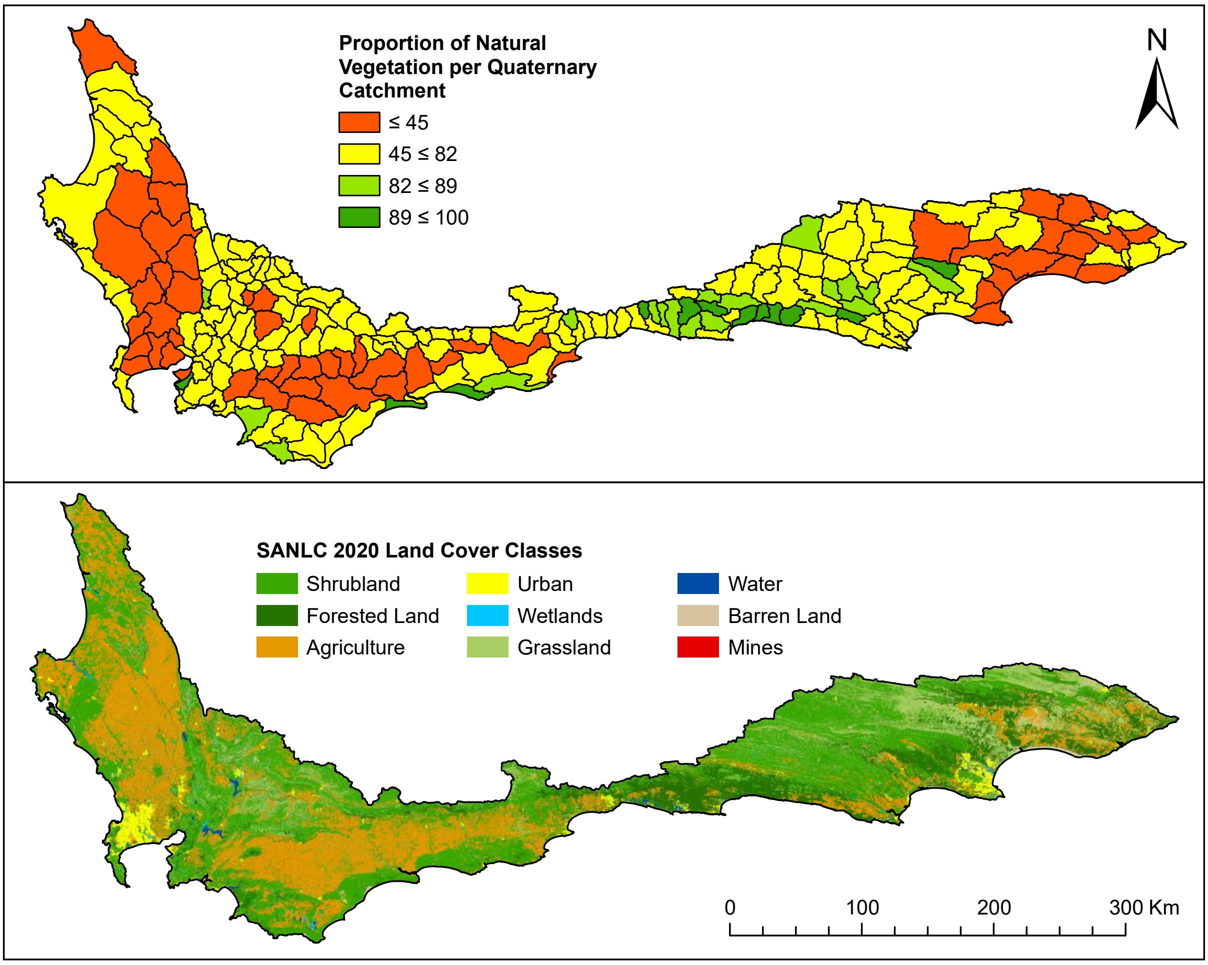


Figure 52. Maps of the study area showing the classification of quaternary catchments according to thresholds of natural vegetation cover (above), which can be compared with the distribution of land cover within the study area according to the 2020 SANLC map (below). Land cover data obtained from DFFE (2020).

Bearing in mind the disproportionate importance of Strategic Water Source Areas (SWSAs) in terms of South Africa's water security, Figure 53 below highlights the classification of the quaternary catchments located within the relevant SWSAs. As is evident from the map, all SWSAs that overlap with the study area contain quaternary catchments in which proportions of natural vegetation are lower than the target threshold of 82%.

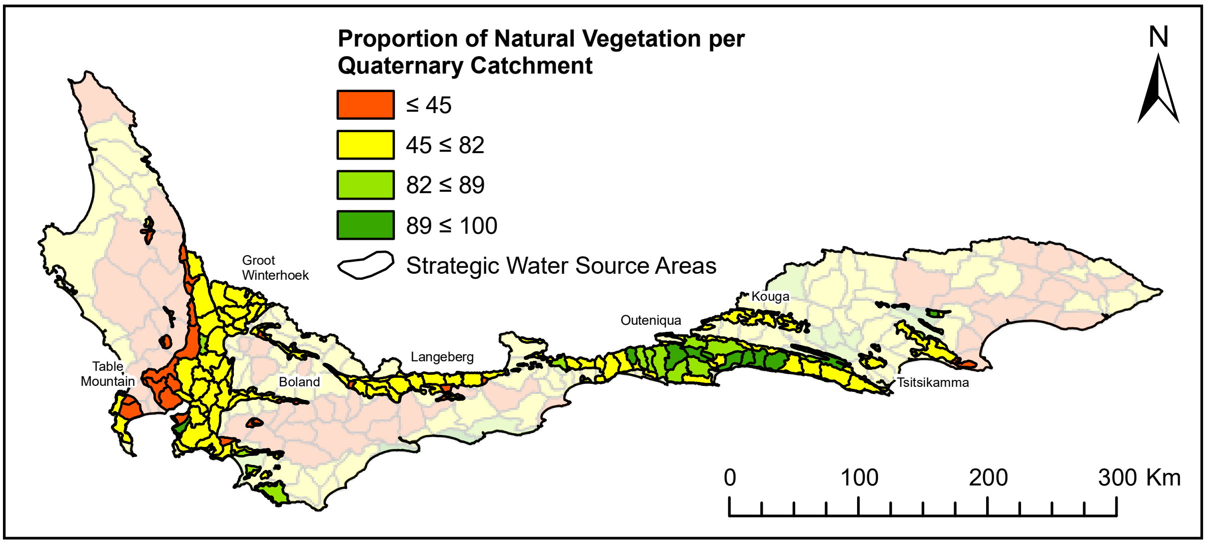


Figure 53. Map highlighting the classified quaternary catchments that fall within the seven Strategic Water Source Areas (SWSAs) located within the study area. SWSA data obtained from Lötter and Le Maitre (2021).

CHAPTER 7:
Discussion

"The preservation of water resources is a worldwide goal that requires continuous research to support the action of decision-makers."
—Fernandes et al. (2021)

Over several decades, researchers who have used statistical approaches to model relationships between land use and water quality have established that while the relationship is undeniably complex and often regionally specific, certain classes of LULC (e.g., urban areas, agricultural land, mining operations, and commercial forestry plantations) tend to be *sources* of diffuse pollution, whereas other classes (e.g., indigenous forests, grasslands, and wetlands) may serve as *sinks* by intercepting, filtering, and remediating contaminated runoff. Given this source/sink dynamic, managing the impacts of LULC on water quality through careful land use planning is an essential component of the Integrated Water Resources Management (IWRM) paradigm. Moreover, researchers in some studies have been able to use statistical approaches to estimate thresholds of LULC for the protection of water quality. While most of the reported thresholds relate to proportions of urban or agricultural land cover, the applicability of these thresholds is arguably limited in certain contexts (especially in mixed land use catchments). By contrast, natural vegetation may provide an alternative, and in many respects superior, land cover metric for which thresholds can be estimated. Although relatively overlooked in the existing research, metrics of natural vegetation, when appropriately classified for the region of interest, will not only have universal applicability as an estimate of a landscape's buffering capacity, but will also reflect the degree to which the same landscape has been disturbed by potentially pollution-generating anthropogenic activity (Griffith, 2002; Wang et al., 2021).

This study therefore aimed to test the hypothesis that, by using simple regression models and data from a cross-sectional sample of sub-catchments, regionally specific thresholds of natural vegetation could be estimated for the integrated management and protection of water quality. In doing so, this study also attempted to address several persistent knowledge gaps and methodological issues pertinent to this area of research. These include ongoing uncertainty about the possible influence of landscape configuration (i.e., the spatial arrangement and distribution of land cover within a landscape), as well as uncertainty regarding the most appropriate scale(s) at which to undertake analyses, develop models, and estimate thresholds. A related consideration was the determination of a contextually appropriate metric by which to classify natural vegetation for this purpose (an issue not explicitly addressed in the reviewed literature). Moreover, in order to ensure the accuracy of LULC-WQ models, the existing literature emphasises the need to control for the potentially confounding influence of extraneous factors, including local environmental variables such as geology, ecology, and climate.

Water Quality Analysis using Nemerow's Pollution Index

In order to fulfil the principal aim of this study, which was to develop statistical models of the relationship between water quality and natural vegetation the study area, it was important to establish a reliable indicator of water quality. However, as explained above, water quality is a holistic concept and is influenced by innumerable physical, chemical, and biological parameters. Thus, according to Shukla et al. (2018, p. 4747), when evaluating the impacts of LULC on water resources it is especially important to understand the *cumulative* effect of all relevant water quality parameters. Accordingly, when assessing the impacts of LULC on water quality, several studies have used composite water quality indices (WQIs) to translate the observed measurements of multiple parameters into a single, unitless numerical score of overall water quality (e.g., Schiff & Benoit, 2007; Wang & Zhang, 2018; Gossweiler et al., 2019; Umwali et al., 2021; Paná et al., 2022; Pandey et al., 2023). In the present study Nemerow's Pollution Index (NPI) was used to quantify the overall degree to which water quality was impaired across a sample of 58 sub-catchments taken to be representative of the study area. Moreover, water quality assessments require that the observed measurements of relevant parameters be evaluated against appropriate standards or guidelines. In the present study, site-specific guideline values for the selected parameters were derived from local reference condition data. These guideline values were intended to reflect local conditions in the absence of anthropogenic disturbance, and thus provide a contextually specific ecological benchmark against which observed water quality measurements could be evaluated (McDowell et al., 2013; van Dam et al., 2014; Duan et al., 2019; Huynh & Hobbs, 2019; van Dam et al., 2019; Urbanič et al., 2021).

Parameter Selection

Nemerow's Pollution Index is flexible in that it allows for the inclusion of any number and combination of water quality parameters for which observed measurements can be evaluated against appropriate guideline values. While the selection of parameters for inclusion in composite WQIs is an admittedly subjective undertaking, the aim is to select a set of water quality parameters that is comprehensive, non-redundant, and relevant to the intended water use. In the present study, parameter selection was limited to the variables measured as part of South Africa's National Chemical Monitoring Programme (NCMP). Although a wide variety of water quality parameters are nominally measured as part of the NCMP's sampling regime, not all of the listed parameters are routinely measured at every sampling location, and for some locations and/or periods, no data are available (DWS, 2022b, p. 72).[66] Nevertheless, after determining which parameters had been regularly sampled in the study area during the period of interest,

[66] This limitation not only influenced parameter selection, but also constrained the identification of suitable monitoring sites for which sufficient water quality data were available for inclusion in the sample of sub-catchments used for subsequent statistical analyses.

five were selected for inclusion in the NPI: electrical conductivity (EC), total inorganic nitrogen (TIN),[67] orthophosphate (PO_4), sulphate (SO_4), and pH. Coincidentally, in a national review of the status of surface waters in South Africa, the Department of Water Affairs (DWA) used a very similar set of parameters to serve as indicators of the overall condition of water bodies, as they were said to provide "insight into the salinity and eutrophication status, mining related impacts, and variability of the country's water resources" (see DEA&DP, 2011, p. 199; DWA, 2011).

Notably absent from this selection are several parameters typically included in most composite WQIs (see Uddin et al., 2021, p. 3 for a list of commonly included parameters). These include total dissolved solids (TDS), total suspended solids (TSS), dissolved oxygen (DO), heavy metals, and an appropriate metric of bacteriological contamination (e.g., faecal coliform counts). Although TDS measurements were not available for all NCMP sites, electrical conductivity (EC) provided a convenient surrogate in the present study (DWAF, 1996; Dallas & Day, 2004; Day & Dallas, 2011; Weiner, 2013; Chapman et al., 2020). Moreover, as EC measurements reflect the concentration of various inorganic ions in solution, they can be a useful indication of a wide range of water quality issues, including mineralisation and heavy metal contamination (Weiner, 2013; Boyd, 2020; USEPA, 2022a). In addition, while DO is routinely considered one of the most important indicators of the condition of aquatic systems (Chapman et al., 2020, p. 105), concentrations are usually dependent on other factors, including salinity and eutrophication (indications of which were provided by conductivity and nutrient measurements, respectively) (Dallas & Day, 2004). Thus, despite restrictions in parameter selection imposed by data availability, the diversity of water quality issues for which the five selected parameters are indicative suggested that they should be sufficient, when incorporated into the NPI, to provide a reasonably complete assessment of overall water quality. These issues include, for instance, salinisation, eutrophication, and acidification, which represent some of the more typical impacts of LULC on water resources.[68]

Determining Site-Specific Guideline Values Using Local Reference Condition Data

In calculating the NPI scores, the observed measurements of each water quality parameter were compared against site-specific guideline values derived from local reference condition data (as per guidelines set out in ANZG, 2018). Reference conditions, which are representative of the natural variation inherent in ecological systems in the absence of significant anthropogenic disturbances, are widely used when setting water quality guidelines (Stein & Yoon, 2007; Hawkins et al., 2010; Chambers et al., 2012a; Chambers et al., 2012b; McDowell et al., 2013; Agboola et al., 2020; Urbanič

[67] In order to reduce the total number of parameters (thus limiting the effect of eclipsing) TIN was calculated as the sum of NO_2+NO_3-N and NH_4-N.
[68] See Chapter 3 and Appendix 1.

et al., 2021). Several national environmental agencies, for instance, have argued that local reference conditions offer a contextually appropriate benchmark of ecological acceptability against which observed water quality measurements can be compared, and are thus preferable to generic water quality standards (DWAF, 1996; USEPA, 2000; CCME, 2016; ANZG, 2018). In the present study, NCMP data recorded over 36 months at 18 undisturbed locations were used to set guideline values for each parameter. The 90^{th} percentile of this data served as the maximum guideline value for each of the selected parameters, while the 10^{th} percentile was additionally used in the case of pH as the minimum guideline value.

Electrical Conductivity (EC)

Rather than stipulating generic EC standards, the South African Water Quality (SAWQ) guidelines have recommended that observed measurements be evaluated against site-specific criteria derived from local reference data (DWAF, 1996, p. 110; see also Dallas & Day, 2004, p. 61). Based on the data collected at the 18 reference sites, the guideline value for EC was estimated at 16.9 mS/m. It was also observed that, at two of the 18 reference locations, median conductivity measurements exceeded the 16.9 mS/m guideline value. As far as could be ascertained from contemporaneous high-resolution satellite imagery used to screen these sites, these two locations contained no obvious signs of anthropogenic disturbance. Thus, while it is conceivable that these high EC measurements are attributable to discrete sources of contamination not visible from the satellite imagery, it may be that they are simply indicative of the high degree of natural variability that characterises water chemistry in the study area (as per Day et al., 1998, p. 194), thus reinforcing the need to base guideline values on appropriate percentiles of local reference data.

Total Inorganic Nitrogen (TIN)

The United States Environmental Protection Agency (USEPA, 2000, 2023) has similarly avoided setting generic water quality guidelines for nutrient concentrations because thresholds of impairment tend to vary regionally. However, Boyd (2020, p. 287) has suggested that, in general, concentrations of total inorganic nitrogen above 0.1–0.75 mg/l may cause eutrophication. The SAWQ guidelines stipulate that inorganic nitrogen concentrations of less than 0.5 mg/l are typical of unimpacted, oligotrophic locations (DWAF, 1996, pp. 81, 84). The estimated maximum guideline value for TIN in this study, based on the reference data, was 0.22 mg/l (approximately half the guideline value specified in the SAWQ guidelines, but falling within the range suggested by Boyd).

Orthophosphate (PO_4)

Concentrations of bioavailable inorganic phosphorous (measured as PO_4) in unpolluted water are usually very low, typically less than about 0.01 mg/l (Dallas & Day, 2004, p. 86; Weiner, 2013, p. 145; Boyd, 2020, p. 291). While guideline values for phosphate concentrations vary depending on the text consulted, they usually range from 0.025 to 0.05 mg/l, above which eutrophic conditions are likely

(USEPA, 1986, p. 246; DWAF, 1996, p. 97; Weiner, 2013, p. 146). Once again, the approach suggested by most national environmental authorities is to use reference data when setting guideline values (DWAF, 1996; USEPA, 2000; CCME, 2016; ANZG, 2018). Dallas and Day (2004) also emphasised the importance of consulting local reference conditions when determining nutrient criteria. Accordingly, based on the available reference data for the study area, the maximum permissible guideline value for PO_4 was estimated as 0.06 mg/l, which is very close to the upper limit of the range of acceptable values quoted above.

Sulphate (SO_4)

Boyd (2020, p. 117) has recorded that the recommended limit of sulphate (SO_4) concentrations for drinking water is 250 mg/l. However, Weiner (2013, p. 527) has also noted that in most surface waters SO_4 concentrations normally vary between 10 and 80 mg/l. Using local reference data, the upper guideline value for SO_4 within the study area was estimated at 13.3 mg/l, which falls near the lower end of this range.

pH

Several reference texts have suggested that pH values between 6.5 and 9 would be protective of freshwater aquatic life (see, for instance, Weiner, 2013, p. 73; Boyd, 2020, p. 177; USEPA, 2022b). Nevertheless, the SAWQ guidelines have once again recommend setting site-specific pH criteria using local reference data (DWAF, 1996, p. 90; see also Dallas & Day, 2004, p. 58). Therefore, based on the data recorded at the 18 reference sites, the minimum and maximum guideline values for pH were estimated as 3.85 and 7.05, respectively (yet again confirming the observation made by Day et al., 1998, p. 194, that surface waters in the region are characterised by low pH).

***

Overall, therefore, there was general agreement between the site-specific guideline values derived from reference data in this study and the more generic standards cited in various reference texts. However, the site-specific guideline values described above are arguably more representative of local baseline conditions, and therefore provide a more precise benchmark against which observed values could be compared when calculating NPI scores (a point also emphasised by Agboola et al., 2020). This is especially true given the significant natural variability that characterises water chemistry within the study area.

Interpreting NPI Scores

With site-specific guideline values providing a contextually appropriate benchmark of ecologically acceptable conditions, it was possible to use the NPI to assess the overall water quality status of the 58 sub-catchments during the period of interest (2013–2014). When evaluated in this manner, most catchments (72% of the sample) were found to be non-compliant to varying degrees. These catchments all had NPI scores ≥ 1.0, suggesting that at least one of the measured water quality parameters exceeded the ecologically acceptable guideline values estimated from local reference data. These conditions are likely to put aquatic fauna under stress while also reducing the availability of water for use by humans. Moreover, several catchments had extreme NPI scores (≥ 10), which were indicative of severe pollution at these sites. Only 11 of the catchments (less than 20% of the sample) had NPI scores below the precautionary index score of 0.7 and were thus considered unpolluted when compared to local reference conditions.

While the final NPI scores only provide an indication of the overall degree of pollution at each location, an examination of the individual sub-index scores allows specific water quality issues to be identified and quantified. In the present study, for instance, sub-index scores revealed that high EC values were frequently the cause of non-compliance. In the most extreme cases, EC measurements at the non-compliant locations were several times higher than the estimated guideline limit of 16.9 mS/m, resulting in very high sub-index scores for this parameter. This suggests that one of the major water quality issues in the study area is an excessive concentration of mineral salts in the water, in all probability due to agricultural runoff, and perhaps worsened by water abstraction for irrigation. This supposition is supported by various reports, which have identified salinity—often attributed to agricultural land use—as one of the more serious and persistent water quality problems in the study area (see, inter alia, Kirchner et al., 1997; DWAF, 2004; Clark & Ractliffe, 2007; De Clercq et al., 2010; DWS, 2017a, 2017b; Cullis et al., 2019; du Plessis, 2019a; van Tonder, 2022). Moreover, 22 (approximately 38%) of the sub-catchments had non-compliant sub-index scores for total inorganic nitrogen. Of these 22 sub-catchments, six also had non-compliant sub-index scores for orthophosphate. This suggests that a further water quality concern in the study area is eutrophication (i.e., elevated nutrient levels leading to nuisance plant and algal growth, with attendant problems such as hypoxic conditions and the presence of toxic cyanobacteria). Once again, it is likely that the elevated nutrient levels are due to diffuse inputs from agricultural activity (especially in cases where inorganic fertiliser has been applied), as well as from contaminated runoff from nearby urban areas and poorly serviced informal settlements (this is corroborated by Görgens & de Clercq, 2005; Clark & Ractliffe, 2007; Struyf et al., 2012; DWS, 2017a, 2017b; Cullis et al., 2018; du Plessis, 2019a). In answer to criticisms of reductivism (i.e., that critical detail is lost in the computation of composite indices; see Cooper et al., 1994; Rosemond et al., 2009) the foregoing demonstrates that the sub-index scores retain important insights which may not be immediately apparent from the aggregate index scores.

While Nemerow's index design largely mitigates problems such as eclipsing and ambiguity (refer to the discussion on p. 99), these two issues were nonetheless apparent in four of the 58 sub-catchments, each of which recorded compliant aggregate index scores (i.e., NPI < 1), despite having non-compliant sub-index scores for at least one of the included water quality parameters. However, as noted by Abbasi and Abbasi (2012, p. 29), by using a modified RMS aggregation function, only a small region of ambiguity exists between NPI scores of 0.7 and 1.0. For this reason, the lower of the two values was adopted in this study as a more conservative standard by which to evaluate compliance. This allowed for an additional precautionary threshold of natural vegetation cover to be estimated.

The first specific objective of this study was to assess the usefulness of Nemerow's Pollution Index (NPI), in combination with site-specific water quality guidelines derived from local reference condition data, as a tool for the evaluation of water quality and as a metric for modelling and threshold estimation. Given the preceding discussion, it is therefore concluded that Nemerow's Pollution Index provided a convenient, intuitive, and sufficiently rigorous means of evaluating the overall water quality status of the 58 sub-catchments over the 24-month period of interest. It was thereafter possible, while simultaneously considering questions relating to scale and landscape configuration, to evaluate the strength and nature of the correlation between water quality and various metrics of natural vegetation across the sample of sub-catchments, with the attendant aim of using regression models to estimate thresholds of the latter (i.e., natural vegetation) for the protection of the former (i.e., water quality). However, this first required the identification of a contextually appropriate metric by which natural vegetation could be classified using available land cover data.

Classifying Natural Vegetation

Most studies, presumably by virtue of the ecological characteristics of the regions in which they were conducted, have equated forests with natural land cover. However, in ecologically disparate regions, forested land may not always be the most appropriate metric of natural vegetation. Moreover, it may also be inappropriate to assume that all indigenous vegetation types can be automatically aggregated into a single land cover class which is presumed to offer water resources with protection from diffuse pollution (e.g., Sponseller et al., 2001; Tiner, 2004; Bierschenk et al., 2012; Pandey et al., 2012; Iñiguez-Armijos et al., 2014). Consequently, in the present study, the process of identifying a suitable aggregate metric by which to classify natural vegetation (which was the second specific objective of the study) was largely informed by the need to determine which categories of locally occurring vegetation would offer the best protection from diffuse pollution when combined into a single aggregate class. This was achieved by evaluating which of the existing classes of vegetative land cover (as per the 2013/14 SANLC map), when combined into a single aggregate land cover class and measured as a proportion of the area under analysis, showed the strongest negative correlation with pollution levels. In order to simultaneously determine the most appropriate scale(s) at which to develop models and estimate thresholds, this evaluation was conducted using land cover data at the whole-catchment scale, as well as within 200, 400, and 800 m riparian buffer zones (RBZs).

It was initially assumed that all classes of naturally occurring indigenous vegetation would offer at least some degree of protection from diffuse pollution and thus be included in the aggregate classification of natural vegetation. Iñiguez-Armijos et al. (2014, p. 3), for instance, when evaluating the importance of vegetation cover for the protection of water quality in Ecuador, aggregated "all types of native vegetation" into a single class. Xu et al. (2016, p. 200) similarly adopted a broad classification of natural vegetation which included "proportions of forest, grassland, and wetland." Correspondingly, it was expected that land cover classes such as commercial forestry would be excluded from the classification as they are generally presumed to have a negative impact on water resources. However, the results of the correlation analysis revealed that the combination of vegetative land cover classes that demonstrated the strongest negative correlation with NPI scores across the sample of sub-catchments included (1) indigenous woody vegetation, (2) commercial forestry plantations, and (3) wetlands. This result was remarkable insofar as commercial forestry was *included* while grasslands were *excluded*. These findings are discussed in turn below. Moreover, while this result was consistent across all scales, correlations were strongest at the whole-catchment and 200 m riparian buffer zone scales.

In general, grasslands are expected to improve water quality by acting as a detention medium (Xiao & Ji, 2007; Malherbe et al., 2019b; Cole et al., 2020; Zhang et al., 2021; Zhou et al., 2022; Deng et al., 2023; Roldán-Arias et al., 2023; Wang et al., 2023b; Zhang et al., 2023b). In support of this assumption, several studies found that increased proportions of grassland within a landscape were associated with improved water quality.[69] However, other studies have demonstrated that grassland may not consistently offer protection from diffuse pollution. Some authors, for instance, have reported mixed results with respect to the effectiveness of grassland as a buffer (e.g., Nash et al., 2009; Nava-López et al., 2016; Morse et al., 2018), while several other studies show that in some cases, and in contrast to what might be anticipated, grasslands may actually be linked to higher levels of impairment or contamination.[70] It is evident from these studies that the relationship between grassland and water quality is complex and likely to be contingent upon several other factors. For instance, if grasslands are poorly managed or used primarily for grazing livestock, they may become sources of contaminated runoff (rather than sinks) and thus have a negative impact on water quality (Yu et al., 2016; Ogbozige & Alfa, 2019; Crooks et al., 2021; de Mello et al., 2022). Moreover, the seasonality of grassland (i.e., its ephemeral nature) may also undermine the consistency of its relationship with water quality (Yu et al., 2016). It is also possible that other classes of land cover, which have a similar spectral profile to grassland but a negative impact on water quality, are incorrectly labelled as grassland during the classification of satellite imagery in land cover mapping procedures (de Oliveira et al., 2017; Asare et al., 2018; Shukla et al., 2018). Bearing this in mind, locations within the study area that had been classified as grassland according to the 2013/14 SANLC map were subsequently examined and

[69] See, for example, Sliva and Williams (2001), Wan et al. (2014), Xu et al. (2016), Kändler et al. (2017), Shi et al. (2017), Mainali and Chang (2018), Gossweiler et al. (2019), Aalipour et al. (2022), Obubu et al. (2022), Zhong et al. (2022), Gani et al. (2023); Liu et al. (2023), and Xu et al. (2023a).
[70] See, for instance, Ahearn et al. (2005), Amiri and Nakane (2006), Xiao and Ji (2007), Ding et al. (2013), Shen et al. (2014), Chen et al. (2016), Vrebos et al. (2017), Asare et al. (2018), Lacher et al. (2019), Chen et al. (2021), Dymek et al. (2021), and Zhou et al. (2022).

compared with contemporaneous high-resolution satellite imagery using Google Earth. From this investigation, it appeared that there was a marked absence of healthy natural vegetation in many of these areas. Therefore, it is plausible that areas labelled as grassland in the SANLC map were in fact areas of bare/degraded ground which had been misclassified. When investigating the impacts of land use change on water quality in the North West Province, South Africa, Asare et al. (2018, pp. 9, 10) also reported the misclassification of bare ground as grassland. It is also worth noting that according to Kleynhans et al. (2005), the ecoregions contained within the study area are typically dominated by fynbos, renosterbos, succulents, thickets, and afromontane forests (see Table 2 on p. 91). True grasslands are therefore not typically characteristic of the region's flora under undisturbed conditions. Thus, in the context of the present study area, areas of grassland may actually be indicative of anthropogenic disturbance (i.e., the degradation of natural woodlands and scrublands through clearing or over-grazing).

It is also widely accepted that commercial forestry plantations tend to have a net negative impact on water resources (Fulton & West, 2002; Jewitt, 2005; Sweeney & Newbold, 2014; Duffy et al., 2020). In South Africa, for example, commercial forestry activities are often listed as a common cause of water quality degradation (CSIR, 2010; Nel et al., 2011a; Bosman et al., 2018; du Plessis, 2019b, 2021). Several local studies have also linked water quality problems to commercial forestry plantations. Slaughter and Mantel (2017, p. 505), for example, suggested that forestry plantations may be responsible for elevated nitrogen concentrations within selected biomes in South Africa. Petersen et al. (2017, pp. 147, 149) also described links between forestry activities and increases in electrical conductivity, chloride, and sulphate concentrations in two rivers located in the southwestern coastal region of South Africa. Moreover, both Petersen et al. (2017) and Nkosi et al. (2021) have noted that forestry plantations (especially non-indigenous species) can cause reduced streamflow, which in turn reduces water quality due to decreased in-stream dilution of contaminants (see also Schultze, 2012; Scott & Gush, 2017; Le Maitre et al., 2018). Finally, Namugize et al. (2018), when investigating the effects of LULC change on water quality in the uMngeni river catchment, also found that elevated levels of total suspended solids, nutrients, and *E. coli* could be attributed to commercial forestry plantations at some locations. However, in the same study, the authors also reported that declines in natural vegetation *and* forestry plantations could be linked to increases in phosphorous concentrations at other locations (ibid., p. 9). Similarly, it has been reported by some authors that commercial forestry plantations, if managed properly, can offer beneficial ecosystem services—including buffering, erosion control, water quality maintenance, and flow regulation—and thereby have positive impacts on water quality in the long-term (Ide et al., 2019; Malherbe et al., 2019b; Duffy et al., 2020). In support of this, in the South African context, forestry plantations were found by du Plessis et al. (2015, p. 658) to be positively correlated with dissolved oxygen concentrations in upper reaches of the Vaal River. A later study also found a positive association between reductions in ammonia and nitrate contamination and forestry plantations in other sections of the same river system (du Plessis, 2021, p. 7). A further study conducted in the uMngeni catchment, KwaZulu-Natal, found that the water quality of rivers in locations dominated by commercial forestry plantations was "consistently good" (van Deventer et al., 2022, p. 10). Further afield in New Zealand, two separate studies found no difference between the impacts of native forests and commercial plantations on water quality (i.e., both indigenous and commercial forests, relative to other categories of land use, were associated with improved water quality) (Larned et al., 2004; Young et al., 2005). It would therefore appear that the impact of commercial forestry depends largely on factors such as the species grown and the manner in which plantations are managed (de Mello et al., 2020). Negative impacts on water quality are usually only evident during planting and harvesting (Young et al., 2005; Namugize et al., 2018; du Preez & van Huyssteen, 2020), or when fertilisers are applied (van Deventer et al., 2022). Thus, when investigating the impacts of LULC on water quality, both Tiner (2004) and Prakoso et al. (2023) included commercial forestry when classifying natural vegetation.

It is therefore evident that when evaluating the impacts of land use on water quality, researchers should be cautious of making assumptions regarding classifications of natural vegetation. As noted above, depending on the ecology of the region of interest, forested land may not always be a contextually appropriate metric of natural land cover. Moreover, as evidenced by this study, it may not be the case that areas of grassland will be associated with improved water quality. Similarly, and contrary to what might be expected, plantations of commercial forestry may, if well-managed, offer water resources with protection from diffuse pollution. Thus, especially when viewing natural vegetation in its role as a sink, careful consideration should be given to which individual categories of vegetative land cover may be grouped together. As studies of this kind expand into ecologically disparate regions, each characterised by different flora, this is likely to be an increasingly important methodological consideration.

It is important to note, however, that defining a contextually appropriate benchmark by which to measure the "naturalness" of vegetation in any given region is a complex task that must consider several factors, each of which will influence the types and composition of flora which is typical of a given biome under "unspoiled" conditions (Sprugel, 1991). Moreover, given the increasingly evident—and potentially irreversible—impacts of climate change, what is considered "natural" in any given region is likely to change over time (Sprugel, 1991; Cramer & Leemans, 1993; Sykes et al., 1999; Albrich et al., 2020; Afuye et al., 2021). By implication, measurable losses of natural vegetation (or transitions to vegetative regimes that would normally be indicative of "degraded" landscapes) may be attributed to the effects of climate change rather than anthropogenic land use changes (such as agricultural expansion or urbanisation) (ibid.). Nevertheless, while these are important considerations, they should not detract from the main practical implications of the present study: namely, that maintaining sufficient areas of natural vegetation (however this may be defined for a given region) is an important strategy for the integrated management and protection of water quality.

Normalised Difference Vegetation Index

Several studies have reported statistically significant relationships between water quality parameters and NDVI-based metrics. It was therefore further hypothesised that mean NDVI values might provide a convenient indicator of the amount and/or condition of natural vegetation across the sample of sub-catchments (Griffith et al., 2002b, p. 846; Torres-Bejarano et al., 2022, p. 4). However, the results of these investigations have been inconsistent, with the scale of analysis and seasonality frequently influencing the nature of the relationship between NDVI values and different water quality parameters. Nevertheless, a number of authors have inferred that water quality is closely linked to the amount and type of vegetation in a catchment and that NDVI measurements can be used to provide an indication of the latter (e.g., Griffith et al., 2002a; Chu et al., 2013; Masocha et al., 2017; Chen et al., 2021; Senbore & Oke, 2021; Wang et al., 2021; Torres-Bejarano et al., 2022; Pandey et al., 2023).

Griffith et al. (2002a), for instance, reported significant (but temporally varying) relationships between selected NDVI values and various water quality parameters in the Central Plains region of the United States. In Taiwan, within the Tseng-Wen Reservoir watershed, Chu et al. (2013) found that when evaluated at the catchment scale, NDVI values were negatively correlated with suspended solids, but that within a 1 km buffer zone NDVI values were positively correlated with nitrate concentrations. Wang et al. (2021) found that in the Danjiangkou Reservoir catchment, China, NDVI was positively correlated with chemical oxygen demand, total organic carbon, and ammonium concentrations, but negatively correlated with electrical conductivity. Based on NDVI measurements, Senbore and Oke (2021) inferred that a loss of natural vegetation within the Mangaung Municipality in South Africa over a 30-year period was responsible for deteriorating water quality. Pandey et al. (2023) reported similar results within the Jharkhand state of India. Finally, Torres-Bejarano et al. (2022) observed a negative correlation between nutrient concentrations and NDVI values (the latter being positively correlated with proportions of natural vegetation cover) within the Atlántico region of Colombia.

In the present study, pollution index scores were positively correlated with mean NDVI values across the sample of sub-catchments (Spearman's $\rho = 0.340$; $p < 0.01$). However, mean NDVI values were also strongly and positively correlated with proportions of agricultural land in these catchments (Spearman's $\rho = 0.752$, $p < 0.01$). This suggests that, rather than providing an indication of the amount of natural vegetation in the landscape, NDVI values were indicative of agricultural productivity (which, in turn, was likely to be a source of diffuse pollution, thus negatively impacting water quality). When remarking on their own mixed results, Griffith et al. (2002a, p. 1703) postulated that NDVI values "may simply be indicative of a more intensively agricultural watershed, or may be indicative of increased fertilizer or chemical applications." It is thus concluded that, among other known limitations of the index, NDVI values can be ambiguous and their interpretation therefore requires contextual knowledge of the vegetational composition of the region of interest (an issue also raised by Ramsey &

Rangoonwala, 2017). Therefore, although convenient, NDVI may not always be an appropriate indicator of natural vegetation.

Addressing Questions of Scale

Evidence has shown that the location of LULC within a catchment has a meaningful influence on the nature and magnitude of its impact on water quality, and that the relationship between these two variables is thus "scale-dependent" (de Oliveira et al., 2017; Lintern et al., 2018; Morse et al., 2018; Lacher et al., 2019; Zhang et al., 2019; Song et al., 2020; Li et al., 2022b; Torres-Bejarano et al., 2022). This has logical implications for attempts to model these relationships, as well as for the estimation and applicability of any LULC thresholds. Accordingly, several studies have attempted to determine the scale at which LULC is most influential in terms of its impact on water quality, with a common emphasis placed on comparing the relative influence of riparian versus catchment-wide land use. For instance, it is frequently assumed that LULC adjacent to water bodies is likely to have a greater impact on water quality than LULC further afield (Osborne & Kovacic, 1993; Johnson et al., 1997; Gove et al., 2001; Tiner, 2004; Waite et al., 2010; Miller et al., 2011; Ou et al., 2016; Ramião et al., 2020; Xu et al., 2023b). However, the results of studies which have compared the relative influence of LULC at different scales have been mixed, and there remains a great deal of uncertainty in this regard. As with many similarly complex issues, the answer appears to be contingent on several contextual factors. Therefore, the available evidence (and growing consensus) seems to suggest that a multi-scale perspective is most appropriate (Strayer et al., 2003; Schiff & Benoit, 2007; Zhou et al., 2012; Ding et al., 2016; de Mello et al., 2018; Park & Lee, 2020; Bohenek & Sulliván, 2022). An important aspect of the third objective of this study was therefore to address this question of scale.

While land use in riparian areas may have a more direct impact on water quality, there are circumstances in which the cumulative impact of LULC across the whole catchment may be just as significant (if not more so), and it is possible that the ability of vegetated buffer zones to provide protection from diffuse pollution may be overcome by the cumulative impacts of land use across the entire catchment (Brabec et al., 2002; Allan, 2004a, 2004b; Brabec, 2009; Tran et al., 2010; Tromboni & Dodds, 2017; de Mello et al., 2020; Ramião et al., 2020; Thomas et al., 2020). In the present study, the relationship between natural vegetation and water quality was found to be just as significant at the whole-catchment scale as it was within riparian buffer zones. Thus, as others have concluded, "the finding that land use in the buffer area, as well as in the catchment as a whole, can modulate water quality has implications for water management" (Nobre et al., 2020, p. 7). As such, it would be inappropriate to focus on managing land use at one spatial scale (e.g., within riparian areas) while ignoring land use at other scales (e.g., across whole catchments) (see also Cole et al., 2020, p. 8). The multi-scale management perspective advocated by other authors is thus endorsed, and the necessity of determining and applying thresholds at both scales is likewise confirmed.

However, notwithstanding the claims made above, the results of any comparison between riparian and catchment-wide land use are likely to be contingent upon the scale at which riparian buffer zones are delineated. It is therefore important at this juncture to admit two methodological concessions. Firstly, the narrowest riparian buffer width evaluated was 200 m (a decision taken due to the relatively coarse spatial resolution of the land cover data available). However, it is possible that, had higher-resolution LULC data been available, a different result may have been obtained if the analysis was conducted using a narrower buffer width (e.g., 100 m or less). Secondly, as described in the Methods & Results section, the riparian buffer zones were delineated using a 1:500,000 stream network layer, which contains only higher-order streams (DWAF, 2006). For reasons outlined earlier, this layer was judged to be more appropriate for the purpose of buffer delineation than the finer scale 1:50,000 stream network (which contains a greater density of lower-order streams). Had the 1:50,000 network been used for RBZ delineation, a much greater proportion of the total catchment area would have been identified as "riparian" due to the greater stream density of the layer (especially when using buffer widths upward of 200 m). This would have made any comparison between riparian and catchment-wide land use effectively meaningless (refer to Figure 8 on p. 67, which illustrates this concern). The implication of this in the context of similar studies is that the scale at which riparian buffer zones are delineated is an important, but largely overlooked, consideration.

Investigating the Potential Influence of Landscape Configuration

An increasing number of studies have demonstrated the influence that landscape configuration can have on water quality (Kearns et al., 2005; Huang & Klemas, 2012; Slaughter & Mantel, 2017; Gorgoglione et al., 2020; Wang et al., 2021; Wu & Lu, 2021; de Mello et al., 2022; Zhang et al., 2022a; Deng et al., 2023; Yao et al., 2023). A particularly relevant (and widely held) assumption is that as natural vegetation becomes more fragmented, its efficacy as a sink, and thus its ability to protect water resources from diffuse pollution, decreases (Gergel et al., 2002; Griffith, 2002; Lee et al., 2009; Shupe, 2013; Lintern et al., 2018; Yirigui et al., 2019; de Mello et al., 2020; Thomas et al., 2020; de Mello et al., 2022; Bowes et al., 2023; Xu et al., 2023a). It is reasoned, for example, that patches of vegetation that are more consolidated (i.e., less fragmented) will be more efficacious as a detention medium, especially in riparian zones. Although there is ample evidence in the literature in broad support of this assumption,[71] several other studies reported that greater degrees of fragmentation are not always associated with poorer water quality (see, for instance, Lee et al., 2009; Qiu & Turner, 2015; Clément et al., 2017; Thomas et al., 2020; Liu et al., 2021; Qiu et al., 2023; Yao et al., 2023). In view of these

[71] See, for example, Hunsaker and Levine (1995), Lee et al. (2009), Liu et al. (2012), Bateni et al. (2013), Bu et al. (2014), Ye et al. (2014), Shen et al. (2015), Ding et al. (2016), Shi et al. (2017), Liu and Yang (2018), Yirigui et al. (2019), Zhang et al. (2019), Liu et al. (2021), Wang et al. (2021), Wu and Lu (2021), de Mello et al. (2022), Li et al. (2022b), Zhong et al. (2022), Zhou et al. (2022), Aalipour et al. (2023), and Qiu et al. (2023).

complexities, Ma et al. (2023, p. 1) recently cautioned that “demonstrating and quantifying the effects of landscape patterns on water quality remain challenging.”

In order to evaluate the possible influence of fragmentation in this study, a new metric was tested that reflects not only the amount of natural vegetation within a landscape but also the degree to which that vegetation is fragmented. The proposed Natural Vegetation Integrity Index (NVII) thus adjusts the proportion of the landscape occupied by natural vegetation by the degree to which patches of that self-same vegetation are fragmented. It is expected, for instance, that as a landscape becomes increasingly disturbed by anthropogenic activity, not only will areas of natural habitat be transformed into other land uses, but patches of natural vegetation will simultaneously become increasingly disaggregated. The NVII is therefore designed to reflect both aspects of ecological disturbance. Ranging from 0 to 1, higher NVII scores simultaneously indicate that a greater proportion of the landscape is occupied by natural vegetation *and* that patches of this vegetation are more aggregated (lower index scores reflect the opposite). The Aggregation Index (AI), proposed by He et al. (2000), was incorporated into the NVII as a class-level measure of fragmentation. In the NVII, AI scores (which also range from 0 to 1, decreasing as patches of natural vegetation become more fragmented) modify the proportion of the landscape occupied by natural vegetation through a simple multiplication function (see Equation 7 on p. 125). The Patch Cohesion Index (Schumaker, 1996) was also tested but found to be insufficiently sensitive to fragmentation when using the 8-cell neighbourhood rule.

Contrary to expectations, when using the NVII to account for fragmentation, it could not be demonstrated in this study that the fragmentation of natural vegetation (either across the whole catchment or within 200 m riparian buffer zones) had a statistically significant influence on its relationship with water quality. The results of correlation analyses conducted at both scales did not offer any indication that including a measure of fragmentation would give statistical models increased explanatory power. Instead, a simple compositional measure of the proportion of the landscape occupied by natural vegetation (when the latter was appropriately classified) showed the strongest correlation with water quality. However, it is important to note that at both scales—and particularly within the 200 m riparian buffer zone—patches of natural vegetation were not especially fragmented. At both scales, mean AI scores were very high (≥ 0.9) and the variance of AI scores very low (standard deviation ≤ 0.06). This meant that, across the sample of 58 sub-catchments, the proportion of the landscape occupied by natural vegetation was not significantly modified by AI scores when the NVII was calculated. However, had there been greater variance across the sample of sub-catchments in the degree to which natural vegetation was fragmented, its impact on water quality may have been more apparent. It is further hypothesised that this effect would have been more readily apparent within riparian zones, where the degree to which vegetation is fragmented is likely to have a greater impact on its ability to intercept contaminated runoff (Cole et al., 2020). However, the generally low and largely unvarying degree of fragmentation across the sample of sub-catchments did not allow its significance to be fully evaluated. Hence, it cannot be concluded from this study that fragmentation is an insignificant factor. Instead, the *apparent* insignificance of fragmentation is more likely due to the fact that fragmentation levels were generally low in this particular sample of sub-catchments. As such, the results of this study are inconclusive in terms of the significance of landscape fragmentation, and further research into the influence of landscape configuration is recommended.

Potentially Confounding Factors

In a paper discussing advances in approaches to modelling the relationship between LULC and water quality, Varadharajan et al. (2022, pp. 2–3) concede that, notwithstanding the "variety of statistical and modelling approaches available," it is nevertheless challenging to make "accurate and timely water quality predictions" owing to "the effect of local characteristics and complex processes on solute transport." Therefore, in order to effectively isolate the impact of LULC on water quality when conducting statistical analyses (which was the fourth specific objective of the present study) the potentially confounding influence of these extraneous factors needs to be minimised. This can be achieved, to some degree, by using multivariate statistical methods which are able to account for the additional influence of other variables (including possible interaction effects). However, due to frequent multicollinearity between environmental variables, the use of multivariate approaches can prove problematic (Detenbeck et al., 1993; Allan, 2004b; Tu, 2011a; de Oliveira et al., 2017; Wang et al., 2021; Li et al., 2022b; Bowes et al., 2023; Yao et al., 2023). Alternatively, in cross-sectional studies, the influence of extraneous variables can be dealt with ex ante in the design of the study by minimizing variation within the sample such that LULC is, as far as possible, the only factor that varies between sites. A common approach is to conduct studies within regions that are relatively homogeneous in terms of variables such as geology, ecology, and climate, thereby minimising differences in these variables within the sample (Klein, 1979; Lenat & Crawford, 1994; Slaughter & Mantel, 2017; Grimstead et al., 2018; de Mello et al., 2022). This makes it more reasonable to attribute changes in water quality to differences in LULC. Therefore, in light of the foregoing, the selection of a suitable study area in the present analysis was largely guided by the work of Day et al. (1998). Explicitly recognising the influence of local geology, climate, and ecology on water quality, the authors identified six distinct regions within South Africa that share similar natural water chemistry "for the purposes of water quality management" (ibid., p. 1). The 58 sub-catchments which subsequently made up the statistical sample for this study were selected from within the south-western coastal region identified by the authors (see Figures 14 and 32 on pp. 87 and 111, respectively).

Geology, Ecology, and Precipitation

Geological variation was limited among the selected sub-catchments, which are chiefly composed of the sedimentary rocks typical of the Cape Supergroup (Day & King, 1995; Day et al., 1998; Johnson et al., 2006; Johnson & Wolmarans, 2008). By virtue of the shared characteristics of these geological formations, the natural chemistry of water bodies in these areas is reasonably similar (Day & King, 1995; Day & Dallas, 2011). In addition, the different ecoregions that characterise the study area are fairly similar in terms of their ecological, topographical, and climatic characteristics (refer to Table 2 on p. 91; see also Kleynhans et al., 2005). Moreover, when evaluated statistically, variations in mean annual precipitation across the sample of 58 sub-catchments (based on data from Fick & Hijmans, 2017) did not appear to have a significant influence on water quality (Spearman's $\rho = -0.162$; $p = 0.226$). In view of the above, when considering variations in water quality across the sample of sub-catchments, it was possible to ascribe causality to differences in LULC with greater confidence.

Seasonality

In addition to the geomorphological and environmental factors noted above, which tend to vary from region to region, many studies have reported seasonal variations in the relationship between LULC and water quality within the same region, attributed primarily to intra-annual variations in precipitation, runoff, and discharge.[72] According to Day and Dallas (2011, p. 85), for example, water quality is "profoundly influenced by flow rate and discharge." However, as the aim of this study was to assess long-term impacts of LULC on water quality with a view to informing integrated land and water resource management plans (for which natural intra-annual variations in water chemistry owing to seasonal differences in precipitation, runoff, or discharge are not particularly relevant), the data used to evaluate water quality spanned a 24-month sampling period. Once averaged, these measurements represented typical water quality conditions across both wet and dry seasons, thereby minimising the significance of intra-annual differences in precipitation, runoff, and discharge. Thus, in both intent and design, seasonality was not a significant factor in this study. The necessity of accounting for seasonal variation by implementing a sampling regime that covers both wet and dry seasons is a consideration highlighted in two South African studies (namely, Nde & Mathuthu, 2018; Nde et al., 2021).

Catchment Size

While the influence of extraneous factors such as geology, ecology, climate, and seasonality were largely accounted for in the design of the study (see above), it was anticipated that the significant variation in catchment size across the sample of sub-catchments might be an influential factor. Relationships between catchment size and water quality are complex. Larger catchments, for instance, have a greater land-surface area from which contaminants can be mobilised during precipitation events. However, given the greater distance that stormwater must travel in larger catchments, the infiltration capacity and interception potential in these catchments may also increase. This may in turn reduce

[72] See, for example, Rhodes et al. (2001), Ye et al. (2014), Ding et al. (2015), Farrell et al. (2015), Moodley et al. (2015), Yu et al. (2016), van der Hoven et al. (2017), Lintern et al. (2018), Mainali and Chang (2018), de Mello et al. (2020), Kim et al. (2020), Palma et al. (2020), Dlamini et al. (2021), Umwali et al. (2021), Wang et al. (2021), Winton et al. (2021), Wu and Lu (2021), Zhang et al. (2021), Kadir et al. (2022), Li et al. (2022b), Zhang et al. (2022a), Zhou et al. (2022), Deng et al. (2023), Han et al. (2023), Wang et al. (2023b), and Xu et al. (2023b).

overland runoff rates and increase lag times, thereby influencing the rates and concentrations at which pollutants are transported into receiving water bodies (Pilgrim et al., 1982; Yang et al., 2017; Botter et al., 2019; Nobre et al., 2020; Dębska et al., 2022). As expected, correlation analysis confirmed that a moderately strong (and positive) relationship existed between pollution index scores and catchment area (i.e., NPI scores tended to increase proportionally with catchment size across the sample) (Spearman's $\rho = 0.513$; $p < 0.01$). However, when catchment area was included as an additional variable in a multiple regression model, it offered no added explanatory power. It was therefore possible, in this instance, to accurately model the relationship between proportions of natural vegetation cover and water quality independent of catchment size. This suggests that the significance of catchment size, such as it was, was largely eclipsed by the much greater influence of land use on water quality. More importantly, as the regression models could be estimated without reference to catchment area, minimum thresholds of natural vegetation cover derived from these models could be applied regardless of differences in catchment size.

Modelling and Threshold Estimation

Correlation and Regression Analysis

Both correlation and regression analysis have been widely used as a means of modelling the relationship between various metrics of LULC and stream health. In the present study, a similar and statistically significant ($p < 0.01$) negative relationship was observed between proportions of natural vegetation and NPI scores at both the whole-catchment and 200 m RBZ scales (Spearman's $\rho = -0.729$ and -0.735, respectively). Hence, as proportions of natural vegetation cover decreased, impairment levels across the sample of sub-catchments tended to increase. Therefore, in accordance with the findings of previous research, the present study confirms that a loss of natural vegetation cover is likely to result in impaired water quality. Although this was not unexpected, the relationship between natural vegetation and water quality was also found to be nonlinear. This suggests that a marked increase in both the magnitude and rate of pollution can be expected when natural vegetation cover drops below a certain threshold. Such nonlinear responses are not atypical of LULC-WQ interactions. Many previous studies—which together have examined the relationship between a broad range of land use and water quality metrics under varying conditions— have reported that changes in LULC often induce abrupt, nonlinear responses in water quality and/or stream health (Dodds et al., 2010; Tayyebi et al., 2015; Tromboni & Dodds, 2017; Grimstead et al., 2018; D'Amario et al., 2019; Chen & Olden, 2020; Liu et al., 2021; Wang et al., 2023a).

There were, however, six unusual observations which did not appear to fit the overall pattern of the rest of the sample (see Figure 41 on p. 134). Despite the evident discordance of these outliers, regression models based on an *uncensored* sample were nevertheless able to explain over 50% of the variability in the sample at both spatial scales. However, once the discordant observations had been excluded from the analysis—a decision justified by the fact that regression analysis, by design, is meant to model "as accurately as possible the underlying process driving the bulk of the data"[73]—not only were the models more precise, but they were subsequently able to explain between 69% and 82% of the variability in the sample (these figures represent the explanatory power of the models at the 200 m RBZ and whole-catchment scales, respectively).

Notwithstanding efforts to minimise the impact of extraneous factors through the selection of an appropriate study area (see "Potentially Confounding Factors" above), the predictive power[74] of these simple bivariate models is remarkable when one considers the complexity that characterises LULC-WQ relationships. Also noteworthy is that while the removal of the outliers greatly improved the performance of the catchment-scale model, the exclusion of the outliers offered less improvement for the model estimated using data at the 200 m RBZ scale (i.e., there appeared to be more inherent variance in the sample at this scale, even with the outliers removed, which the model was unable to account for). Nevertheless, owing to the significant improvements gained by removing the outliers in both the fit and precision of the regression models, these "censored" samples were preferred for threshold estimation.

Threshold Estimation

Capon et al. (2015, p. 123), in discussing thresholds and regime shifts in freshwater ecosystems, note "the increasingly prevalent notion that dramatic ecological change can occur suddenly, and without warning, potentially causing stark or irreversible shifts in ecosystem state." The ability to predict when such changes might occur, through the identification of nonlinear ecological tipping points, has become increasingly important for the management and protection of natural resources (Muradian, 2001; Groffman et al., 2006; Johnson, 2013; Foley et al., 2015; Kelly et al., 2015; Munson et al., 2018; Zhang et al., 2018). However, as not all ecosystems exhibit abrupt or dramatic nonlinear responses to external perturbations, it is also possible to define regulatory thresholds that denote acceptable trade-offs between environmental protection and socioeconomic development (Antoniuk, 2006; Johnson, 2013; Guntenspergen & Gross, 2014; Kelly et al., 2014). Moreover, regulatory thresholds can themselves be hierarchical, with precautionary and target thresholds indicative of different levels of "acceptable" ecological disturbance (see Figure 13 on p. 77).

In the present study, both precautionary and target thresholds of natural vegetation were estimated from the regression models at both spatial scales. The precautionary thresholds (associated with an NPI score of 0.7) are estimates of the amount of natural vegetation cover at or below which unacceptable levels

[73] Quoted from Chatterjee and Simonoff (2013, pp. 54–56). See also Judd et al. (2017, p. 326ff).
[74] The reader will recall from the preceding chapter that, for the purposes of threshold estimation, and contrary to presumed causality, proportions of natural vegetation cover assumed the role of the response variable (rather than the explanatory variable). Although transposing the variables in this way alters the slope of the regression line (due to the fact that OLS regression only seeks to minimise error along the axis of the dependent variable), it does not affect the ability of the model to explain variance in the sample (i.e., the model's explanatory power, R^2, is unaffected and remains the same regardless of which variable is used as the independent variable.

of contamination start to become increasingly likely. The target thresholds (associated with an NPI score of 1.0) represent the amount natural vegetation cover at or below which pollution levels are predicted to exceed permissible limits, thus putting the health of aquatic ecosystems at risk. Conversely, if proportions of natural vegetation are maintained above these regulatory thresholds, water quality is expected to remain within acceptable levels.

In addition, owing to the curvilinear nature of the relationship observed at both scales, it was also possible to estimate critical nonlinear thresholds of natural vegetation cover using piecewise regression analysis. These represent the point at which dramatic increases in the magnitude and rate of pollution are expected. The relevant thresholds, estimated from the regression models, are shown below in Table 18.

Table 18. Summary of thresholds of natural vegetation cover estimated at the whole-catchment and 200 m riparian buffer zone scales.

Threshold Type	Whole Catchment (% Natural Vegetation Cover)	200 m Riparian Buffer Zone (% Natural Vegetation Cover)
Precautionary	89	90
Target	82	85
Nonlinear "Tipping Point"	45	60

From the table above it is evident that, irrespective of the scale at which one intends to manage land use, fairly high proportions of natural vegetation cover are necessary to protect water resources from diffuse pollution. It would thus seem that aquatic systems are highly sensitive to the impacts of land use degradation and that relatively minor disturbances are sufficient to drive levels of contamination beyond ecologically acceptable levels. For instance, if one takes a precautionary view, the results of this study suggest that in order to sustain water quality at ecologically acceptable standards, natural vegetation cover should be maintained at close to 90% of the landscape (allowing for some rounding-off, this figure applies both across the whole catchment and within riparian areas). The threshold is "precautionary" in the sense that if proportions of natural vegetation cover drop below this level, the models suggest that unacceptable levels of impairment become increasingly likely. As such, the precautionary threshold could be used to trigger preventative or pre-emptive management interventions in relatively pristine catchments of high ecological importance.

By contrast, the slightly less conservative "target" thresholds of 82% and 85% natural vegetation cover (applicable at the whole catchment and 200 m RBZ scales, respectively) might serve as general management objectives at which to maintain—or restore, in cases of retrospective application—levels of natural vegetation. If levels of natural vegetation can be sustained above these levels at the relevant scales (thus allowing for less than 18% of the catchment, and 15% of a 200 m riparian buffer zone, to be developed), the risk of unacceptable impairment remains low. The models further suggest that if the extent of natural vegetation cover drops below approximately 60% (within riparian areas) or 45%

(across the whole catchment), dramatic increases in the rate and magnitude of impairment can be expected. However, it should be noted that by the time these tipping points are exceeded, the models predict that pollution levels are likely to have already exceeded ecologically acceptable limits by a factor of approximately three.

These results are comparable with the findings of several other studies in which various thresholds of natural vegetation were found to be protective of water quality. As discussed earlier, presumably owing to the ecological characteristics of the regions in which they were conducted, most studies based these thresholds on metrics of forest cover. Black et al. (2004), for example, found that the health of instream macroinvertebrate communities began to decline rapidly when forest cover across the catchment fell below 70–80%. Sheeder and Evans (2007), when considering nutrient concentrations and sediment loads, reported that “unimpaired” catchments had an average of 78% forest cover. Death and Collier (2010) observed negative changes in the structure of macroinvertebrate communities when natural vegetation cover fell below 80–90%. Iñiguez-Armijos et al. (2014) reported that the ecological condition and macroinvertebrate biodiversity of Andean streams in Ecuador was “good” when vegetation cover was above 70%. Kändler et al. (2017) also found that catchments with more than 70% forest cover tended to have the lowest concentrations of nutrients and heavy metals. When considering both biotic and physiochemical indicators of water quality, Pond et al. (2017) concluded that impairment occurred when the proportion of catchments occupied by forests fell below 60%. When evaluating both physiochemical and biological indicators, Clément et al. (2017) found that in areas dominated by agriculture, eutrophication was prevalent in catchments with less than 47% forest cover. Ding et al. (2021) identified a significant decline in in-stream taxa abundance when catchment vegetation fell below approximately 60%. Zhong et al. (2022) concluded that a minimum of 45% natural vegetation cover is required to maintain nitrogen concentrations within acceptable levels.

In a review published by the Open Space Institute (which includes some of the above references), Morse et al. (2018) concluded that, depending on the context, water quality tends to deteriorate when natural vegetation cover falls below 60–90% of the catchment area, while observing that a threshold of at least 70% forest cover appears to represent the consensus. The wide range of reported thresholds is likely due to a combination of methodological inconsistencies and regional differences between the study areas. Nevertheless, the results of the current investigation fit neatly within the ranges reported in the existing literature.

Thus, notwithstanding several important qualifications (which are discussed below), it can be recommended that, as part of a broader integrated strategy for the management and protection of water quality in the study area, natural vegetation cover levels of between approximately 82 and 90% should be maintained, not only across catchments but also within riparian areas. This will assist in preserving water quality at ecologically acceptable levels. Furthermore, the models suggest that the risk of severe contamination increases significantly if natural vegetation levels are allowed to fall below 60% (when measured as a proportion of a 200 m riparian buffer zone), or 45% (when measured as a proportion of the whole catchment). Admittedly, respecting these thresholds would impose very strict restrictions on urban and agricultural development (allowing, in some cases, for less than 20% of catchment and riparian areas to be developed). While such high thresholds may seem impracticable, they nevertheless stress the sensitivity of aquatic systems to LULC transformations and the subsequent importance, from an integrated catchment management perspective, of regulating land use by minimising the loss of natural land cover. Given the geographical scope of the existing research—which has, until recently, been largely restricted to temperate regions of North America and Europe—the present study adds support to the fact that the preservation and/or restoration of generous areas of natural land cover is a water quality management principle which has universal application. It is also worth adding, however, that the need to maintain such high thresholds of natural vegetation may be offset, to some degree, by the adoption of best management practices (BMPs) that may help to mitigate the negative impacts of anthropogenic land use activities on water resources. Relevant BMPs might include limiting the amount and type of fertiliser applied to agricultural land, or the implementation of Water Sensitive Urban Design (WSUD) principles in built-up environments (D'Arcy & Frost, 2001; Ahammed, 2017; Liu et al., 2017; Kajitvichyanukul & D'Arcy, 2022).

The Utility of Natural Vegetation as a Metric for Modelling and Threshold Estimation

As noted above, the present study confirms that water quality is likely to deteriorate as proportions of natural vegetation cover decrease. While this result was anticipated, it nevertheless validates the earlier supposition that natural vegetation cover, when appropriately classified, can serve as a useful land cover metric for water quality modelling and threshold estimation. Moreover, in contrast to thresholds based on urban or agricultural land cover, thresholds of natural vegetation have universal applicability (provided the latter is classified appropriately for the region of interest). As reasoned earlier, proportions of natural vegetation in a catchment not only reflect the landscape's buffering capacity (its ability to intercept, filter, and assimilate pollutants, and thus treat contaminated runoff) but are also likely to be inversely proportional to, and thus indicative of, the degree to which the same landscape has been disturbed by pollution-generating anthropogenic activities (such as agriculture or urban land use). In the current study, for example, proportions of natural vegetation cover showed significant negative correlation with proportions of both urban (Spearman's ρ = –0.484; $p < 0.01$) and agricultural (Spearman's ρ = –0.808; $p < 0.01$) land cover across the sample of sub-catchment (see Table 13 on p. 132). Considered in this way, natural vegetation has universal applicability as a dual indicator of (1) the capacity of the landscape to intercept diffuse pollution and thus protect water quality, and (2) the probability that the same landscape contains classes of LULC that are typical sources of diffuse pollution and thus have a detrimental impact on water quality (Griffith, 2002; Wang et al., 2021). This remains true regardless of the other land uses present in the catchment. Thresholds of either urban or agricultural land cover, however, have limited applicability in catchments where land use is mixed. This is illustrated in a study by Moodley et al. (2015), which highlighted the difficulty of attributing water quality degradation to distinct categories of land use (e.g., agricultural or built-up land) in mixed land use catchments (see Appendix 5 for a critical summary of the study). Moreover, in the present study, correlation analysis showed that natural vegetation, classified as it was, was more strongly correlated with water quality (Spearman's $\rho = -0.729$; $p < 0.01$) than proportions of either urban (Spearman's $\rho = -0.333$; $p < 0.01$) or agricultural (Spearman's $\rho = -0.621$; $p < 0.05$) land cover. In addition, as noted above, the ability of the natural vegetation regression models to explain up to 82% of the variation in the sample, albeit with six discordant observations removed, is remarkable. Thus, as hypothesised, natural vegetation cover was, in many ways, a superior metric for the estimation of thresholds for the management and protection of water quality.

However, at least five important provisos must be considered in the interpretation and application of these findings. These caveats chiefly concern (1) the implications of OLS regression as a statistical method, (2) the presence of multiple outliers in the sample, (3) improper inferences related to scale, (4) the need for an integrated approach in the management and protection of water quality, and (5) the regional specificity of the results. Each of these qualifications are discussed in turn below.

Caveat 1: Implications of Ordinary Least Squares Regression

It is important to bear in mind that the thresholds described above are estimates based on ordinary least squares (OLS) regression models. Therefore, these models are only approximations of how the dependent variable responds, *on average*, to changes in the independent variable. As such, any minimum thresholds of natural vegetation estimated from these models should be interpreted as what would typically be sufficient to maintain water quality at the specified standard. However, there are (and will always be) instances where this is not the case. In some circumstances, water quality may become unacceptably impaired even if levels of natural vegetation cover are maintained above the threshold values. Similarly, it is possible that water quality will remain within acceptable levels even if proportions of natural vegetation fall below this threshold. The fact that the models are an approximation of typical conditions can be seen from the scatter of the datapoints above and below the regression lines in the plots shown in Figure 46 on p. 144.[75] In this sense, the estimated thresholds can only serve as guidelines that are reflective of what might normally be expected. There are, however, always exceptions that will not fit the model's estimated response exactly (extreme examples of which are the six outliers discussed next).

[75] The fact that the residual error of these points is unbiased (i.e., randomly distributed above and below the regression line) and homoscedastic makes the model a reasonable estimation of the sample.

Caveat 2: Proving (and Qualifying) the Rule with Outliers

By design, OLS regression attempts to minimise the sum of the squared residual error when fitting the regression line to the sample. Consequently, one of the limitations of OLS regression is that it is highly sensitive to outliers (which, owing to their discordance, will have disproportionately large residual errors when squared). It is for this reason that quantile regression, which attempts to minimise *absolute* residual error (rather than the square of the residuals) is more resistant to the influence of extreme observations. Hence, when employing OLS regression, outliers can have an especially deleterious effect on model estimation. Thus, if it can be shown using formal discordancy tests that outliers are genuinely unrepresentative and do, in fact, have an improper influence on the fit of the model, it may be an acceptable strategy to exclude them from the analysis. However, several statistical texts (including those that advocate for the judicial exclusion of outliers when appropriate) have stressed that, unless the outliers are due to an uncorrectable error, the underlying causes of discordancy should be investigated (see, for example, Chatterjee & Simonoff, 2013; Judd et al., 2017; Helsel et al., 2020). These texts argue further that if outliers do in fact represent legitimate (albeit unusual or extreme) cases, they may be the most important and/or insightful observations, possibly signalling critical limitations for the applicability of the model(s).

Thus, while the six outlying observations in the sample may be seen as the proverbial exceptions that prove the rule, they also demonstrate that, under certain circumstances, the rule may not apply. As outliers are, by definition, atypical from the rest of the data, their very existence is proof that a general rule or pattern exists in the cases not excepted.[76] In other words, for outliers to be considered exceptions in the first place, there must be a "rule" (i.e., a pattern or model) from which they deviate. However, the existence of atypical observations also demonstrates that, under specific conditions, the rule may not always hold true. This second consideration is especially germane. It is these peculiar conditions, which cause a deviation from the general rule, that are of particular importance.

In the case of the six outliers observed in this study, the catchments in question had unusually high pollution index scores relative to the proportions of natural vegetation they contained (regardless of whether the latter was measured across the whole catchment or within a 200 m riparian buffer zone). Further investigation revealed that in four of the six cases there appeared to be significant anthropogenic disturbance—principally in the form of agricultural activity—directly upstream of, or adjacent to, the water quality monitoring points. The unexpectedly high NPI scores recorded in these cases could thus reasonably be attributed to contaminated runoff originating from these areas. This has important implications for the applicability of both the models and the estimated thresholds. As emphasised above, while it is true *in most cases* that water quality is likely to remain within ecologically acceptable limits

[76] The idiom originates from the Latin phrase "*exceptio probat regulam in casibus non exceptis*", which literally means that "the exception confirms the rule in cases not excepted" (Knowles, 2005).

provided that proportions of natural vegetation are maintained above the relevant thresholds, this may not *always* be the case. Specifically, in instances where there is significant anthropogenic activity or disturbance directly adjacent to receiving water bodies, the estimated thresholds of natural vegetation may not be sufficient to protect water quality. With this qualification noted, the following two caveats naturally follow.

Caveat 3: Improper Inferences with Respect to Scale

From a resource management perspective, it would be especially convenient to conclude that, provided a certain amount of natural vegetation cover is maintained within riparian zones, water quality would be protected irrespective of land use elsewhere in the catchment. However attractive such a conclusion might be, this would be a grossly inappropriate inference based on the present findings. Several studies have stressed that while maintaining vegetated riparian buffers can improve water quality, this does not mean that catchment-wide land use—including proportions of natural vegetation cover at this scale—is unimportant and can be disregarded (Lorion & Kennedy, 2009; Iñiguez-Armijos et al., 2014; Cole et al., 2020). Similarly—and perhaps more obviously—it cannot be concluded that, provided a certain amount of natural vegetation cover is maintained across the whole catchment, land use within riparian areas is of no consequence to water quality. Being able to estimate minimum thresholds of natural vegetation from models at either spatial scale does not mean that only one of these thresholds needs to be honoured in order to protect water quality. In fact, insofar as water quality is dependent on LULC, the findings of this study indicate that land use at *both* scales is equally imported (a conclusion also reached by Xu et al., 2023b). Based on their results, Grimstead et al. (2018) likewise considered scale-specific thresholds of LULC. A multi-scale perspective is thus essential, and sufficient proportions of natural vegetation must be maintained at both scales in order to protect water quality. However, this last point is itself subject to a further proviso, as discussed below.

Caveat 4: The Necessity of an Integrated Approach

The preceding caveats all stress that, notwithstanding the critical influence of LULC, maintaining natural vegetation at or above the thresholds described above cannot guarantee that water resources will be protected from pollution. Xu et al. (2023a, p. 1), for instance, have observed that “due to the many causes and complicated processes causing water quality changes, controlling and preventing stream water quality degradation remains challenging.” It must therefore be borne in mind that there are several other potential sources and/or causes of impairment that cannot be addressed through land use management alone (including, for instance, point-source discharges from wastewater treatment works). The maintenance of sufficient areas of natural vegetation within catchments and riparian areas must thus be considered as only one of several water quality management strategies and not as a panacea. Kajitvichyanukul and D'Arcy (2022, p. xv), for instance, likewise speak of “landscape interventions to prevent/trap/stabilise or capture mobilised contaminants” as being implemented alongside “the various other good practice measures which can be taken.” Hence, although LULC is certainly a key determinant of water quality, and while the models demonstrate that the amount of natural vegetation within a landscape is without doubt an essential consideration, there are many other factors that must be taken into account when developing policies and plans for the management and protection of water resources. Indeed, fundamental to IWRM is the notion that water resources must be managed holistically, embracing comprehensive, multisectoral, and multidisciplinary approaches (Swatuk & Qader, 2023). It is for this reason that the Global Water Partnership promotes a diverse “toolbox” of socioeconomic and ecological water management strategies (GWP, 2018). Similarly, with specific reference to a reliance on vegetated buffer strips to mitigate water pollution, Cole et al. (2020, p. 1) have warned that such measures should be viewed as part of “a wider management framework that controls pollutants at the source.” The management of LULC (and, more specifically, the application of minimum thresholds of natural vegetation cover) should be seen as one of a range of strategies that might be leveraged as part of a broader “multifocal” approach to the protection of water resources.

Caveat 5: Regional Specificity

Owing to the combined influence of several environmental factors (including climate, geology, ecology, and topography), the relationship between LULC and water quality tends to be regionally specific (Baker, 2005; Day & Dallas, 2011; Morse et al., 2018; Chiang et al., 2021; Bohenek & Sullicán, 2022; Li et al., 2022b). For example, several times in their article on the impacts of LULC change on water quality in the uMngeni catchment, in KwaZulu Natal, South Africa, the authors stressed “the *site-specific* nature of relationships between land use types and water quality parameters” (Namugize et al., 2018, p. 247 emphasis added). It must therefore be borne in mind that the results of this study (including the thresholds and the regression models from which they are derived) are specific to the geographical region from which the data were obtained. Consequently, it would be inappropriate to extrapolate the findings of a study conducted in one region and apply them to a region where local conditions are dissimilar (Dallas & Day, 2004; Chiang et al., 2021).

Applications for the Integrated Management and Protection of Water Quality in South Africa

The practical implementation of an integrated management approach can be challenging, especially given the inherent complexity of the multiple, overlapping, and interconnected socioeconomic and ecological systems that require coordinated management under the rubric of IWRM (GWP, 2000; Jeffrey & Gearey, 2006; Funke et al., 2007; Giordano & Shah, 2014; Kadi, 2014; Ibisch et al., 2016; Jønch-Clausen, 2016; Borden & Goodwin, 2022). Fatehi et al. (2015, p. 5056), for instance, have written that the holistic, systems-based nature of IWRM requires a “full consideration of the factors that can affect the quantity and quality of water, as well as understanding the processes involved.” Likewise, Pahl-Wostl et al. (2011b, p. 302) speak of the need for “an awareness of, and sensitivity to, the huge number of interacting phenomena and processes… which characterise a river catchment." Fulfilling this admittedly ambitious mandate is fraught with conceptual and practical complexities, leading some to conclude that the IWRM paradigm is impractical and unrealistic (Grison et al., 2023). However, if water resources are to be managed sustainably and equitably, the integrated approach advocated by proponents of IWRM, however lofty it may seem, is indispensable (GWP, 2004; Snellen & Schrevel, 2004; Anderson et al., 2008; Kadi, 2014; Donoso & Bosch, 2015; Badham et al., 2019; Kumar et al., 2019).

Although South Africa's various water management policies are essentially underpinned by the principles of IWRM, most commentators agree that there has been a general failure to effectively translate these principles into practice (Merry, 2008; Mauck, 2012; Schreiner, 2013; Karar, 2017; Palmer & Munnik, 2018; Stuart-Hill et al., 2020; Adom & Simatele, 2022; Lukat et al., 2022a; Lukat et al., 2022b; Awuah et al., 2023). In theory, at least, South Africa aims to manage its water resources in an integrated manner according to catchment-based Water Management Areas (WMAs). However, in reality, the establishment multistakeholder Catchment Management Agencies (CMAs), the formation of participatory Catchment Management Forums (CMFs), and the development of integrated Catchment Management Strategies (CMSs) has been very slow, with the result that water resource management in South Africa remains fragmented (Pollard, 2002; Funke et al., 2007; Pollard & du Toit, 2008; Claassen, 2013; Schreiner, 2013; Movik et al., 2016; Meissner et al., 2017). Furthermore, several authors have noted a distinct lack of integration in the management of land use and water resources in South Africa, attributing many of the country's water quality problems to this particular shortcoming (Claassen, 2013; Musakwa & Niekerk, 2013; Movik et al., 2016; DWS, 2017c; Knight, 2019b; Stats SA, 2019b; Adom & Simatele, 2022).[77] This necessitates urgent and ongoing work to develop tools and strategies that can facilitate the translation of the theoretical principles of IWRM into effective, on-the-ground management practices. In view of the above, the findings of the present study have several potential applications and implications for the integrated management and protection of water resources. While these may be especially pertinent to water resources management in South Africa, they are likely to be relevant in other contexts as well.

1. Focussing Attention on the Land-Water Nexus

Whereas one of IWRM's central principles is the need for cross-sectoral coordination in the management of water and other related sectors and resources, Lukat et al. (2023) has cautioned that an ongoing failure, in practice, to pay sufficient attention to the links between water and other sectors

[77] The negative impacts of land use on water resources in South Africa are frequently mentioned in various reports and publications. See, for instance, CSIR (2010), Dabrowski et al. (2013), du Plessis et al. (2014), Griffin et al. (2014), du Plessis et al. (2015), Moodley et al. (2015), Chidamba et al. (2016), Slaughter and Mantel (2017), van der Hoven et al. (2017), DWS (2018), Le Maitre et al. (2018), Namugize et al. (2018), Nde and Mathuthu (2018), Malherbe et al. (2019a), Petersen et al. (2020), Dlamini et al. (2021), Koekemoer et al. (2021), Nde et al. (2021), Nkosi et al. (2021), and Senbore and Oke (2021).

places the resource at risk of degradation and overuse. Swatuk and Qader (2023, p. 3) have also suggested that “what exactly is to be integrated is not very clear.” Therefore, while cross-sectoral coordination is a vital aspect of the IWRM paradigm, it may not always be clear to stakeholders which specific intersectoral issues require integrated management. In particular, Falkenmark et al. (2014, p. 406) have claimed that “for too long land issues have not been addressed properly within the IWRM discourse.” They have further asserted that while IWRM embraces the link between land and water in theory, it is often ignored in practice. The authors therefore have stressed the need for improved management tools which will give greater cross-sectoral visibility to the land-water nexus (ibid., p. 391ff) (see also Bandaragoda, 2006; Duda, 2017). Caldwell et al. (2023, p. 2ff) have similarly advocated for the development of “data and tools” which link natural vegetation and water quality, stating that such tools will enable policymakers and natural resource managers to make informed decisions regarding the integrated management of these connected resources. Finally, towards the end of her recently published book entitled *South Africa’s Water Predicament*, du Plessis (2023, p. 138), has asserted that “the quality of South Africa’s water resources will continue to worsen if no changes are made in how land and water resources are managed.” In the present case, the models provide incontrovertible proof that within catchments and riparian areas, land use in general—and the amount of natural vegetation cover in particular—is a critical determinant of water quality. Indeed, as per Day and Davies (2023, p. 232), while there are several factors that may affect water quality in a given region, “it is the ways in which the land is used by humans that often has the greatest effect of all.” Stakeholders and policymakers, who may have an interest in, or are otherwise responsible for, the management of these interlinked resources are thus equipped with further evidence of the need to manage land and water in a coordinated manner, being especially cognisant of how land use decisions will affect water resources. For instance, Falkenmark (2011, p. 13) has elsewhere emphasised that, owing to the nexus between the two resources, land use decisions are effectively water decisions. As the findings of this study support the validity of this assertion using robust scientific methods, they can be used in multistakeholder forums (such as CMAs and CMFs) to support an agenda of integrated land and water resources management. Nonetheless, it is essential to view land use management as one aspect of a broader integrated management strategy that is cognisant of the need to address the many complex issues that affect water quality (see “Caveat 4: The Necessity of an Integrated Approach” on pp. 179f).

2. Emphasising the Logic of (and need for) Catchment-Scale Management

Another key pillar of IWRM, which is strongly informed by the systems perspective that the framework adopts, is the devolution of responsibility for the management of water and related resources to the catchment scale (Molle, 2006; Cervoni et al., 2008; UNESCO, 2009; de Oliveira Vieira, 2020; GWP, 2022a; Kikoyo, 2023; Sugam et al., 2023). This principle is chiefly implemented through the establishment of institutional structures that support multidisciplinary research, inclusive participation, and intersectoral decision-making at this scale (so-called River Basin Organisations). This study reinforces the logic of this approach and emphasises the need to conduct research, develop plans, and implement management strategies within distinct drainage regions and the (sub-)catchments which constitute them. For instance, the models developed in this study, which provide strong evidence of catchment-scale relationships between natural vegetation cover and water quality, support IWRM's endorsement to devolve management to this scale. In other words, to quote Kikoyo (2023, p. 1), the results of this study strongly support "catchment-based research and application." Moreover, by conducting this research at an appropriate regional scale, it was possible to effectively minimise the potentially confounding influence of local environmental factors and thus isolate the impacts of LULC. This further reinforces the logic of conducting research within, and developing management strategies for, individual drainage regions that share similar geophysical and ecological characteristics.

Furthermore, governments, through the drafting and subsequent implementation of relevant policies and legislation, have a responsibility as the primary enablers of IWRM for creating an "enabling institutional environment" that fosters inclusive, participatory management at the "lowest appropriate level" (GWP, 2000, pp. 33–34). This includes, among other considerations, the promulgation of institutional arrangements that allow for coordinated land and water resources management at the catchment scale. Once again, the findings of the present study provide strong support for the establishment of such institutional arrangements, and further emphasise the pressing need in South Africa to focus on managing water resources at appropriate spatial scales (i.e., within individual drainage regions and the sub-catchments which they comprise). The proposed consolidation of South Africa's Water Management Areas (WMAs) into increasingly larger areas that are, from IWRM's catchment-management perspective, essentially unmanageable, is therefore a highly questionable strategy.[78] Centralising the administration of water resources management at increasingly larger geographical scales is not only the antithesis of IWRM's emphasis on subsidiarity but is also a policy which is unsupported by the findings of empirical studies such as this.

3. Providing Actors with Knowledge that is Supportive of Informed, Data-Driven, and Environmentally Sustainable Decision-Making

Participants of the 2023 United Nations Water Conference recently affirmed that science-based policies and information systems are critical for "strengthening the water sector and allowing for informed decision-making" and thus asserted that "decisions driven by data and information reinforce accountability, cooperation and stakeholder buy-in" (Kőrösi, 2023, pp. 3, 12). Given the inherent

[78] In 2012, in order to expedite the establishment of CMAs, the Department of Water Affairs consolidated the 19 original catchment-based WMAs into nine larger WMAs. Five years later, in 2017, the Department then announced a plan to create a single, national CMA (a decision that was rescinded the following year) (Munnik, 2020). The Department's latest strategy, according to the 2022 *National State of Water Report*, is to "reduce the number of CMAs from nine to six through the consolidation of WMAs" (DWS, 2022b, p. 5).

complexity that characterises the systems being managed, IWRM stresses that responsible actors not only need to operate from a shared knowledge base that fosters consensus-building, but also that they be provided with timely, accurate, and relevant information that will enable them to make informed decisions. Empowering stakeholders and policymakers with this kind of knowledge is essential if complex social-ecological systems are to be managed sustainably (Rogers et al., 2000; Turton et al., 2007; McDonnell, 2008; Roldán-Arias et al., 2023). However, incorporating scientific knowledge into water-related policies and plans presents its own unique challenges (Gooch & Stålnacke, 2010; Reed et al., 2014; Olander et al., 2017; Oliver & Cairney, 2019; Borden & Goodwin, 2022). According to Halbe et al. (2013, p. 2561), new tools and methods are required which can account for the "real-world" complexity that characterises water resources management, and thus enable knowledge transfer between scientists, policymakers, and stakeholders. Similarly, Grigg (2021, p. 3) has argued that researchers have the responsibility to provide water managers with information that is both understandable and trustworthy. Models are key tools in this respect, as they can help to reduce epistemological uncertainty among decision-makers by providing insights into the drivers, pressures, states, impacts, and responses of complex social-ecological and hydrological systems. The chief value of models in this respect is their ability to translate large quantities of "raw" data into useful information that can be more easily incorporated into integrated management plans by the relevant decision-makers. As explained in the *Encyclopaedia of Hydrological Sciences*, "raw data, in themselves, may be of little value unless some process of interpretation and presentation is applied to make them accessible and understandable to the users… policy makers, and the public" (Chapman et al., 2005, p. 1388). Many authors explicitly refer to models as tools that can promote informed intersectoral decision-making in the context of IWRM (Jeffrey & Gearey, 2006; Grigg, 2016; Ibisch et al., 2016; Stärz et al., 2016; Badham et al., 2019; de Oliveira Vieira, 2020). The GWP (2017), for instance, has noted that models are essential for translating the large quantities of data generated by different sectors into information that is understandable to stakeholders and decision-makers (see also, Rogers et al., 2000; McDonnell, 2008; GWP, 2013). This is particularly important considering the added complexity and uncertainty linked to climate change (Vollmer et al., 2023).

As demonstrated in the present study, not only can models provide actors with vital information about the systems being managed (e.g., the strong, nonlinear relationship found to exist between proportions of natural vegetation and water quality in the study area), but they can also be used to provide policymakers with specific, quantifiable guidelines that can assist them in achieving a sustainable balance between socioeconomic development and environmental protection. In the present study, for example, it was estimated that between 82 and 90% natural vegetation cover is required, on average, to maintain water quality at ecologically acceptable standards. The models also showed that these thresholds are not only applicable across the whole catchment but also within riparian areas, thus emphasising the need for a multi-scale approach to land use management. The models also suggest that if natural vegetation cover falls below 45% (at the catchment scale) or 60% (within riparian areas), significant increases in the rate and magnitude of pollution are likely. Estimated thresholds such as these, which are regionally specific and implementable at the catchment scale, can be incorporated, for example, into the integrated Catchment Management Strategies developed by CMAs for the WMAs under their management. As noted earlier, not only can these thresholds be applied retroactively to guide catchment restoration efforts, but they can also be applied proactively to protect catchments from levels of ecological disturbance that are likely to result in water quality problems.[79] By defining a "safe operating space" within which development can be pursued without causing unacceptable or irreversible harm to aquatic systems, these thresholds also relate directly to IWRM's attempt to balance socioeconomic development and resource protection.

It was further demonstrated that such thresholds can be used as benchmarks by which to evaluate the condition of individual sub-catchments, which can then be classified and/or prioritised for management interventions based on the likelihood of land-use-related water quality impairment. For instance, within the region for which the models were developed, it was possible to identify 55 quaternary catchments that contained less than the critical threshold of 45% natural vegetation cover. These catchments could therefore be prioritised for management interventions focused on restoring proportions of natural habitat to acceptable levels. Similarly, it was possible to identify catchments containing proportions of natural vegetation cover above the target threshold of 82%. In these catchments, proactive management efforts might be focused on maintaining the amount of natural vegetation at or above this threshold in order to protect water quality (see Figure 52 on p. 154).

It was also possible to evaluate the status of sub-catchments located within the Strategic Water Supply Areas (SWSAs) that overlap with the study area (see Figure 53 on p. 155). Given the disproportionate significance of these areas for national water security, protecting SWSAs from threats related to land use change is imperative (WWF, 2013; CER, 2023b; Stats SA, 2023). Lötter and Le Maitre (2021, p. 10), for instance, have identified land degradation, including the loss of natural vegetation through urban and agricultural expansion, as one of the major pressures that affect the ability of these areas to provide water. While all SWSAs in the study area were found to contain quaternary catchments with less natural vegetation cover than the target threshold of 82%, of far greater concern is the fact that some of these regions (to wit, the Table Mountain, Boland, Langeberg, and Tsitsikamma SWSAs) contained sub-catchments within which there was even less natural vegetation than the critical threshold of 45% (indicating a high likelihood of severe water quality impairment in these areas). Applying the thresholds in these strategically important areas facilitates an informed evaluation of the risk to water quality posed by land use transformations, thus highlighting sub-catchments in which urgent attention may be required. This methodology stands in contrast to the approach of Malherbe et al. (2019a) to

[79] Indeed, du Plessis (2023, p. 84) stresses the need for proactive water management strategies in South Africa.

identifying at-risk catchments, which, although simple and convenient, was not based on quantified, empirical relationships between observed LULC and water quality data for the region in question (see Appendix 5 for a critical review of their study).

Finally, the NPI itself served as a useful decision-support tool by translating the observed measurements of several water quality parameters into a single unitless score of overall water quality. By using the NPI in conjunction with site-specific water quality guidelines derived from local reference condition data, the index offered a contextually appropriate means by which to evaluate the degree to which water resources had been impacted by anthropogenic contamination. The value of this for IWRM is manifold. In the first instance, overall water quality cannot be adequately evaluated by considering any single parameter. A composite index such as the NPI, however, allows the aggregate impact of several parameters to be considered simultaneously. In addition, the NPI is able to translate large volumes of "raw" water quality data into a comparatively simple score of overall quality that is intuitively understandable to stakeholders and policymakers, empowering them to make data-driven decisions. Finally, as in the present study, the index can function as a convenient metric for use in further analyses—such as in the development of models and the estimation of thresholds—which themselves support consensus-building and informed decision-making among multiple stakeholders.

Limitations

1. Model and Threshold Specificity

The thresholds of natural vegetation cover estimated in this study, as well as the models from which they were derived, are necessarily contingent upon, and thus particular to, the specific methods and metrics by which water quality and natural vegetation were measured. Hence, had different methods and/or metrics been used in the measurement of either of these variables, the models and thresholds estimated using these data would have been different. For instance, in the present study, water quality was evaluated using Nemerow's Pollution Index and a particular selection of physiochemical parameters. Moreover, the observed measurements of these parameters were evaluated against guideline values derived from data collected over a particular period of time and from a specific set of reference sites. Had any of these methodological choices been modified, the results of the water quality analysis would have been altered. The same consideration holds true for (1) the aggregate metric used to classify natural vegetation, (2) the spatial scales at which proportions of natural vegetation were estimated, and (3) the metrics used to assess fragmentation. Acknowledging this is especially important when making comparisons between the findings of studies that have employed different metrics and methods in their analyses of either water quality or LULC. Nevertheless, the fact that there is considerable agreement across such a methodologically and geographically diverse body of research is particularly remarkable.

2. Sample Bias

The aim of this study was to model the relationship between LULC and water quality using a statistically unbiased and representative sample of sub-catchments that not only covered a wide variety of land use conditions (i.e., ranging from pristine to heavily modified) but which also contained a diverse mix of land uses (including, for instance, different combinations and proportions of agricultural, urban, and natural land cover). While the range and extent of natural vegetation varied widely across the sample, the same cannot be said of urban and agricultural land cover. There was, for instance, relatively little urban land in the sample of sub-catchments (many of the 58 sub-catchments contained no urban land use at all, and the maximum extent of urban land cover in any single sub-catchment was approximately 37% of the total catchment area). Although proportions of agricultural land cover varied to a much greater degree, there were nevertheless relatively few catchments in which agricultural land cover occupied more than 50% of the catchment area. Thus, a more broadly representative sample might also have contained a greater variety of sub-catchments with higher proportions and mixes of urban and agricultural land cover. Wilson and Weng (2010) also recognised the bias of most studies in this regard and suggested that there tends to be a focus on investigating the relationship between LULC and water quality in regions characterised by a particular kind of land use. However, due to the unavailability of water quality data at some NCMP monitoring locations, there were limits to the degree to which a truly independent and representative sample could be obtained. Nevertheless, proportions of natural vegetation cover—the key variable in this study—varied sufficiently across the sample to allow for fairly robust models to be estimated.

3. Limitations of Water Quality Indices

It was noted earlier that all composite water quality indices, including Nemerow's Pollution Index, are subject to several limitations. Among these limitations, criticisms of reductivism and issues relating to eclipsing and ambiguity have already been addressed in some detail. The subjective nature of parameter selection was also acknowledged, and restrictions imposed on the latter by data availability were disclosed. However, it is worth noting that if sufficient data were available, several additional parameters would also have been considered for inclusion in the index. Data for suspended solids and faecal coliform counts, for example, would have been particularly valuable as these parameters provide an indication of two important water quality issues[80] not reflected by any of the parameters that were available for selection in this study. In addition, notwithstanding the versatility of EC measurements, data for trace elements and heavy metals may have revealed other water quality issues not reflected by the selected parameters.

It must also be recognised that an evaluation of water quality based on data collected over any significant period of time will not reflect short-term water quality problems (Hallock, 2002;

[80] Namely, turbidity and microbiological contamination, which are often associated with anthropogenic land use.

Mladenović-Ranisavljević et al., 2018). For example, an apparently compliant index score based on data collected over several months (as in the present study) cannot unambiguously rule out shorter periods of non-compliance. Nevertheless, index scores based on measurements collected over longer periods should reflect any chronic water quality problems, which are arguably more relevant when considering the impacts of LULC on water quality (ibid.). It is also admittedly difficult, when using a composite water quality index, to account for possible interaction effects (i.e., synergism or antagonism) between different contaminants (e.g., the influence of pH on the toxicity of heavy metals). Ongoing work in the field of multiple criteria decision-making and machine learning may, in time, address some of the current shortcomings associated with composite water quality indices (see, for instance, Ding et al., 2023; Tabassum et al., 2023).

4. The "Ghost of Land Use Past"

One of the potentially confounding factors not accounted for in this study is the lag-time that may exist between changes in LULC and associated water quality impacts. Several authors, for instance, have noted that it may take a considerable period of time before the impacts of land use change on water quality become apparent. This phenomenon has been variously referred to as the "legacy effect" of land use change and, in some cases, the "ghost of land use past" (Harding et al., 1998; Allan, 2004a; Feld, 2013; Tayyebi et al., 2015; Martin et al., 2017; Vrebos et al., 2017; Morse et al., 2018; Chen & Olden, 2020; de Mello et al., 2020; Ramião et al., 2020; Zhang et al., 2023b). However, without access to reliable long-term LULC and water quality data spanning several decades, it is difficult to evaluate the legacy effect of land use change on water quality. Moreover, the results of the present study suggest that, potential legacy effects notwithstanding, contemporaneous LULC and water quality data can be effectively used to model the relationship between these two variables.

CHAPTER 8:
Conclusion

"Understanding statistically derived relationships between measures of LULC change and water quality and applying that understanding to land use planning is essential for the long-term protection of water resources."
—Lacher et al. (2019)

The use of statistical approaches to quantify the impacts of land use/land cover (LULC) on water quality is well documented in an established and yet rapidly growing body of literature. This includes the use of statistical models to estimate land use thresholds for water quality management. However, the potential utility of natural vegetation as a LULC metric for which thresholds can be estimated remains comparatively underexplored. This study therefore aimed to develop statistical models of the relationship between natural vegetation and water quality from which minimum thresholds of the former (i.e., natural vegetation) could be estimated for the integrated management and protection of the latter (i.e., water quality). Furthermore, given the enduring knowledge gaps, areas of uncertainty, and methodological issues that have been identified in this field, the ancillary objectives of this study included (1) evaluating the usefulness of Nemerow's Pollution Index, when used in combination with site-specific water quality guidelines derived from local reference data, as a tool for assessing overall water quality; (2) determining a contextually appropriate metric by which to classify natural vegetation for the region of interest; (3) assessing the significance of the location and/or fragmentation of natural vegetation (questions of scale and landscape configuration, respectively); and (4) minimising the potentially confounding influence of extraneous variables to isolate the impacts of LULC on water quality.

This chapter highlights the key findings of this study and reviews the significance and contribution of each finding to the existing body of research. The chapter also offers a synopsis of the relevance of these findings for the IWRM paradigm, specifically highlighting the value of models and thresholds of natural vegetation as tools that can facilitate the integration of scientific knowledge into multistakeholder policy and decision-making processes at appropriate geographical and administrative scales. The chapter closes by offering recommendations for future research.

Water Quality Analysis

Nemerow's Pollution Index (NPI) was used to evaluate the degree to which water quality was impaired across a representative sample of 58 sub-catchments located within the study area. Five water quality parameters (EC, TIN, PO_4, SO_4, and pH) were selected for inclusion in the index. Local reference condition data, collected from 18 undisturbed sites and thus assumed to be representative of natural conditions in the study area, were used to determine site-specific water quality guidelines against which the observed measurements of the selected parameters were evaluated.

> **Key Finding 1**
> The use of site-specific water quality guidelines, in concert with Nemerow's Pollution Index, provided a flexible, intuitive, and methodologically rigorous means by which to reduce the observed measurements of several parameters into a single, unitless score that reflected the overall level of impairment in each sub-catchment.

When evaluated using the NPI, contamination levels in 42 of the 58 sub-catchments were found to have exceeded ecologically acceptable limits to varying degrees. Eleven of these catchments had pollution index scores several times higher than the target value, indicating severe contamination at these locations. By examining the sub-index scores for each parameter, it was also possible to identify specific water quality concerns at the non-compliant sites (see Table 4 on p. 108). While high conductivity values were frequently the cause of non-compliance (indicative of high dissolved solid concentrations), several sub-catchments also had non-compliant sub-index scores for nitrogen and phosphorous (indicative of potentially eutrophic conditions). While a variety of methods have been used to evaluate water quality in the surveyed literature—including the use of composite water quality indices—this study demonstrated that the use of site-specific water quality guidelines, in concert with a Nemerow's Pollution Index, provided a flexible, intuitive, and methodologically rigorous means by which to reduce the observed measurements of several parameters into a single, unitless score that reflected the overall level of impairment in each of the selected sub-catchments.

Classifying Natural Vegetation

While most studies have focused on quantifying the negative impacts of either urban or agricultural land on water quality, thresholds based on metrics of these land cover classes may have limited applicability in mixed land use catchments. In contrast, irrespective of the mosaic of LULC present in a given catchment, the proportion of natural vegetation not only indicates the buffering potential of the landscape—and thus the level of protection from diffuse pollution offered to water resources—but also the degree to which the landscape may

> **Key Finding 2**
> When appropriately classified for a given region, natural vegetation may have greater predictive power than other more commonly used land use metrics (e.g., urban or agricultural land) and thus offer superior utility for modelling and threshold estimation.

have been disturbed by pollution-generating anthropogenic land use activities. When suitably classified, it therefore has universal applicability in most contexts. While most of the reviewed studies have equated natural vegetation with forests (an arguably improper assumption for regions in which other types of vegetation are dominant), this study demonstrates the advantage of identifying categories of vegetative land cover that, when classified together into a single aggregate land cover class, offer the most protection from diffuse pollution. Of all possible combinations of vegetative land cover found in the study area,[81] the aggregate class of natural vegetation that demonstrated the strongest negative correlation with pollution index scores across the sample of sub-catchments comprised (1) indigenous woody vegetation (itself an aggregation of indigenous forests, thickets, woodlands, and shrubland), (2) commercial forestry plantations, and (3) wetlands (see Table 6 on p. 118). The exclusion of grassland (higher proportions of which are typically associated with improved water quality) and the inclusion of commercial forestry plantations (which are usually assumed to be a source of diffuse pollution) is significant insofar as it demonstrates (1) the erroneousness of presuming that all locally occurring classes of indigenous flora should be included when classifying natural vegetation and (2) the subsequent importance of determining a contextually appropriate metric by which to classify natural vegetation when attempting to estimate minimum thresholds of the latter necessary for the protection of water resources.

Based on the results of previous studies, mean NDVI values were also considered as a possible metric by which to estimate the extent and health of natural vegetation cover across the sample of sub-catchments. However, contrary to expectations, it was found that pollution scores across the sample of sub-catchments were positively correlated with NDVI values (Spearman's $\rho = 0.340$; $p < 0.01$). Further investigation revealed that, rather than reflecting the extent of natural vegetation, NDVI values were strongly correlated with proportions of agricultural land cover in the catchments (Spearman's $\rho = 0.752$, $p < 0.01$) (see Figure 40 on p. 124). NDVI values can be ambiguous and must therefore be interpreted with care and reference to the landscape context.

However, when classified as described above and measured as a proportion of the catchment, natural vegetation was more strongly correlated with water quality (Spearman's $\rho = -0.729$; $p < 0.01$) than either agricultural (Spearman's $\rho = 0.621$; $p < 0.05$) or urban land cover (Spearman's $\rho = 0.333$; $p < 0.01$). Similarly, regression models that included natural vegetation as a land cover metric were able to explain up to 82% of the variation in pollution levels across the sample of sub-catchments. The foregoing thus supports the hypothesis that context-specific metrics of natural vegetation may have greater predictive power than other more commonly used land use metrics (e.g., urban or agricultural land) and thus offer superior utility for modelling and threshold estimation.

[81] Viz. indigenous forests, thickets, woodlands, commercial forestry plantations, shrubland, grassland, and wetlands.

Location and Scale

> **Key Finding 3**
> A multiscale approach to investigating and managing the impacts of land use on water quality is essential. It is not sufficient to manage land use at one scale (e.g., within riparian areas) while disregarding the potential impacts of land use at other scales. If minimum thresholds of natural vegetation are to be estimated and applied, it is important to do so at multiple spatial scales.

Research has shown that the relationship between LULC and water quality is scale-dependent and that the location of land use within a catchment can influence its impact on water resources. However, the scale at which LULC is reported to have the greatest influence on water quality varies among studies. Of the spatial scales evaluated in the present study, the strength of the correlation between proportions of natural vegetation and NPI scores was strongest at the whole-catchment scale (Spearman's ρ = –0.729; $p < 0.01$) and within a 200 m riparian buffer zone (RBZ) (Spearman's ρ = –0.735; $p < 0.01$) (see Table 6 on p. 118). The difference between the strength of the correlation at these two scales was statistically insignificant (i.e., the influence of land use at both scales was equally significant). This being the case, as other authors have also concluded, adopting a multiscale approach to investigating and managing the impacts of land use on water quality is essential (Strayer et al., 2003; Schiff & Benoit, 2007; Zhou et al., 2012; Ding et al., 2016; de Mello et al., 2018; Park & Lee, 2020; Song et al., 2021). The immediate implication of this is that in order to protect water resources from the impacts of diffuse pollution, it is not sufficient to manage land use at only one scale (e.g., within riparian areas) while disregarding the potential impacts of land use at other scales. If minimum thresholds of natural vegetation are to be estimated and applied, it is important to do so at multiple spatial scales.

Landscape Configuration

It is commonly assumed that as natural vegetation cover becomes more fragmented, its efficacy as a sink (and thus its ability to protect water resources from diffuse pollution) is reduced. This supposition is supported by the findings of several studies in which the fragmentation of natural vegetation was associated with poorer water quality.[82] In the present study, a novel landscape metric was proposed and tested to assess the possible significance of fragmentation. By incorporating a measure of fragmentation, the proposed Natural Vegetation Integrity Index (NVII) reflects both the amount of natural vegetation within the landscape *and* the degree to which that vegetation is fragmented. However, contrary to expectations, it could not be demonstrated in this study that the fragmentation of natural

[82] See, for example, Lee et al. (2009), Liu et al. (2012), Bateni et al. (2013), Bu et al. (2014), Ye et al. (2014), Shen et al. (2015), Ding et al. (2016), Shi et al. (2017), Liu and Yang (2018), Yirigui et al. (2019), Zhang et al. (2019), Liu et al. (2021), Wang et al. (2021), Wu and Lu (2021), de Mello et al. (2022), Li et al. (2022b), Zhong et al. (2022), Zhou et al. (2022), Aalipour et al. (2023), and Qiu et al. (2023).

vegetation in the study area had a statistically significant influence on its relationship with water quality**.** Instead, at all spatial scales evaluated, the proportion of the area under analysis occupied by natural vegetation (i.e., a simple compositional metric) was more strongly correlated with water quality than NVII scores (see Tables 9 and 11). It was proposed, however, that the generally low and largely unvarying degree of fragmentation across the sample of sub-catchments did not allow the significance of fragmentation to be fully evaluated. Consequently, the potential significance of landscape configuration should not be discounted.

> **Key Finding 4**
> Contrary to expectations, it could not be demonstrated that the fragmentation of natural vegetation in the study area had a statistically significant influence on its relationship with water quality. It was proposed, however, that the generally low and largely unvarying degree of fragmentation across the sample of sub-catchments did not allow the significance of fragmentation to be fully evaluated. Consequently, the potential significance of landscape configuration should not be discounted.

Local Environmental Variables and Seasonality

Previously published studies have demonstrated that local environmental variables (such as geology, ecology, and climate) can have an influence on LULC-WQ interactions. By selecting a study area across which such variables showed minimal variation (see the description of the study area in Chapter 5), the potentially confounding influence of these factors was effectively minimised. Geologically, for example, the study area chiefly comprises the sandstones, shales, and mudstones that are typical of the Cape Supergroup (thus reducing the influence of geological variation across the sample on water quality) (see Figure 19 on p. 90). Moreover, across the sample of sub-catchments, no statistically significant relationship was found between NPI scores and the estimated mean annual precipitation received by each sub-catchment (Spearman's ρ = –0.162; p = 0.226). Similarly, by using water quality data collected over a 24-month sampling period when calculating NPI scores, the latter reflected average long-term water quality conditions over both wet and dry seasons. The influence of intra-annual (i.e., seasonal) variations in precipitation, runoff, and discharge on water quality observations was thereby effectively eliminated.

> **Key Finding 5**
> Minimising the additional influence of environmental variables by conducting research at a regional scale made it possible to isolate the influence of LULC on water quality and thus ascribe causation with greater confidence. This confirms the necessity of conducting research of this kind within catchments on a regional basis, with associated requirements for management strategies to be developed and implemented at similar scales.

Therefore, in accordance with received wisdom, minimising the additional influence of these variables by conducting research at an appropriate regional scale made it possible to isolate the influence of LULC on water quality and thus ascribe causation with greater confidence. This confirms the necessity of conducting research of this kind within catchments on a regional basis, with associated requirements for management strategies to be developed and implemented at similar scales.

Catchment Size

> **Key Finding 6**
> The extent of natural vegetation cover in a catchment has sufficient explanatory power to model variances in water quality irrespective of differences in catchment size. Consequently, the estimated thresholds of natural vegetation are applicable across catchments of different size within the region for which the models were developed.

A positive correlation of moderate strength was found to exist between catchment size and NPI scores across the sample of sub-catchments (Spearman's ρ = 0.513; p < 0.01). The fact that larger catchments have a greater land-surface area from which contaminants can be mobilised during precipitation events may explain this, although given the greater distance that stormwater must travel in larger catchments, the infiltration capacity and interception potential in these catchments likewise increase (Pilgrim et al., 1982; Yang et al., 2017; Botter et al., 2019; Nobre et al., 2020; Dębska et al., 2022). Nevertheless, the subsequent inclusion of catchment area as an additional variable in multiple regression models did not offer any increased predictive power or improvements in model accuracy (i.e., the explanatory power of natural vegetation cover was not improved on by including catchment size as an additional variable). Importantly, this suggests that the extent of natural vegetation cover in a catchment has sufficient explanatory power to account for variances in water quality irrespective of differences in catchment size. Consequently, the estimated thresholds of natural vegetation are applicable across catchments of different size within the region for which the models were developed.

Threshold Estimation

Statistical analyses revealed a negative and nonlinear relationship between proportions of natural vegetation cover and the degree to which water quality was impaired at both the whole-catchment and 200 m RBZ scales (see Figures 41 and 48 on pp. 134 and 146). This not only suggests that a loss of natural vegetation cover is likely to result in water quality impairment (corroborating a well-established finding in the existing literature), but also that a marked increase in both the magnitude and rate of pollution can be expected when natural vegetation cover drops below certain critical thresholds. In addition, six outliers that did not conform to the overall pattern of the data were also detected in the sample. In each case, the catchments in question had anomalously high NPI scores relative to the proportions of natural vegetation they contained. In four of these instances, this was attributed to anthropogenic land use directly upstream of the water quality monitoring points. Through iterative analyses of the residual error of the observations, the discordancy of the six outliers was formally confirmed as statistically unreasonable and the points themselves were thus found to be unrepresentative of the larger sample. Once removed from the sample, not only did the regression models contain less error, but the models were subsequently able to explain between 69% and 82% of the variability in the sample (at the 200 m RBZ and whole-catchment scales, respectively).

> **Key Finding 7**
> It was estimated that, at both spatial scales, very high proportions of natural vegetation cover (82–90%) must be maintained to prevent unacceptable levels of contamination. Furthermore, if proportions of natural vegetation cover fall below approximately 60% (when measured within riparian areas) or 45% (if measured across the whole catchment), already non-compliant pollution levels are expected to increase rapidly and dramatically. These results are comparable with those reported in other studies.

Target and precautionary NPI scores provided water quality benchmarks upon which tiered regulatory thresholds of natural vegetation could be based. From the regression equations, it was therefore estimated that, at both spatial scales, very high proportions of natural vegetation cover (82–90%) must be maintained to prevent unacceptable levels of contamination. The upper threshold value, which is approximately 90% at both scales, is proposed as a precautionary threshold at which preventative management interventions are triggered in relatively pristine catchments of high ecological importance. The lower threshold values, which range from 82–85% at the whole-catchment and RBZ scales respectively, are recommended as more general management targets at which to maintain levels of natural vegetation in order to protect water resources from unacceptable contamination (see Table 18 on p. 174 for a summary). Furthermore, breakpoint analysis also suggests that if proportions of natural vegetation cover fall below approximately 60% (when measured within riparian areas) or 45% (if measured across the whole catchment), already non-compliant pollution levels are expected to increase rapidly and dramatically (see Figures 50 and 51). These results are comparable with the results of other studies in which various thresholds of natural vegetation, ranging from 45% (Zhong et al., 2022) to between 80 and 90% (Death & Collier, 2010), were found to be protective of water quality. The review by Morse et al. (2018) similarly concluded that water quality tends to deteriorate when natural vegetation falls below 60–90% of the catchment area.

As proof of principle, the estimated thresholds were applied across the study area to highlight quaternary catchments in which proportions of natural vegetation fell below the specified values (see Figure 52 on p. 154). This allowed for the identification of catchments in which pollution derived from anthropogenic land use was likely to, or may have already, exceeded ecologically acceptable limits.

Implications and Applications for IWRM

While the deadline for achieving the SDGs is fast approaching (Tollefson, 2023), the United Nations (2023a, 2023b) has alarmingly reported that progress towards achieving several of these goals is off track (including progress towards the sustainable management of water resources through the implementation of IWRM, as outlined in SDG 6). Moreover, despite multi-level commitments to the implementation of IWRM in South Africa, water resources remain particularly vulnerable to diffuse pollution owing to a persistent lack of data-driven coordination in the management of land and water resources (Pollard, 2002; Funke et al., 2007; Pollard & du Toit, 2008; Dabrowski et al., 2013; Movik et al., 2016; DWS, 2017e; Hughes, 2019; Stats SA, 2019a). While several previous studies have investigated links between land use and water quality in South Africa, the majority have simply affirmed that agricultural land and human settlements are associated with negative water quality impacts (see Appendix 5). Few studies have offered quantifiable, site-specific management targets (e.g., land use thresholds) based on robust empirical analyses. The present study, however, provides several specific applications and recommendations for integrated water resources management.

1. Focussing Attention on the Land-Water Nexus

Although the need to manage land and water resources in an integrated manner is frequently emphasised in the literature, there are concerns that, in practice, land use management has not received sufficient attention in the context of IWRM. A number of authors have claimed that not enough is currently being done to manage the two resources in a coordinated manner and that improved tools are therefore needed to give the land-water nexus greater visibility, thereby highlighting the need for integrated land and water management strategies (e.g., Bandaragoda, 2006; Calder, 2012; Falkenmark et al., 2014; Duda, 2017). Research that promotes an improved understanding of the land-water nexus among policymakers and stakeholders, thus strengthening their ability to build consensus around this issue, is essential. This study therefore adds to the ever-growing body of evidence that demonstrates a clear link between land use and water quality and thus reinforces the need for intersectoral coordination in the management of land and water resources. The study also demonstrates that the health of receiving waters is closely associated with the extent of natural vegetation preserved across catchments and within riparian areas. The results further suggest that relatively high proportions of natural vegetation need to be maintained in these areas in order to protect water quality. Moreover, the study indicates that there are critical thresholds of vegetation loss beyond which water quality is likely to deteriorate rapidly, rendering the resource unusable. These findings further emphasise the necessity of fostering awareness among stakeholders and policymakers about the fact that land use decisions have major implications for water quality and availability.

2. Emphasising Catchment-Scale Management

The systems perspective of IWRM emphasises the need to manage water and related resources at appropriate scales. This is typically achieved through catchment-scale management at various geographic and administrative levels (including international transboundary catchments, sub-national regional catchments, and local sub-catchments). This study demonstrates the necessity of conducting research at an appropriate regional scale in order to account for the influence of environmental variables when investigating and managing interactions between land and water resources. Moreover, the models developed in this study provide robust empirical evidence of catchment-scale relationships between LULC and water quality, thus reinforcing IWRM's emphasis on catchment-scale management. Therefore, in support of IWRM's call to devolve management to appropriate geographic and administrative scales, this study confirms that research, planning, and management can be logically implemented within distinct drainage regions and the (sub-)catchments which constitute them. Institutional arrangements (including funding and organisational structures) that support and facilitate ongoing research, policy development, and administration at these scales are thus imperative.

3. Providing Actors with Knowledge that is Supportive of Informed, Data-Driven, and Environmentally Sustainable Decision-Making

IWRM requires that stakeholders and policymakers make informed, data-driven decisions about the complex systems in which they have an interest or for which they have administrative responsibility. This requires that these actors have access to relevant and accurate information about these systems. However, incorporating empirical scientific knowledge into multistakeholder planning and policymaking processes remains a persistent challenge. Models have thus been widely advocated as decision-support tools by which raw data can be translated into useful information that is readily understandable to policymakers and other stakeholders, thus enabling them to make informed, rational decisions. Furthermore, thresholds derived from these models can also provide actors with objective targets that can guide their planning and decision-making efforts. By addressing several of the key knowledge gaps and methodological questions in the literature (see above), the present study has demonstrated the utility of relatively simple statistical models as tools for the estimation of region-specific, catchment-scale thresholds of natural vegetation cover that can guide the development of informed, balanced, and integrated resource management strategies. Thresholds such as those estimated in this study, in so far as they stipulate minimum areas of natural vegetation deemed necessary to protect water resources from diffuse pollution, are also supportive of IWRM's goal of achieving a sustainable balance between socioeconomic development and environmental protection. Moreover, the study also demonstrated the potential utility of composite water quality indices such as the NPI—specifically when used in conjunction with site-specific water quality guidelines derived from local reference condition data—as convenient tools for evaluating water quality in a way that not only provides stakeholders and policymakers with an intuitively understandable assessment of the status of water resources and the degree to which they have been impacted by human activity, but which also facilitates secondary analyses and the generation of additional knowledge to guide complex decision-making processes.

Limitations

In line with its principal aim, this study demonstrates the feasibility of using relatively simple statistical methods (as opposed to complex process-based models, such as SWAT, or emerging technologies such as artificial intelligence) to determine minimum thresholds of natural vegetation cover necessary to protect water resources from diffuse pollution. However, as observed by Cox and Cohen (2017, p. 28), the results of any scientific study are preliminary, subject to certain limitations, and open to correction, revision, and/or refinement. The findings of this study, for instance, are specific to the particular methods and metrics used, as well as to the region in which the study was conducted. Moreover, it must be noted that the models from which the thresholds were derived are themselves estimates based on a limited sample of catchments. The reported thresholds can therefore only serve as general guidelines. As the six outliers in the present sample emphasise, external factors not accounted for by the models mean that there will always be exceptions to the rule. A holistic, integrated approach to the management of water resources is thus essential. In line with the overall IWRM philosophy, the maintenance of natural vegetation above the recommended thresholds should thus be seen as complementary to a broad range of transdisciplinary strategies put in place to manage water quality. In addition, as the results make clear, it is not sufficient to maintain natural vegetation at or above the recommended thresholds only within riparian areas (nor is it advisable to apply the thresholds across the whole catchment while ignoring riparian land use). A multi-scale land use management approach is essential.

Notwithstanding these caveats, this thesis confirms the hypothesis that natural vegetation, when classified appropriately, offers remarkable utility as a metric for the purposes of statistical modelling and threshold estimation. While definite answers regarding the influence and/or significance of scale and landscape configuration remain elusive, thresholds estimated from these models have the potential to inform integrated, catchment-scale management approaches and therefore support the implementation of IWRM and the achievement of SDG 6 as it relates to the sustainable and integrated management of water resources.

Recommendations

The present work attempts to address several of the more significant knowledge gaps identified in the literature. Nevertheless, some of these relate to questions that will need to be continually considered in all ongoing work of this kind. For example, there is no definitive answer regarding the scale at which LULC is most significant. Moreover, it is not possible to conclude with any finality whether, or to what extent, the configuration of a landscape will influence this relationship. It is apparent that the answers to these questions depend largely on the context of the study. All that can be said with any certainty is that these are important considerations that need to be given due attention when studying the impacts of LULC on water quality.

Nevertheless, the present study was able to demonstrate that simple regression analysis can be used to model the relationship between water quality and natural vegetation cover, and that it is possible to use these models to estimate thresholds of the latter for the integrated management and protection of the former. It also explored the determination of suitable metrics for this purpose and discussed potential applications for the management of water quality in the region. It is therefore recommended that the methods developed here be extended to other regions (both within South Africa and beyond the country's borders) so that results can be compared and the methods further refined. It is possible, for example, that new methods for computing a composite water quality index, which are both less ambiguous and more statistically rigorous, may provide a superior means by which to evaluate water quality. As indicated above, research in the fields of fuzzy logic, machine learning, and multiple criteria decision-making shows promise in this regard (Abbasi & Abbasi, 2012; Banda & Kumarasamy, 2020b; Chidiac et al., 2023; Tabassum et al., 2023). A similar study using the SASS index (Dickens & Graham, 2002) may also prove insightful.

While the present study was conducted to test the proposed hypothesis within one of the management regions identified by Day et al. (1998), it would be of particular interest and utility to conduct a similar investigation at a national level, estimating thresholds of natural vegetation for the management of water quality at alternative geographical scales. It may be useful, for instance, to estimate thresholds for each of the biomes identified by Kleynhans et al. (2005), or for each of the primary drainage regions into which South Africa has been divided for management purposes (Pitman et al., 1998).

Finally, beyond hypothesising, it is impossible to gauge the degree to which the findings of this study may contribute to the implementation of IWRM and/or the protection of water quality in a given region. However, monitoring any implementation of the recommendations contained herein, and evaluating how they may support the integrated management and protection of water resources, provides another opportunity for further research.

References

Aalipour, M., Antczak, E., Dostál, T., & Jabbarian Amiri, B. (2022). Influences of Landscape Configuration on River Water Quality. *Forests*, *13*(2), 222. https://doi.org/10.3390/f13020222

Aalipour, M., Wu, N., Fohrer, N., Kianpoor Kalkhajeh, Y., & Jabbarian Amiri, B. (2023). Examining the Influence of Landscape Patch Shapes on River Water Quality. *Land*, *12*(5), 1011. https://doi.org/10.3390/land12051011

Abbasi, T., & Abbasi, S. A. (2011). Water quality indices based on bioassessment: The biotic indices. *Journal of Water and Health*, *9*(2), 330–348. https://doi.org/10.2166/wh.2011.133

Abbasi, T., & Abbasi, S. A. (2012). *Water Quality Indices*. Elsevier. https://doi.org/10.1016/C2010-0-69472-7

Abiodun, B. J., Naik, M., Mogebisa, T., Makhanya, N., Nguvava, M., Adaramola, R., & Yocgo, R. (2021). *Using Land-Use Change to Mitigate Impacts of Future Droughts on Water Yield in South Africa [WRC Project No. 2835/1/21]*. Water Research Commission.

Adom, R. K., & Simatele, M. D. (2022). Systemic and Structural Challenges to Sustainable Water Management in South Africa. *Journal of Environmental Assessment Policy and Management*, *22*(01n02), 2250002. https://doi.org/10.1142/s1464333222500028

Afuye, G. A., Kalumba, A. M., & Orimoloye, I. R. (2021). Characterisation of Vegetation Response to Climate Change: A Review. *Sustainability*, *13*(13), 7265. https://doi.org/10.3390/su13137265

Agboola, O. A., Downs, C. T., & O'Brien, G. (2020). A Multivariate Approach to the Selection and Validation of Reference Conditions in KwaZulu-Natal Rivers, South Africa [Original Research]. *Frontiers in Environmental Science*, *8*. https://doi.org/10.3389/fenvs.2020.584923

Ahearn, D. S., Sheibley, R. W., Dahlgren, R. A., Anderson, M., Johnson, J., & Tate, K. W. (2005). Land use and land cover influence on water quality in the last free-flowing river draining the western Sierra Nevada, California. *Journal of Hydrology*, *313*(3), 234–247. https://doi.org/10.1016/j.jhydrol.2005.02.038

Ahmed, J., Thakur, A., & Goyal, A. (2022). Industrial Wastewater and Its Toxic Effects. In *Biological Treatment of Industrial Wastewater* (pp. 1–14). The Royal Society of Chemistry. https://doi.org/10.1039/9781839165399-00001

Aighewi, I. T., Nosakhare, O. K., & Ishaque, A. B. (2013). Land Use-Land Cover Changes and Sewage Loading in the Lower Eastern Shore Watersheds and Coastal Bays of Maryland: Implications for Surface Water Quality. *Journal of Coastal Research*, *29*(5), 1073–1082. https://doi.org/10.2112/Jcoastres-D-11-00195.1

Albrich, K., Rammer, W., & Seidl, R. (2020). Climate change causes critical transitions and irreversible alterations of mountain forests. *Global Change Biology*, *26*(7), 4013-4027. https://doi.org/10.1111/gcb.15118

Allafta, H., & Opp, C. (2022). Understanding the Combined Effects of Land Cover, Precipitation and Catchment Size on Nitrogen and Discharge - A Case Study of the Mississippi River Basin. *Water*, *14*(6). https://doi.org/10.3390/w14060865

Allan, J. D. (2004a). Influence of land use and landscape setting on the ecological status of rivers. *Limnetica*, *23*(3-4), 187–197. https://ddd.uab.cat/record/26087

Allan, J. D. (2004b). Landscapes and riverscapes: The influence of land use on stream ecosystems. *Annual Review of Ecology Evolution and Systematics*, *35*(1), 257–284. https://doi.org/10.1146/annurev.ecolsys.35.120202.110122

Allan, J. D., Erickson, D. L., & Fay, J. (1997). The influence of catchment land use on stream integrity across multiple spatial scales. *Freshwater Biology*, *37*(1), 149–161. https://doi.org/10.1046/j.1365-2427.1997.d01-546.x

Allan, J. D., & Johnson, L. (1997). Catchment-scale analysis of aquatic ecosystems. *Freshwater Biology*, *37*(1), 107–111. https://doi.org/10.1046/j.1365-2427.1997.00155.x

Amiri, B. J., & Nakane, K. (2006). Modeling the Relationship Between Land Cover and River Water Quality in the Yamaguchi Prefecture of Japan. *Journal of Ecology and Environment*, *29*(4), 343–352. https://doi.org/10.5141/JEFB.2006.29.4.343

Amiri, B. J., & Nakane, K. (2008). Entire catchment and buffer zone approaches to modeling linkage between river water quality and land cover - A case study of Yamaguchi Prefecture, Japan. *Chinese Geographical Science*, *18*(1), 85–92. https://doi.org/10.1007/s11769-008-0085-6

Anderson, A., Karar, E., & Farolfi, S. (2008). Synthesis: IWRM Lessons for Implementation. *Water SA*, *34*(6), 665–669. https://doi.org/10.4314/wsa.v34i6.183667

Anderson, J. R. (1976). *A land use and land cover classification system for use with remote sensor data* (Vol. 964). US Government Printing Office.

Anderson, M. G., & McDonnell, J. J. (2005). *Encyclopedia of Hydrological Sciences*. Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa192

Antoniuk, T. (2006). *Developing and Implementing Thresholds in the Northwest Territories - A Discussion Paper [Report prepared for Environment Canada, Northern Division]*. Salmo Consulting Inc.

ANZG. (2018). *Australian and New Zealand Guidelines for Fresh and Marine Water Quality*. Australian and New Zealand Governments and Australian State and Territory Governments. Retrieved 5 September 2022 from https://www.waterquality.gov.au/anz-guidelines

Archer, E., du Toit, J., Engelbrecht, C., Hoffman, M. T., Landman, W., Malherbe, J., & Stern, M. (2022). The 2015-19 multi year drought in the Eastern Cape, South Africa: its evolution and impacts on agriculture. *Journal of Arid Environments*, *196*, 104630. https://doi.org/10.1016/j.jaridenv.2021.104630

Armitage, N., Fisher-Jeffes, L., Carden, K., Winter, K., Naidoo, V., Spiegel, A., Mauck, B., & Coulson, D. (2014). *Water Sensitive Urban Design (WSUD) for South Africa: Framework and Guidelines [WRC Report No. TT 588/14]*. Water Research Commission.

Armstrong McKay, D. I., Staal, A., Abrams, J. F., Winkelmann, R., Sakschewski, B., Loriani, S., Fetzer, I., Cornell, S. E., Rockström, J., & Lenton, T. M. (2022). Exceeding 1.5°C global warming could trigger multiple climate tipping points. *Science*, *377*(6611), eabn7950. https://doi.org/10.1126/science.abn7950

Arnold, C. L., & Gibbons, C. J. (1996). Impervious surface coverage - The emergence of a key environmental indicator. *Journal of the American Planning Association*, *62*(2), 243–258. https://doi.org/10.1080/01944369608975688

Asare, F., Palamuleni, L. G., & Ruhiiga, T. (2018). Land Use Change Assessment and Water Quality of Ephemeral Ponds for Irrigation in the North West Province, South Africa. *International Journal of Environmental Research and Public Health*, *15*(6). https://doi.org/10.3390/ijerph15061175

Attua, E. M., Ayamga, J., & Pabi, O. (2014). Relating land use and land cover to surface water quality in the Densu River basin, Ghana. *International Journal of River Basin Management*, *12*(1), 57–68. https://doi.org/10.1080/15715124.2014.880711

Awuah, A. K., Stuart-Hill, S., & Trotter-Boardman, D. (2023). Pandora's Box: assessing the current trends and challenges of IWRM in the uMngeni catchment. *Water Policy*, *25*(1), 23–37. https://doi.org/10.2166/wp.2023.183

Aziz, H. A., Abu Amr, S. S., & Hung, Y.-T. (2021). Surface Water Quality and Analysis. In L. K. Wang, M.-H. S. Wang, Y.-T. Hung, & N. K. Shammas (Eds.), *Integrated Natural Resources Management: Handbook of Environmental Engineering* (pp. 63–114). Switzerland: Springer Nature. https://doi.org/10.1007/978-3-030-55172-8_3

Badham, J., Elsawah, S., Guillaume, J. H. A., Hamilton, S. H., Hunt, R. J., Jakeman, A. J., Pierce, S. A., Snow, V. O., Babbar-Sebens, M., Fu, B., Gober, P., Hill, M. C., Iwanaga, T., Loucks, D. P., Merritt, W. S., Peckham, S. D., Richmond, A. K., Zare, F., Ames, D., & Bammer, G. (2019). Effective Modeling for Integrated Water Resource Management: a guide to contextual practices by phases and steps and future opportunities. *Environmental Modelling & Software*, *116*, 40–56. https://doi.org/10.1016/j.envsoft.2019.02.013

Bailey, A. K., & Pitman, W. V. (2016). *Water Resources of South Africa, 2012 Study (WR2012)*. Water Research Commission. https://waterresourceswr2012.co.za/

Bajjali, W. (2018). Watershed Delineation. In *ArcGIS for Environmental and Water Issues* (pp. 235–245). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-61158-7_14

Baker, A. (2005). Land Use and Water Quality. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 2925–2930). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa195

Baltodano, A., Agramont, A., Reusen, I., & van Griensven, A. (2022). Land Cover Change and Water Quality: How Remote Sensing Can Help Understand Driver & Impact Relations in the Lake Titicaca Basin. *Water*, *14*(7), 1021. https://doi.org/10.3390/w14071021

Banda, T. D., & Kumarasamy, M. V. (2020a). Aggregation Techniques Applied in Water Quality Indices. *Pollution Research*, *39*(2), 400–412.

Banda, T. D., & Kumarasamy, M. V. (2020b). Development of Water Quality Indices (WQIs): A Review. *Polish Journal of Environmental Studies*, *29*(3), 2011–2021. https://doi.org/10.15244/pjoes/110526

Banda, T. D., & Kumarasamy, M. V. (2020c). A Review of Existing Water Quality Indices (WQIs). *Pollution Research*, *39*(2), 489–514.

Bandaragoda, D. (2006). Water-Land Linkages: A relatively neglected issue in IWRM. In P. P. Mollinga, A. Dixit, & K. Athukorala (Eds.), *Integrated Water Resources Management. Global Theory, Emerging Practices and Local Needs.* (pp. 172–185). SAGE.

Barnard, S., Morgenthal, T. L., Stolz, M., & Venter, A. (2021). Impact of land-use and flow conditions on the phytoplankton of the Sabie River, South Africa. *Bothalia - African Biodiversity & Conservation*, *51*(1), 1–18. https://doi.org/10.38201/btha.abc.v51.i1.6

Barnett, V. (2004). *Environmental Statistics: Methods and Applications*. Chichester: John Wiley & Sons.

Barnett, V., & Lewis, T. (1994). *Outliers in Statistical Data* (3rd ed.). New York: Wiley.

Bartlett, K. (2022). *Fears Taps Could Run Dry in South Africa's Eastern Cape*. VOA News. Retrieved 7 September 2022 from https://www.voanews.com/a/fears-taps-could-run-dry-in-south-africa-s-eastern-cape-/6631973.html

Basnyat, P., Teeter, L. D., Flynn, K. M., & Lockaby, B. G. (1999). Relationships Between Landscape Characteristics and Nonpoint Source Pollution Inputs to Coastal Estuaries. *Environmental Management*, *23*(4), 539–549. https://doi.org/10.1007/s002679900208

Bate, G., Smailes, P., & Adams, J. (2004). A water quality index for use with diatoms in the assessment of rivers. *Water SA*, *30*(4), 493–499. https://doi.org/10.4314/wsa.v30i4.5101

Bateni, F., Fakheran, S., & Soffianian, A. (2013). Assessment of land cover changes & water quality changes in the Zayandehroud River Basin between 1997–2008. *Environmental Monitoring and Assessment*, *185*(12), 10511–10519. https://doi.org/10.1007/s10661-013-3348-3

Bates, B., Kundzewicz, Z., Wu, S., & Palutikof, J. (2008). *Climate Change and Water (Technical Paper of the Intergovernmental Panel on Climate Change)*. IPCC Secretariat. https://www.ipcc.ch/publication/climate-change-and-water-2/

Benkov, I., Varbanov, M., Venelinov, T., & Tsakovski, S. (2023). Principal Component Analysis and the Water Quality Index: A Powerful Tool for Surface Water Quality Assessment: A Case Study on Struma River Catchment, Bulgaria. *Water*, *15*(10), 1961. https://doi.org/10.3390/w15101961

Bennett, A. F., & Radford, J. Q. (2003). Know your ecological thresholds. *Thinking Bush*, *2*, 1–3. http://hdl.handle.net/10536/DRO/DU:30015256

Bhatt, G., Linker, L., Shenk, G., Bertani, I., Tian, R., Rigelman, J., Hinson, K., & Claggett, P. (2023). Water quality impacts of climate change, land use, and population growth in the Chesapeake Bay watershed. *JAWRA Journal of the American Water Resources Association*. https://doi.org/10.1111/1752-1688.13144

Bierschenk, A. M., Savage, C., Townsend, C. R., & Matthaei, C. D. (2012). Intensity of Land Use in the Catchment Influences Ecosystem Functioning Along a Freshwater-Marine Continuum. *Ecosystems*, *15*(4), 637–651. https://doi.org/10.1007/s10021-012-9536-0

Bilalova, S., Newig, J., Tremblay-Lévesque, L.-C., Roux, J., Herron, C., & Crane, S. (2023). Pathways to water sustainability? A global study assessing the benefits of integrated water resources management. *Journal of Environmental Management*, *343*, 118179. https://doi.org/10.1016/j.jenvman.2023.118179

Bischoff-Mattson, Z., Maree, G., Vogel, C., Lynch, A., Olivier, D., & Terblanche, D. (2020). Shape of a water crisis: practitioner perspectives on urban water scarcity and 'Day Zero' in South Africa. *Water Policy*, *22*(2), 193–210. https://doi.org/10.2166/wp.2020.233
Biswas, A. K. (1976). *Systems Approach to Water Management*. New York: McGraw-Hill.
Biswas, A. K. (2004). Integrated Water Resources Management: A Reassessment. *Water International*, *29*(2), 248–256. https://doi.org/10.1080/02508060408691775
Biswas, A. K. (2008a). Current directions: integrated water resources management – a second look. *Water International*, *33*(3), 274–278. https://doi.org/10.1080/02508060802272812
Biswas, A. K. (2008b). Integrated Water Resources Management: Is it Working? *Water Resources Development*, *24*(1), 5–22. https://doi.org/10.1080/07900620701871718
Biswas, A. K., & Tortajada, C. (2016). Water security, economic growth and sustainable development: linking society, economy and environment. *Geographer*, 18–19. https://eprints.gla.ac.uk/241599/
Biswas, A. K., & Tortajada, C. (2019). Water quality management: a globally neglected issue. *International Journal of Water Resources Development*, *35*(6), 913–916. https://doi.org/10.1080/07900627.2019.1670506
Black, R. W., Munn, M. D., & Plotnikoff, R. W. (2004). Using macroinvertebrates to identify biota–land cover optima at multiple scales in the Pacific Northwest, USA. *Journal of the North American Benthological Society*, *23*(2), 340–362. https://doi.org/10.1899/0887-3593(2004)023<0340:Umtibc>2.0.Co;2
Blatná, D. (2006). Outliers in Regression. *Trutnov*, *30*, 1–6.
Bohenek, J. R., & Sulliván, S. M. P. (2022). Inland Waters—Rivers: Land Use and Water Quality. In T. Mehner & K. Tockner (Eds.), *Encyclopedia of Inland Waters (Second Edition)* (pp. 453–470). Oxford: Elsevier. https://doi.org/10.1016/B978-0-12-819166-8.00167-5
Bonansea, M., Bazán, R., Germán, A., Ferral, A., Beltramone, G., Cossavella, A., & Pinotti, L. (2021). Assessing land use and land cover change in Los Molinos reservoir watershed and the effect on the reservoir water quality. *Journal of South American Earth Sciences*, *108*, 103243. https://doi.org/10.1016/j.jsames.2021.103243
Bonansea, M., Ledesma, C., & Rodriguez, M. (2016). Assessing the impact of land use and land cover on water quality in the watershed of a reservoir. *Applied Ecology and Environmental Research*, *14*(2), 447–456. https://doi.org/10.15666/aeer/1402_447456
Booth, D. B., Hartley, D., & Jackson, R. (2002). Forest Cover, Impervious-Surface Area, and the Mitigation of Stormwater Impacts. *JAWRA Journal of the American Water Resources Association*, *38*(3), 835–845. https://doi.org/10.1111/j.1752-1688.2002.tb01000.x
Booth, D. B., & Jackson, C. R. (1997). Urbanization of Aquatic Systems: Degradation Thresholds, Stormwater Detection, and the Limits of Mitigation. *JAWRA Journal of the American Water Resources Association*, *33*(5), 1077–1090. https://doi.org/10.1111/j.1752-1688.1997.tb04126.x
Borchardt, D., Ibisch, R. B., & Bogardi, J. J. (2016). *Integrated Water Resources Management: Concept, Research and Implementation*. Cham: Springer. https://doi.org/10.1007/978-3-319-25071-7_1
Borden, C., & Goodwin, P. (2022). A framework tool for conceptualizing integrated water resources for sustainable water management. *River*, 1–20. https://doi.org/10.1002/rvr2.14
Bosman, C., & Kidd, M. (2009). Water Pollution. In H. A. Strydom, N. D. King, R. F. Fuggle, & M. A. Rabie (Eds.), *Environmental Management in South Africa* (2nd ed., pp. 630–698). Cape Town: Juta.
Bosman, C., Kidd, M., & Alberts, R. (2018). Water Quality Management. In N. King, H. Strydom, & F. Retief (Eds.), *Environmental Management in South Africa* (3rd ed., pp. 995–1054). Cape Town: Juta.
Botter, M., Burlando, P., & Fatichi, S. (2019). Anthropogenic and catchment characteristic signatures in the water quality of Swiss rivers: a quantitative assessment. *Hydrol. Earth Syst. Sci.*, *23*(4), 1885–1904. https://doi.org/10.5194/hess-23-1885-2019
Bowes, R. E., Bergman, E., Donadi, S., Greenberg, L., Sandin, L., & Lind, L. (2023). Landscape features control river's confluences water quality and tributary fish composition. *River Research and Applications*. https://doi.org/10.1002/rra.4133

Boyd, C. E. (2020). *Water Quality: An Introduction* (3rd ed.). Cham, Switzerland: Springer Nature. https://doi.org/10.1007/978-3-030-23335-8
Brabec, E., Schulte, S., & Richards, P. L. (2002). Impervious surfaces and water quality: a review of current literature and its implications for watershed planning. *Journal of Planning Literature*, *16*(4), 499–514. https://doi.org/10.1177/088541202400903563
Brabec, E. A. (2009). Imperviousness and Land-Use Policy: Toward an Effective Approach to Watershed Planning. *Journal of Hydrologic Engineering*, *14*(4), 425–433. https://doi.org/10.1061/(ASCE)1084-0699(2009)14:4(425)
Brady, J. P., Ayoko, G. A., Martens, W. N., & Goonetilleke, A. (2015). Development of a hybrid pollution index for heavy metals in marine and estuarine sediments. *Environmental Monitoring and Assessment*, *187*(5), 306. https://doi.org/10.1007/s10661-015-4563-x
Breulmann, M., Khurelbaatar, G., Sanne, M., van Afferden, M., Subah, A., & Müller, R. A. (2022). Integrated Wastewater Management for the Protection of Vulnerable Water Resources in the North of Jordan. *Sustainability*, *14*(6), 3574. https://doi.org/10.3390/su14063574
Briciu, A. E., Graur, A., & Oprea, D. I. (2020). Water Quality Index of Suceava River in Suceava City Metropolitan Area. *Water*, *12*(8), 2111. https://doi.org/10.3390/w12082111
Brogna, D., Dufrêne, M., Michez, A., Latli, A., Jacobs, S., Vincke, C., & Dendoncker, N. (2018). Forest cover correlates with good biological water quality. Insights from a regional study (Wallonia, Belgium). *Journal of Environmental Management*, *211*, 9–21. https://doi.org/10.1016/j.jenvman.2018.01.017
Brogna, D., Michez, A., Jacobs, S., Dufrêne, M., Vincke, C., & Dendoncker, N. (2017). Linking Forest Cover to Water Quality: A Multivariate Analysis of Large Monitoring Datasets. *Water*, *9*(3), 176. https://doi.org/10.3390/w9030176
Bu, H., Meng, W., Zhang, Y., & Wan, J. (2014). Relationships between land use patterns and water quality in the Taizi River basin, China. *Ecological Indicators*, *41*, 187–197. https://doi.org/10.1016/j.ecolind.2014.02.003
Buck, O., Niyogi, D. K., & Townsend, C. R. (2004). Scale-dependence of land use effects on water quality of streams in agricultural catchments. *Environmental Pollution*, *130*(2), 287–299. https://doi.org/10.1016/j.envpol.2003.10.018
Calder, I. R. (1993). Hydrologic Effects of Land Use Change. In D. Maidment (Ed.), *Handbook of Hydrology*. New York: McGraw Hill.
Calder, I. R. (2005). Integrated Land and Water Resources Management. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 2880–2893). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa192
Calder, I. R. (2012). *Blue revolution: Integrated land and water resources management* (2nd ed.). London: Routledge.
Caldwell, P. V., Martin, K. L., Vose, J. M., Baker, J. S., Warziniack, T. W., Costanza, J. K., Frey, G. E., Nehra, A., & Mihiar, C. M. (2023). Forested watersheds provide the highest water quality among all land cover types, but the benefit of this ecosystem service depends on landscape context. *Science of The Total Environment*, *882*, 163550. https://doi.org/10.1016/j.scitotenv.2023.163550
Calijuri, M. L., Castro, J. d. S., Costa, L. S., Assemany, P. P., & Alves, J. E. M. (2015). Impact of land use/land cover changes on water quality and hydrological behavior of an agricultural subwatershed. *Environmental Earth Sciences*, *74*(6), 5373–5382. https://doi.org/10.1007/s12665-015-4550-0
Canning, A. D., & Death, R. G. (2019). Ecosystem Health Indicators—Freshwater Environments. In B. Fath (Ed.), *Encyclopedia of Ecology* (2nd ed., pp. 46–60). Oxford: Elsevier. https://doi.org/10.1016/B978-0-12-409548-9.10617-7
Capon, S. J., Lynch, A. J. J., Bond, N., Chessman, B. C., Davis, J., Davidson, N., Finlayson, M., Gell, P. A., Hohnberg, D., Humphrey, C., Kingsford, R. T., Nielsen, D., Thomson, J. R., Ward, K., & Nally, R. M. (2015). Regime shifts, thresholds and multiple stable states in freshwater ecosystems; a critical appraisal of the evidence. *Science of The Total Environment*, *534*, 122–130. https://doi.org/10.1016/j.scitotenv.2015.02.045

Cardwell, H. E., Cole, R. A., Cartwright, L. A., & Martin, L. A. (2006). Integrated Water Resources Management: Definitions and Conceptual Musings. *Journal of Contemporary Water Research & Education*, *135*, 8–18. https://doi.org/10.1111/j.1936-704X.2006.mp135001002.x

Carle, M. V., Halpin, P. N., & Stow, C. A. (2005). Patterns of watershed urbanization and impacts on water quality. *JAWRA Journal of the American Water Resources Association*, *41*(3), 693–708. https://doi.org/10.1111/j.1752-1688.2005.tb03764.x

Carpio, O. V., & Fath, B. D. (2011). Assessing the environmental impacts of urban growth using land use/land cover, water quality and health indicators: A case study of Arequipa, Peru. *American Journal of Environmental Sciences*, *7*(2), 90–101. https://doi.org/10.3844/ajessp.2011.90.101

Carr, E. R., Wingard, P. M., Yorty, S. C., Thompson, M. C., Jensen, N. K., & Roberson, J. (2007). Applying DPSIR to sustainable development. *International Journal of Sustainable Development & World Ecology*, *14*(6), 543–555. https://doi.org/10.1080/13504500709469753

CCME. (2016). *Guidance Manual for Developing Nutrient Guidelines for Rivers and Streams*. Canadian Council of Ministers of the Environment.

Cecílio, R. A., Pimentel, S. M., & Zanetti, S. S. (2019). Modeling the influence of forest cover on streamflows by different approaches. *CATENA*, *178*, 49–58. https://doi.org/10.1016/j.catena.2019.03.006

CER. (2023a). *The Backdrop*. Centre for Environmental Rights. Retrieved 20 July 2023 from https://water.cer.org.za/about/the-backdrop#

CER. (2023b). *Threats*. Centre for Environmental Rights. Retrieved 20 July 2023 from https://water.cer.org.za/about/threats

Cervoni, L., Biro, A., & Beazley, K. (2008). Implementing Integrated Water Resources Management: The Importance of Cross-Scale Considerations and Local Conditions in Ontario and Nova Scotia. *Canadian Water Resources Journal / Revue canadienne des ressources hydriques*, *33*(4), 333–350. https://doi.org/10.4296/cwrj3304333

Chambers, P. A., Culp, J. M., Roberts, E. S., & Bowerman, M. (2012a). Development of Environmental Thresholds for Streams in Agricultural Watersheds. *Journal of Environmental Quality*, *41*(1), 1–6. https://doi.org/10.2134/jeq2011.0338

Chambers, P. A., McGoldrick, D. J., Brua, R. B., Vis, C., Culp, J. M., & Benoy, G. A. (2012b). Development of Environmental Thresholds for Nitrogen and Phosphorus in Streams. *Journal of Environmental Quality*, *41*(1), 7–20. https://doi.org/10.2134/jeq2010.0273

Chaplin-Kramer, R., Hamel, P., Sharp, R., Kowal, V., Wolny, S., Sim, S., & Mueller, C. (2016). Landscape configuration is the primary driver of impacts on water quality associated with agricultural expansion. *Environmental Research Letters*, *11*(7), 074012. https://doi.org/10.1088/1748-9326/11/7/074012

Chapman, D. V., Meybeck, M., & Peters, N. E. (2005). Water Quality Monitoring. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 1387–1408). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa195

Chapman, P., Kay, P., Mitchell, G., & Pitts, C. (2020). Surface Water Quality. In J. Holden (Ed.), *Water Resources: An Integrated Approach* (2nd ed., pp. 99–150). London: Routledge. https://doi.org/10.4324/9780429448270

Chatterjee, S., & Hadi, A. S. (2012). *Regression Analysis By Example* (5th ed.). Hokoken, New Jersey: John Wiley & Sons.

Chatterjee, S., & Simonoff, J. S. (2013). *Handbook of Regression Analysis*. Hoboken, New Jersey: Wiley.

Chemeri, L., Cabassi, J., Taussi, M., & Venturi, S. (2023). Development and testing of a new flexible, easily and widely applicable chemical water quality index (CWQI). *Journal of Environmental Management*, *348*, 119383. https://doi.org/10.1016/j.jenvman.2023.119383

Chen, C. W. S., Chan, J. S. K., Gerlach, R., & Hsieh, W. Y. L. (2011). A comparison of estimators for regression models with change points. *Statistics and Computing*, *21*(3), 395–414. https://doi.org/10.1007/s11222-010-9177-0

Chen, K., & Olden, J. D. (2020). Threshold responses of riverine fish communities to land use conversion across regions of the world. *Global Change Biology*, *26*(9), 4952–4965. https://doi.org/10.1111/gcb.15251

Chen, W., Wang, J., Cao, X., Ran, H., Teng, D., Chen, J., He, X., & Zheng, X. (2021). Possibility of using multiscale normalized difference vegetation index data for the assessment of total suspended solids (TSS) concentrations in surface water: A specific case of scale issues in remote sensing. *Environmental Research*, *194*, 110636. https://doi.org/10.1016/j.envres.2020.110636

Chen, X., Zhou, W., Pickett, S. T. A., Li, W., & Han, L. (2016). Spatial-Temporal Variations of Water Quality and Its Relationship to Land Use and Land Cover in Beijing, China. *International Journal of Environmental Research and Public Health*, *13*(5), 449. https://doi.org/10.3390/ijerph13050449

Cheng, C., Zhang, F., Shi, J., & Kung, H.-T. (2022). What is the relationship between land use and surface water quality? A review and prospects from remote sensing perspective. *Environmental Science and Pollution Research*, *29*(38), 56887–56907. https://doi.org/10.1007/s11356-022-21348-x

Chiang, L.-C., Wang, Y.-C., Chen, Y.-K., & Liao, C.-J. (2021). Quantification of land use/land cover impacts on stream water quality across Taiwan. *Journal of Cleaner Production*, *318*, 128443. https://doi.org/10.1016/j.jclepro.2021.128443

Chidamba, L., Cilliers, E., & Bezuidenhout, C. C. (2016). Spatial and Temporal Variations in Pollution Indicator Bacteria in the Lower Vaal River, South Africa. *Water Environment Research*, *88*(11), 2142–2149. https://doi.org/10.2175/106143016X14733681695528

Chidiac, S., El Najjar, P., Ouaini, N., El Rayess, Y., & El Azzi, D. (2023). A comprehensive review of water quality indices (WQIs): history, models, attempts and perspectives. *Reviews in Environmental Science and Bio/Technology*. https://doi.org/10.1007/s11157-023-09650-7

Chikozho, C., & Mapedza, E. (2017). Free-Market Economics and Developmental Statism as Political Paradigms: Implications for Water Governance Theory and Practice in Developing Countries. In E. Karar (Ed.), *Freshwater Governance for the 21st Century* (pp. 51–79). Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-43350-9

Chu, H.-J., Liu, C.-Y., & Wang, C.-K. (2013). Identifying the Relationships between Water Quality and Land Cover Changes in the Tseng-Wen Reservoir Watershed of Taiwan. *International Journal of Environmental Research and Public Health*, *10*(2), 478–489. https://doi.org/10.3390/ijerph10020478

Ciampittiello, M., Marchetto, A., & Boggero, A. (2023). Water Resources Management under Climate Change: A Review. *Preprints*. https://doi.org/10.20944/preprints202306.0726.v1

Claassen, M. (2013). Integrated water resource management in South Africa. *International Journal of Water Governance*, *1*(3-4), 323–338. https://doi.org/10.7564/13-IJWG12

Clapcott, J. E., Collier, K. J., Death, R. G., Goodwin, E. O., Harding, J. S., Kelly, D., Leathwick, J. R., & Young, R. G. (2012). Quantifying relationships between land-use gradients and structural and functional indicators of stream ecological integrity. *Freshwater Biology*, *57*(1), 74–90. https://doi.org/10.1111/j.1365-2427.2011.02696.x

Clark, B., & Ractliffe, G. (2007). *Berg River Baseline Monitoring Programme (Final Report - Volume 5: Synthesis) [DWAF Report No. P WMA 19/G10/00/2107]*. Pretoria: Department of Water Affairs & Forestry.

Clark, K. E., Bravo, V. D., Giddings, S. N., Davis, K. A., Pawlak, G., Torres, M. A., Adelson, A. E., César-Ávila, C. I., Boza, X., & Collin, R. (2022). Land Use and Land Cover Shape River Water Quality at a Continental Caribbean Land-Ocean Interface [Original Research]. *Frontiers in Water*, *4*. https://doi.org/10.3389/frwa.2022.737920

Claros, M., & de Oliveira Vieira, E. (2020). Preface. In E. de Oliveira Vieira, S. Sandoval-Solis, V. de Albuquerque Pedrosa, & J. P. Ortiz-Partida (Eds.), *Integrated Water Resource Management: Cases from Africa, Asia, Australia, Latin America and USA* (pp. vi–vii). Switzerland: Springer. https://doi.org/10.1007/978-3-030-16565-9

Clément, F., Ruiz, J., Rodríguez, M. A., Blais, D., & Campeau, S. (2017). Landscape diversity and forest edge density regulate stream water quality in agricultural catchments. *Ecological Indicators*, *72*, 627–639. https://doi.org/10.1016/j.ecolind.2016.09.001

Clift, R., Sim, S., King, H., Chenoweth, J. L., Christie, I., Clavreul, J., Mueller, C., Posthuma, L., Boulay, A.-M., Chaplin-Kramer, R., Chatterton, J., DeClerck, F., Druckman, A., France, C., Franco, A., Gerten, D., Goedkoop, M., Hauschild, M. Z., Huijbregts, M. A. J., . . . Murphy, R.

(2017). The Challenges of Applying Planetary Boundaries as a Basis for Strategic Decision-Making in Companies with Global Supply Chains. *Sustainability*, *9*(2), 279. https://doi.org/10.3390/su9020279

Cole, L. J., Stockan, J., & Helliwell, R. (2020). Managing riparian buffer strips to optimise ecosystem services: A review. *Agriculture, Ecosystems & Environment*, *296*, 106891. https://doi.org/10.1016/j.agee.2020.106891

Congalton, R. G., & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices* (3rd ed.). CRC Press. https://doi.org/10.1201/9780429052729

Cooke, S. J., Vermaire, J. C., Baulch, H. M., Birnie-Gauvin, K., Twardek, W. M., & Richardson, J. S. (2022). Our failure to protect the stream and its valley: A call to back off from riparian development. *Freshwater Science*, *41*(2), 183–194. https://doi.org/10.1086/719958

Cooper, J. A. G., Rammn, A. E. L., & Harrison, T. D. (1994). The Estuarine Health Index: A New Approach to Scientific Transfer. *Ocean & Coastal Management*, *25*, 103–141. https://doi.org/10.1016/0964-5691(94)90043-4

Cosgrove, W., & Rijsberman, F. (2000). *World Water Vision: Making Water Everybody's Business*. London: Earthscan/World Water Council. https://doi.org/10.4324/9781315071763

Cox, B., & Cohen, A. (2017). *Forces of Nature*. HarperCollins Publishers.

Cramer, W. P., & Leemans, R. (1993). Assessing Impacts of Climate Change on Vegetation Using Climate Classification Systems. In A. M. Solomon & H. H. Shugart (Eds.), *Vegetation Dynamics & Global Change* (pp. 190-217). Boston, MA: Springer US. https://doi.org/10.1007/978-1-4615-2816-6_10

Crooks, E. C., Harris, I. M., & Patil, S. D. (2021). Influence of Land Use Land Cover on River Water Quality in Rural North Wales, UK. *JAWRA Journal of the American Water Resources Association*, *57*(3), 357–373. https://doi.org/10.1111/1752-1688.12904

CSIR. (2010). *A CSIR Perspective on Water in South Africa - 2010 [CSIR Report No. CSIR/NRE/PW/IR/2011/0012/A]*. Council for Scientific & Industrial Research.

CSIR. (2023). *Strategic Water Source Areas of South Africa*. Council for Scientific & Industrial Research. Retrieved 20 July 2023 from https://www.csir.co.za/strategic-water-source-areas-south-africa

Cuffney, T. F., Meador, M. R., Porter, S. D., & Gurtz, M. E. (2000). Responses of Physical, Chemical, and Biological Indicators of Water Quality to a Gradient of Agricultural Land Use in the Yakima River Basin, Washington. In S. S. Sandhu, B. D. Melzian, E. R. Long, W. G. Whitford, & B. T. Walton (Eds.), *Monitoring Ecological Condition in the Western United States: Proceedings of the Fourth Symposium on the Environmental Monitoring and Assessment Program (EMAP), San Francisco, CA, April 6–8, 1999* (pp. 259–270). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-011-4343-1_21

Cullis, J. D., Rossouw, N., Du Toit, G., Petrie, D., Wolfaardt, G., De Clercq, W., & Horn, A. (2018). Economic risks due to declining water quality in the Breede River catchment. *Water SA*, *44*(3), 464–473. https://doi.org/10.4314/wsa.v44i3.14

Cullis, J. D. S., Horn, A., Rossouw, N., Fisher-Jeffes, L., Kunneke, M. M., & Hoffman, W. (2019). Urbanisation, climate change and its impact on water quality and economic risks in a water scarce and rapidly urbanising catchment: case study of the Berg River Catchment. *H2Open Journal*, *2*(1), 146–167. https://doi.org/10.2166/h2oj.2019.027

CWP. (2003). *Impacts of impervious cover on aquatic systems [Watershed Protection Research Monograph No. 1]*. Ellicott City, MD: Centre for Watershed Protection.

D'Arcy, B. J., Kay, D., Napier, F., Haygarth, P., Sun, Y. Y., & Wada, K. (2022a). Land use and diffuse pollution: are perceptions part of the problem? In P. Kajitvichyanukul & B. D'Arcy (Eds.), *Land Use and Water Quality: The Impacts of Diffuse Pollution* (pp. 1–23). IWA Publishing. https://doi.org/10.2166/9781789061123_001

D'Arcy, B. J., Morison, P., Braskerud, B. C., & Kajitvichyanukul, P. (2022b). Landscapes for pollution risk management. In P. Kajitvichyanukul & B. D'Arcy (Eds.), *Land Use and Water Quality: The Impacts of Diffuse Pollution* (pp. 265–278). IWA Publishing. https://doi.org/10.2166/9781789061123_265

D’Amario, S. C., Rearick, D. C., Fasching, C., Kembel, S. W., Porter-Goff, E., Spooner, D. E., Williams, C. J., Wilson, H. F., & Xenopoulos, M. A. (2019). The prevalence of nonlinearity and detection of ecological breakpoints across a land use gradient in streams. *Scientific Reports*, *9*(1), 3878. https://doi.org/10.1038/s41598-019-40349-4

Dabrowski, J. M., Bruton, S., Dent, M., Graham, M., Hill, T., Murray, K., Rivers-Moore, N., & van Deventer, H. (2013). *Linking Land Use to Water Quality for Effective Water Resource and Ecosystem Management [WRC Report No. 1984/1/13]*. Water Research Commission.

Dabrowski, J. M., & de Klerk, L. (2013). An assessment of the impact of different land use activities on water quality in the upper Olifants River catchment. *Water SA*, *39*(2), 231–244. https://doi.org/10.4314/wsa.v39i2.6

Dai, X., Zhou, Y., Ma, W., & Zhou, L. (2017). Influence of spatial variation in land-use patterns and topography on water quality of the rivers inflowing to Fuxian Lake, a large deep lake in the plateau of southwestern China. *Ecological Engineering*, *99*, 417–428. https://doi.org/10.1016/j.ecoleng.2016.11.011

Dallas, H., & Day, J. (2004). *The Effect of Water Quality Variables on Aquatic Ecosystems: A Review [WRC Report No. TT 224/04]*. Water Research Commission.

Dalu, T., Mwedzi, T., Wasserman, R. J., Madzivanzira, T. C., Nhiwatiwa, T., & Cuthbert, R. N. (2022). Land use effects on water quality, habitat, and macroinvertebrate and diatom communities in African highland streams. *Science of The Total Environment*, *846*, 157346. https://doi.org/10.1016/j.scitotenv.2022.157346

Darlington, R. B., & Hayes, A. F. (2017). *Regression Analysis and Linear Models: Concepts, Applications, and Implementation*. New York: Guilford Press.

Dauer, D. M., Ranasinghe, J. A., & Weisberg, S. B. (2000). Relationships between benthic community condition, water quality, sediment quality, nutrient loads, and land use patterns in Chesapeake Bay. *Estuaries*, *23*(1), 80–96. https://doi.org/10.2307/1353227

Davino, C., Furno, M., & Vistocco, D. (2014). *Quantile Regression: Theory and Applications*. Chichester, West Sussex: John Wiley & Sons, Ltd.

Dawson, J. J. C., & Smith, P. (2010). Integrative management to mitigate diffuse pollution in multi-functional landscapes. *Current Opinion in Environmental Sustainability*, *2*(5), 375–382. https://doi.org/10.1016/j.cosust.2010.09.005

Day, J., & Dallas, H. (2011). Understanding the basics of water quality. In K. Hussey & R. Q. Grafton (Eds.), *Water Resources Planning and Management* (pp. 68–89). Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511974304.007

Day, J., & Davies, B. (2023). *Vanishing Waters* (3rd Revised ed.). Water Research Commission.

Day, J. A., Dallas, H. F., & Wackernagel, A. (1998). Delineation of management regions for South African rivers based on water chemistry. *Aquatic Ecosystem Health and Management*, *1*(2), 183–197. https://doi.org/10.1016/S1463-4988(98)00022-0

Day, J. M., & King, J. A. (1995). Geographical patterns, and their origins, in the dominance of major ions in South African rivers. *South African Journal of Science*, *91*(6), 299–306. https://doi.org/10.10520/AJA00382353_6757

De Clercq, W., Jovanovic, N., & Fey, M. (2010). *Land use impacts on salinity in Berg River water [WRC Report No. 1503/01/10]*. Water Research Commission.

de Mello, K., Randhir, T. O., Valente, R. A., & Vettorazzi, C. A. (2017). Riparian restoration for protecting water quality in tropical agricultural watersheds. *Ecological Engineering*, *108*, 514–524. https://doi.org/10.1016/j.ecoleng.2017.06.049

de Mello, K., Taniwaki, R. H., Paula, F. R. d., Valente, R. A., Randhir, T. O., Macedo, D. R., Leal, C. G., Rodrigues, C. B., & Hughes, R. M. (2020). Multiscale land use impacts on water quality: Assessment, planning, and future perspectives in Brazil. *Journal of Environmental Management*, *270*, 110879. https://doi.org/10.1016/j.jenvman.2020.110879

de Mello, K., Valente, R. A., Randhir, T. O., dos Santos, A. C. A., & Vettorazzi, C. A. (2018). Effects of land use and land cover on water quality of low-order streams in Southeastern Brazil: Watershed versus riparian zone. *CATENA*, *167*, 130–138. https://doi.org/10.1016/j.catena.2018.04.027

de Mello, K., Valente, R. A., Ribeiro, M. P., & Randhir, T. (2022). Effects of forest cover pattern on water quality of low-order streams in an agricultural landscape in the Pirapora river basin, Brazil. *Environmental Monitoring and Assessment*, *194*(3), 189. https://doi.org/10.1007/s10661-022-09854-4 de Oliveira, L. M., Maillard, P., & de Andrade Pinto, E. J. (2017). Application of a land cover pollution index to model non-point pollution sources in a Brazilian watershed. *CATENA*, *150*, 124–132. https://doi.org/10.1016/j.catena.2016.11.015

de Oliveira Vieira, E. (2020). Integrated Water Resources Management: Theoretical Concepts, Basis, Responsibilities, and Challenges of IWRM. In E. de Oliveira Vieira, S. Sandoval-Solis, V. de Albuquerque Pedrosa, & J. P. Ortiz-Partida (Eds.), *Integrated Water Resource Management: Cases from Africa, Asia, Australia, Latin America and USA* (pp. 1–12). Switzerland: Springer. https://doi.org/10.1007/978-3-030-16565-9

de Oliveira Vieira, E., Sandoval-Solis, S., de Albuquerque Pedrosa, V., & Ortiz-Partida, J. P. (2020). *Integrated Water Resources Management: Case Studies from Africa, Asia, Australia, Latin America and USA*. Switzerland: Springer Nature. https://doi.org/10.1007/978-3-030-16565-9

de Souza, R. S., Silva, G. C., Bazzan, T., de la Torre, F., Nebo, C., Siqueira-Silva, D. H., Cardoso-Silva, S., Pompêo, M. L. M., de Paiva, T. C. B., da Silva, F. T., & da Silva, D. C. V. R. (2022). Connections among Land Use, Water Quality, Biodiversity of Aquatic Invertebrates, and Fish Behavior in Amazon Rivers. *Toxics*, *10*(4), 182. https://doi.org/10.3390/toxics10040182

DEA. (2012). *2nd South Africa Environment Outlook. A report on the state of the environment*. Pretoria: Department of Environmental Affairs. https://www.dffe.gov.za/reports

DEA&DP. (2011). Chapter 7: Water Quality. In *Western Cape Integrated Water Resources Management Action Plan*. Western Cape Department of Environmental Affairs & Development Planning.

DEAT. (2006). Inland Water. In *South Africa Environment Outlook. A report on the state of the environment* (pp. 143–168). Pretoria: Department of Environmental Affairs & Tourism. https://www.dffe.gov.za/reports

Death, R. G., & Collier, K. J. (2010). Measuring stream macroinvertebrate responses to gradients of vegetation cover: when is enough enough? *Freshwater Biology*, *55*(7), 1447–1464. https://doi.org/10.1111/j.1365-2427.2009.02233.x

Dębska, K., Rutkowska, B., & Szulc, W. (2022). Influence of the catchment area use on the water quality in the Utrata River. *Environmental Monitoring and Assessment*, *194*(3), 165. https://doi.org/10.1007/s10661-022-09821-z

Denby, K., Movik, S., Mehta, L., & van Koppen, B. (2016). The 'trickle down' of IWRM: A case study of local-level realities in the Inkomati Water Management Area, South Africa. *Water Alternatives*, *9*(3), 473–492.

Deng, L., Li, W., Liu, X., Wang, Y., & Wang, L. (2023). Landscape Patterns and Topographic Features Affect Seasonal River Water Quality at Catchment and Buffer Scales. *Remote Sensing*, *15*(5), 1438. https://doi.org/10.3390/rs15051438

Detenbeck, N. E., Johnston, C. A., & Niemi, G. J. (1993). Wetland effects on lake water quality in the Minneapolis/St. Paul metropolitan area. *Landscape Ecology*, *8*(1), 39–61. https://doi.org/10.1007/BF00129866

DFFE. (2020). *South African National Land Cover (SANLC) 2020*. Department of Forestry, Fisheries & the Environment. https://egis.environment.gov.za

DFFE. (2022a). *South African Environment [State of the Environment Report]*. Pretoria: Department of Forestry, Fisheries & the Environment. https://soer.environment.gov.za

DFFE. (2022b). *South African National Land-Cover 1990 / 2020 Change Assessment Report (Public Release Report)*. Pretoria: Department of Forestry, Fisheries & the Environment. https://egis.environment.gov.za/

DFFE. (2023). *Environmental Geographical Information Systems (E-GIS)*. Department of Forestry, Fisheries & the Environment. https://egis.environment.gov.za

Dickens, C. W., & Graham, P. M. (2002). The South African Scoring System (SASS) Version 5 Rapid Bioassessment Method for Rivers. *African Journal of Aquatic Science*, *27*(1), 1–10. https://doi.org/10.2989/16085914.2002.9626569

Ding, F., Zhang, W., Cao, S., Hao, S., Chen, L., Xie, X., Li, W., & Jiang, M. (2023). Optimization of water quality index models using machine learning approaches. *Water Research*, *243*, 120337. https://doi.org/10.1016/j.watres.2023.120337

Ding, J., Jiang, Y., Fu, L., Liu, Q., Peng, Q., & Kang, M. (2015). Impacts of Land Use on Surface Water Quality in a Subtropical River Basin: A Case Study of the Dongjiang River Basin, Southeastern China. *Water*, *7*(8), 4427–4445. https://doi.org/10.3390/w7084427

Ding, J., Jiang, Y., Liu, Q., Hou, Z., Liao, J., Fu, L., & Peng, Q. (2016). Influences of the land use pattern on water quality in low-order streams of the Dongjiang River basin, China: A multi-scale analysis. *Science of The Total Environment*, *551-552*, 205–216. https://doi.org/10.1016/j.scitotenv.2016.01.162

Ding, S., Li, F., Lin, J., Zhang, Y., & Jia, X. (2021). Assessing limitation factors and thresholds for macroinvertebrate communities in response to land use gradients. *E3S Web Conf.*, *259*, 01007. https://doi.org/10.1051/e3sconf/202125901007

Ding, S., Zhang, Y., Liu, B., Kong, W., & Meng, W. (2013). Effects of riparian land use on water quality and fish communities in the headwater stream of the Taizi River in China. *Frontiers of Environmental Science & Engineering*, *7*(5), 699–708. https://doi.org/10.1007/s11783-013-0528-x

Dlamini, M., Chirima, G., Jovanovic, N., & Adam, E. (2021). Assessing the Effects of Land Use on Surface Water Quality in the Lower uMfolozi Floodplain System, South Africa. *International Journal of Environmental Research and Public Health*, *18*(2), 561. https://doi.org/10.3390/ijerph18020561

Dodds, W. K., Clements, W. H., Gido, K., Hilderbrand, R. H., & King, R. S. (2010). Thresholds, breakpoints, and nonlinearity in freshwaters as related to management. *Journal of the North American Benthological Society*, *29*(3), 988–997. https://doi.org/10.1899/09-148.1

Donnenfeld, Z., Crookes, C., & Hedden, S. (2018). A delicate balance: water scarcity in South Africa. *ISS Southern Africa Report*, *2018*(13), 1–24. https://doi.org/10.10520/EJC-1486c3180a

Donohue, I., McGarrigle, M. L., & Mills, P. (2006). Linking catchment characteristics and water chemistry with the ecological status of Irish rivers. *Water Research*, *40*(1), 91–98. https://doi.org/10.1016/j.watres.2005.10.027

Donoso, M. C., & Bosch, M. C. (2015). Integrated Water Resources Management in Latin America and the Caribbean. In S. G. Setegn & M. C. Donoso (Eds.), *Sustainability of Integrated Water Resources Management: Water Governance, Climate and Ecohydrology* (pp. 9–24). Cham: Springer.

du Plessis, A. (2019a). Current Water Quality Risk Areas for Berg-Olifants, Breede-Gouritz and Mzimvubu-Tsitsikamma WMAs. In A. du Plessis (Ed.), *Water as an Inescapable Risk: Current Global Water Availability, Quality and Risks with a Specific Focus on South Africa* (pp. 247–279). Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-03186-2

du Plessis, A. (2019b). *Water as an Inescapable Risk: Current Global Water Availability, Quality and Risks with a Specific Focus on South Africa*. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-03186-2

du Plessis, A. (2021). Necessity of making water smart for proactive informed decisive actions: A case study of the Upper Vaal catchment, South Africa. *Environmental Challenges*, *4*, 100100. https://doi.org/10.1016/j.envc.2021.100100

du Plessis, A. (2023). *South Africa's Water Predicament: Freshwater's Unceasing Decline*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-24019-5_1

du Plessis, A., Harmse, T., & Ahmed, F. (2014). Quantifying and Predicting the Water Quality Associated with Land Cover Change: A Case Study of the Blesbok Spruit Catchment, South Africa. *Water*, *6*(10), 2946–2968. https://doi.org/10.3390/w6102946

du Plessis, A., Harmse, T., & Ahmed, F. (2015). Predicting water quality associated with land cover change in the Grootdraai Dam catchment, South Africa. *Water International*, *40*(4), 647–663. https://doi.org/10.1080/02508060.2015.1067752

du Preez, C. C., Kotzé, E., & van Huyssteen, C. W. (2019). Soils, Agriculture and Food. In J. Knight & C. M. Rogerson (Eds.), *The Geography of South Africa: Contemporary Changes and New Directions* (pp. 111–121). Cham, Switzerland: Springer Nature. https://doi.org/10.1007/978-3-319-94974-1

du Preez, C. C., & van Huyssteen, C. W. (2020). Threats to soil and water resources in South Africa. *Environmental Research*, *183*, 109015. https://doi.org/10.1016/j.envres.2019.109015

Duan, M., Du, X., Peng, W., Zhang, S., & Yan, L. (2019). A Revised Method of Surface Water Quality Evaluation Based on Background Values and Its Application to Samples Collected in Heilongjiang Province, China. *Water*, *11*(5), 1057. https://doi.org/10.3390/w11051057

Dube, T., Mashao, F. M., Chari, M., Nakin, M. D. V., Addo-Bediako, A., Mashala, M., Xayimpi, O., Foxi, G., & Ayisi, K. K. (2023). Chapter 2: Assessing the effect of Land Use and Land Cover Change on water quality and quantity in three catchments in South Africa. In K. K. Ayisi (Ed.), *Earth Observation and the In-Situ-Based Assessment of the Impacts of Land Use and Land Cover Changes on Water Quality in Key Water Resources of Limpopo and the Eastern Cape, South Africa [WRC Report No. 3064/1/23]* (pp. 35–74). Pretoria: Water Research Commission.

Duda, A. M. (2017). *Co-Managing Land and Water for Sustainable Development [Global Land Outlook Working Paper]*. United Nations Convention to Combat Desertification. https://www.unccd.int/resources/publications/co-managing-land-and-water-sustainable-development

Duffy, C., O'Donoghue, C., Ryan, M., Kilcline, K., Upton, V., & Spillane, C. (2020). The impact of forestry as a land use on water quality outcomes: An integrated analysis. *Forest Policy and Economics*, *116*, 102185. https://doi.org/10.1016/j.forpol.2020.102185

Dunea, D., Bretcan, P., Tanislav, D., Serban, G., Teodorescu, R., Iordache, S., Petrescu, N., & Tuchiu, E. (2020). Evaluation of Water Quality in Ialomita River Basin in Relationship with Land Cover Patterns. *Water*, *12*(3), 735. https://doi.org/10.3390/w12030735

DWA. (2011). *Resource directed management of water quality. Planning level review of water quality in South Africa. Sub-series No. WQP 2.0*. Directorate Water Resources Planning Systems: Water Quality Planning, Department of Water Affairs.

DWAF. (1996). *South African Water Quality Guidelines Volume 7: Aquatic Ecosystems*. Pretoria: Department of Water Affairs & Forestry

DWAF. (1997). *White Paper on a National Water Policy for South Africa*. Pretoria: Department of Water Affairs & Forestry

DWAF. (2004). *State-of-Rivers Report: Berg River System - 2004*. Pretoria: Department of Water Affairs & Forestry.

DWAF. (2006). *The construction of a hydrologically-correct, annotated 1:500 000 spatial dataset of the rivers of South Africa and contiguous basins [Report Number N/0000/00/REH/0701]*. Pretoria: Department of Water Affairs & Forestry.

DWS. (2015). *National Chemical Monitoring Programme for Surface Water*. Department of Water & Sanitation. Retrieved 5 September 2022 from https://www.dws.gov.za/iwqs/water_quality/NCMP/default.aspx

DWS. (2017a). *Determination of Water Resources Classes and Associated Resource Quality Objectives in the Berg Catchment: Status Quo Report. Project Number WP10987. [Report No. RDM/WMA9/00/CON/CLA/0516.]*. Pretoria: Department of Water & Sanitation. https://www.dws.gov.za/rdm/WRCS/projberg.aspx

DWS. (2017b). *Determination of Water Resources Classes and Resource Quality Objectives for the Water Resources in the Breede-Gouritz Water Management Area: Status Quo. [Report No. RDM/WMA8/00/CON/CLA/0516]*. Pretoria: Department of Water & Sanitation. https://www.dws.gov.za/rdm/WRCS/projbg.aspx

DWS. (2017c). *Quality Management Policies and Strategies for South Africa. Report No. 1.2.3: A Review of the Water Quality Management Instruments in South Africa. Water Resource Planning Systems Series, DWS Report No.: 000/00/21715/4*. Pretoria: Department of Water & Sanitation

DWS. (2017d). *Resource Quality Information Services (GIS Data)*. Department of Water & Sanitation https://www.dws.gov.za/iwqs/gis_data/

DWS. (2017e). *Water Quality Management Policies and Strategies for South Africa. Report No. 1.2.1: A Review of Water Quality Management Policies and Strategies for South Africa and International Experience. DWS Report No.: 000/00/21715/2*. Pretoria: Department of Water & Sanitation

DWS. (2018). *National Water and Sanitation Master Plan: Volume 1: Call to Action (Version 10.1)*. Pretoria: Department of Water & Sanitation. https://www.dws.gov.za/National%20Water%20and%20Sanitation%20Master%20Plan/

DWS. (2019). *Ecoregions of South Africa - levels 1 and 2*. Department of Water & Sanitation. http://www.dwa.gov.za/iwqs/gis_data/ecoregions/get-ecoregions.aspx

DWS. (2021). *National Water Resource Strategy (Third Edition) [draft version 2.6 gazetted for public comment]*. Pretoria: Department of Water & Sanitation,

DWS. (2022a). *National State of Water Report 2021. Integrated Water Studies Report Number WII/IWS/NSoW 2021 (Ver.2.0)*. Pretoria: Department of Water & Sanitation.

DWS. (2022b). *National State of Water Report 2022*. Department of Water & Sanitation. https://www.dws.gov.za/Projects/National%20State%20of%20Water%20Report/Default.aspx

DWS. (2023). *Spatial Data Download Tool*. Department of Water & Sanitation. https://gia.dws.gov.za/DWSPortalApplication/

Dymek, D., Zgłobicki, W., & Baran-Zgłobicka, B. (2021). The Impact of Mosaic Land Use and Land Cover on the Quality of River Waters (Case Study: Lubelskie Province, E Poland). *Land*, *10*(12), 1318. https://doi.org/10.3390/land10121318

Effendi, H. (2016). River Water Quality Preliminary Rapid Assessment Using Pollution Index. *Procedia Environmental Sciences*, *33*, 562–567. https://doi.org/10.1016/j.proenv.2016.03.108

Elizabeth, E. A. (2009). Imperviousness and Land-Use Policy: Toward an Effective Approach to Watershed Planning. *Journal of Hydrologic Engineering*, *14*(4), 425–433. https://doi.org/10.1061/(ASCE)1084-0699(2009)14:4(425)

Ene, E., & McGarigal, K. (2023a). *(C3) Aggregation Index*. Retrieved 16 May 2023 from https://www.fragstats.org/index.php/fragstats-metrics/aggregation-metrics/c3-aggregation-index

Ene, E., & McGarigal, K. (2023b). *(C7) Patch Cohesion Index*. Retrieved 16 May 2023 from https://www.fragstats.org/index.php/fragstats-metrics/aggregation-metrics/c7-patch-cohesion-index

Ene, E., & McGarigal, K. (2023c). *(C9) Patch Density*. Retrieved 17 May 2023 from https://www.fragstats.org/index.php/fragstats-metrics/aggregation-metrics/c9-patch-density

Ene, E., & McGarigal, K. (2023d). *Fragstats*. Retrieved 17 May 2023 from https://www.fragstats.org/

Ene, E., & McGarigal, K. (2023e). *Landscape Metrics*. Retrieved 17 May 2023 from https://www.fragstats.org/index.php/background/landscape-metrics

Engberg, R. A. (2014). AWRA at 50: The Future of Water Resources in the United States. *Water Resources Impact*, *16*(1), 3–4. www.jstor.org/stable/wateresoimpa.16.1.fm

Esri. (2023). *ArcGIS Pro 3.1.2*. Environmental Systems Research Institute. https://www.esri.com

Falkenmark, M. (2011). Water—A Reflection of Land Use: Understanding of Water Pathways and Quality Genesis. *International Journal of Water Resources Development*, *27*(1), 13–32. https://doi.org/10.1080/07900627.2010.536943

Falkenmark, M., Andersson, L., Castensson, R., Sundblad, K., Batchelor, C., Gardiner, J., Lyle, C., Peters, N., Pettersen, B., Quinn, P., Rockström, J., & Yapijakis, C. (1999). *Water: A Reflection of Land Use*. Stockholm: Swedish Natural Science Research Council.

Falkenmark, M., Jägerskog, A., & Schneider, K. (2014). Overcoming the land–water disconnect in water-scarce regions: time for IWRM to go contemporary. *International Journal of Water Resources Development*, *30*(3), 391–408. https://doi.org/10.1080/07900627.2014.897157

Farrell, K., van Vuren, J. H. J., & Ferreira, M. (2015). Do aquatic macroinvertebrate communities respond to land-use effects in the Wilge River, Mpumalanga, South Africa? *African Journal of Aquatic Science*, *40*(2), 165–173. https://doi.org/10.2989/16085914.2015.1025220

Fatehi, I., Amiri, B. J., Alizadeh, A., & Adamowski, J. (2015). Modeling the Relationship between Catchment Attributes and In-stream Water Quality. *Water Resources Management*, *29*(14), 5055–5072. https://doi.org/10.1007/s11269-015-1103-y

Fatichi, S., Vivoni, E. R., Ogden, F. L., Ivanov, V. Y., Mirus, B., Gochis, D., Downer, C. W., Camporese, M., Davison, J. H., Ebel, B., Jones, N., Kim, J., Mascaro, G., Niswonger, R., Restrepo, P., Rigon, R., Shen, C., Sulis, M., & Tarboton, D. (2016). An overview of current applications, challenges, and future trends in distributed process-based models in hydrology. *Journal of Hydrology*, *537*, 45–60. https://doi.org/10.1016/j.jhydrol.2016.03.026

Fausch, K. D., Karr, J. R., & Yant, P. R. (1984). Regional Application of an Index of Biotic Integrity Based on Stream Fish Communities. *Transactions of the American Fisheries Society*, *113*(1), 39–55. https://doi.org/10.1577/1548-8659(1984)113<39:RAOAIO>2.0.CO;2

Feld, C., K. (2013). Response of three lotic assemblages to riparian and catchment-scale land use: implications for designing catchment monitoring programmes. *Freshwater Biology*, *58*(4), 715–729. https://doi.org/10.1111/fwb.12077

Feng, W., Deng, Y., Yang, F., Miao, Q., & Ngien, S. K. (2023a). Systematic Review of Contaminants of Emerging Concern (CECs): Distribution, Risks, and Implications for Water Quality and Health. *Water*, *15*(22), 3922. https://doi.org/10.3390/w15223922

Feng, Z., Xu, C., Zuo, Y., Luo, X., Wang, L., Chen, H., Xie, X., Yan, D., & Liang, T. (2023b). Analysis of water quality indexes and their relationships with vegetation using self-organizing map and geographically and temporally weighted regression. *Environmental Research*, *216*, 114587. https://doi.org/10.1016/j.envres.2022.114587

Fernandes, A. C. P., de Oliveira Martins, L. M., Pacheco, F. A. L., & Fernandes, L. F. S. (2021). The consequences for stream water quality of long-term changes in landscape patterns: Implications for land use management and policies. *Land Use Policy*, *109*, 105679. https://doi.org/10.1016/j.landusepol.2021.105679

Fernández, N., Ramírez, A., & Solano, F. (2004). Physico-Chemical Water Quality Indices - A Comparative Review. *Bistua: Revista de la Facultad de Ciencias Básicas*, *2*(1), 19–30. https://www.redalyc.org/articulo.oa?id=90320103

Ficetola, F. G., & Denoël, M. (2009). Ecological thresholds: an assessment of methods to identify abrupt changes in species–habitat relationships. *Ecography*, *32*(6), 1075–1084. https://doi.org/10.1111/j.1600-0587.2009.05571.x

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://www.worldclim.org/data/worldclim21.html

Firdaus, R., & Nakagoshi, N. (2013). Assessment of the relationship between land use land cover and water quality status of the tropical watershed: a case of Batang Merao Watershed, Indonesia. *Journal of Biodiversity and Environmental Sciences (JBES)*, *3*(11), 21–30. https://www.cabdirect.org/cabdirect/abstract/20143050515

Fitzpatrick, F. A., Scudder, B. C., Lenz, B. N., & Sullivan, D. J. (2001). Effects of Multi-Scale Environmental Characteristics on Agricultural Stream Biota in Eastern Wisconsin. *JAWRA Journal of the American Water Resources Association*, *37*(6), 1489–1507. https://doi.org/10.1111/j.1752-1688.2001.tb03655.x

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2005). Global Consequences of Land Use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Foley, J. A., Kucharik, C. J., Twine, T. E., Coe, M. T., & Donner, S. D. (2004). Land use, land cover, and climate change across the Mississippi basin: Impacts on selected land and water resources. *Ecosystems and Land Use Change*, *15*, 249–261. https://doi.org/10.1029/153GM19

Foley, M. M., Martone, R. G., Fox, M. D., Kappel, C. V., Mease, L. A., Erickson, A. L., Halpern, B. S., Selkoe, K. A., Taylor, P., & Scarborough, C. (2015). Using ecological thresholds to inform resource management: current options and future possibilities. *Frontiers in Marine Science*, *2*, 95. https://doi.org/10.3389/fmars.2015.00095

Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models* (3rd ed.). London: Sage.

Francis, D., & Webster, E. (2019). Poverty and inequality in South Africa: critical reflections. *Development Southern Africa*, *36*(6), 788–802. https://doi.org/10.1080/0376835x.2019.1666703

Fraser, A. I. (2002). Development of Geographical Information Systems for Assessing Hydrological Aspects of Diffuse Nutrient and Sediment Transfer from Agriculture. In P. M. Haygarth & S. C. Jarvis (Eds.), *Agriculture, Hydrology and Water Quality* (pp. 303–319). Wallingford: CABI. https://doi.org/10.1079/9780851995458.0303

Fuller, D. O., Hardiono, M., & Meijaard, E. (2011). Deforestation Projections for Carbon-Rich Peat Swamp Forests of Central Kalimantan, Indonesia. *Environmental Management*, *48*(3), 436–447. https://doi.org/10.1007/s00267-011-9643-2

Fulton, S., & West, B. (2002). Forestry Impacts on Water Quality. *Southern forest resource assessment*, *21*, 635.

Funke, N., Oelofse, S. H. H., Hattingh, J., Ashton, P. J., & Turton, A. R. (2007). IWRM in developing countries: Lessons from the Mhlatuze Catchment in South Africa. *Physics and Chemistry of the Earth, Parts A/B/C, 32*(15), 1237–1245. https://doi.org/10.1016/j.pce.2007.07.018

Fynn, B. M., & Abiye, T. A. (2022). Modelling the impact of climate variability and land-use changes in the Upper Crocodile River Basin, South Africa [Preprint]. https://doi.org/10.21203/rs.3.rs-1525364/v1

Galbraith, L. M., & Burns, C. W. (2007). Linking Land-use, Water Body Type and Water Quality in Southern New Zealand. *Landscape Ecology*, *22*(2), 231–241. https://doi.org/10.1007/s10980-006-9018-x

Gani, M. A., Sajib, A. M., Siddik, M. A., & Md, M. (2023). Assessing the impact of land use and land cover on river water quality using water quality index and remote sensing techniques. *Environmental Monitoring and Assessment*, *195*(4), 449. https://doi.org/10.1007/s10661-023-10989-1

García, L., Rodríguez, D., Wijnen, M., & Pakulski, I. (2016). *Earth Observation for Water Resources Management: Current Use and Future Opportunities for the Water Sector*. Washington, DC: World Bank Group. https://doi.org/10.1596/978-1-4648-0475-5

Gazzaz, N. M., Yusoff, M. K., Ramli, M. F., Juahir, H., & Aris, A. Z. (2015). Artificial Neural Network Modeling of the Water Quality Index Using Land Use Areas as Predictors. *Water Environment Research*, *87*(2), 99–112. https://doi.org/10.2175/106143014X14062131179276

Gebel, M., Bürger, S., Wallace, M., Malherbe, H., Vogt, H., & Lorz, C. (2017). Simulation of land use impacts on sediment and nutrient transfer in coastal areas of Western Cape, South Africa. *Change and Adaptation in Socio-Ecological Systems*, *3*(1), 1–17. https://doi.org/10.1515/cass-2017-0001

Gelman, A., & Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511790942

GeoSmart. (2023). *5 m Stellenbosch University Digital Elevation Model (SUDEM)*. GeoSmart. https://geosmart.space/products/sudem.html

Geoterra Image. (2015). *2013-2014 South African National Land-Cover Dataset. DEA/CARDNO SCPF002: Implementation of Land-Use Maps for South Africa. Project Specific Data User Report and MetaData. July 2015, version 05b (pivot code corrected data)*. Geoterra Image Pty Ltd. www.geoterraimage.com

Gergel, S. E., Turner, M. G., Miller, J. R., Melack, J. M., & Stanley, E. H. (2002). Landscape indicators of human impacts to riverine systems. *Aquatic Sciences*, *64*(2), 118–128. https://doi.org/10.1007/s00027-002-8060-2

Gevao, B., & Jones, K. C. (2002). Pesticides and Persistent Organic Pollutants. In P. M. Haygarth & S. C. Jarvis (Eds.), *Agriculture, Hydrology and Water Quality* (pp. 83–106). Wallingford: CABI. https://doi.org/10.1079/9780851995458.0083

Gevorgyan, G., Khudaverdyan, S., & Vaseashta, A. (2016). Environmental risk assessment of heavy metal pollution in Armenian river ecosystems: Case study of Lake Sevan and Debed River catchment basins. *Polish Journal of Environmental Studies*, *25*(6), 2387–2400.

Gikas, G. D., Lergios, D., & Tsihrintzis, V. A. (2023). Comparative Assessment of the Application of Four Water Quality Indices (WQIs) in Three Ephemeral Rivers in Greece. *Water*, *15*(8), 1443. https://doi.org/10.3390/w15081443

Gillson, L., Wakeling, J. L., & Midgley, G. F. (2012). Exploring the significance of land-cover change in South Africa. *South African Journal of Science*, *108*(5). https://hdl.handle.net/10520/EJC121908

Giordano, M., & Shah, T. (2014). From IWRM back to integrated water resources management. *International Journal of Water Resources Development*, *30*(3), 364–376. https://doi.org/10.1080/07900627.2013.851521

Giri, C. P. (2012). *Remote Sensing of Land Use and Land Cover: Principles and Applications*. CRC Press. https://doi.org/10.1201/b11964

Giri, S., & Qiu, Z. (2016). Understanding the relationship of land uses and water quality in Twenty First Century: A review. *Journal of Environmental Management*, *173*, 41–48. https://doi.org/10.1016/j.jenvman.2016.02.029

Gitau, M. W., Chen, J., & Ma, Z. (2016). Water Quality Indices as Tools for Decision Making and Management. *Water Resources Management*, *30*, 2591–2610. https://doi.org/10.1007/s11269-016-1311-0

Giupponi, C., & Gain, A. K. (2017). Integrated water resources management (IWRM) for climate change adaptation. *Regional Environmental Change*, *17*(7), 1865–1867. https://doi.org/10.1007/s10113-017-1173-x

Gleeson, T., Wang-Erlandsson, L., Zipper, S. C., Porkka, M., Jaramillo, F., Gerten, D., Fetzer, I., Cornell, S. E., Piemontese, L., Gordon, L. J., Rockström, J., Oki, T., Sivapalan, M., Wada, Y., Brauman, K. A., Flörke, M., Bierkens, M. F. P., Lehner, B., Keys, P., . . . Famiglietti, J. S. (2020). The Water Planetary Boundary: Interrogation and Revision. *One Earth*, *2*(3), 223–234. https://doi.org/10.1016/j.oneear.2020.02.009

Gobry, J. J., Twisa, S. S., Ngassapa, F., & Kilulya, K. F. (2023). Impact of land-use/cover change on water quality in the Mindu Dam drainage, Tanzania. *Water Practice and Technology*, *18*(5), 1086–1098. https://doi.org/10.2166/wpt.2023.067

Gomes, E., Inácio, M., Bogdzevič, K., Kalinauskas, M., Karnauskaitė, D., & Pereira, P. (2021). Future land-use changes and its impacts on terrestrial ecosystem services: A review. *Science of The Total Environment*, *781*, Article 146716. https://doi.org/10.1016/j.scitotenv.2021.146716

Gooch, G. D., Allan, A., Rieu-Clarke, A., & Baggett, S. (2010). The Science-Policy-Stakeholder Interface in Sustainable Water Management: Creating Interactive Participatory Scenarios together with Stakeholders. In G. D. Gooch & P. Stålnacke (Eds.), *Science, Policy and Stakeholders in Water Management: An Integrated Approach to River Basin Management* (pp. 51–82). London: Earthscan. https://doi.org/10.4324/9781849775151

Gooch, G. D., & Stålnacke, P. (2010). *Science, Policy and Stakeholders in Water Management: An Integrated Approach to River Basin Management*. London: Earthscan. https://doi.org/10.4324/9781849775151

Goodspeed, R., Wang, R., Lizundia, C., Du, L., & Jaipuria, S. (2022). Incorporating water quality into land use scenario analysis with random forest models. *Environment and Planning B: Urban Analytics and City Science*. https://doi.org/10.1177/23998083221138842

Görgens, A., & de Clercq, W. (2005). *Research on Berg River Water Management: Summary of Water Quality Information System and Soil Quality Studies [WRC Report No. TT 252/05]*. Water Research Commission.

Görgens, A., Pegram, G., Uys, M., Grobicki, A., Loots, L., Tanner, A., & Bengu, R. (1998). *Guidelines for catchment management to achieve integrated water resources management in South Africa [WRC Report No. 108/98]*. Water Research Commission.

Gorgoglione, A., Gregorio, J., Ríos, A., Alonso, J., Chreties, C., & Fossati, M. (2020). Influence of land use/land cover on surface-water quality of Santa Lucìa river, Uruguay. *Sustainability*, *12*(11), 4692. https://doi.org/10.3390/su12114692

Gossweiler, B., Wesström, I., Messing, I., Romero, A. M., & Joel, A. (2019). Spatial and Temporal Variations in Water Quality and Land Use in a Semi-Arid Catchment in Bolivia. *Water*, *11*(11), 2227. https://doi.org/10.3390/w11112227

Goswami, G., Mandal, S., Basack, S., Mukherjee, R., & Karakouzian, M. (2023). Assessing the Impacts of Land Use and Land Cover Changes on the Water Quality of River Hooghly, West Bengal, India: A Case Study. *Hydrology*, *10*(3), 71. https://doi.org/10.3390/hydrology10030071

Gove, N. E., Edwards, R. T., & Conquest, L. L. (2001). Effects of Scale on Land Use and Water Quality Relationships: A Longitudinal Basin-Wide Perspective. *JAWRA Journal of the American Water Resources Association*, *37*(6), 1721–1734. https://doi.org/10.1111/j.1752-1688.2001.tb03672.x

Goyette, J. O., Bennett, E. M., & Maranger, R. (2018). Low buffering capacity and slow recovery of anthropogenic phosphorus pollution in watersheds. *Nature Geoscience*, *11*(12), 921–925. https://doi.org/10.1038/s41561-018-0238-x

Graybill, F. A., & Iyer, H. K. (1994). Diagnostic Procedures. In *Regression Analysis: Concepts and Applications* (pp. 351–401). Belmont, California: Duxbury. https://www.stat.colostate.edu/regression_book/

Griffin, N., Palmer, C., & Scherman, P. A. (2014). *Critical Analysis of Environmental Water Quality in South Africa: Historic and Current Trends [WRC Report No. 2184/1/14]*. Water Research Commission.

Griffith, J. A. (2002). Geographic Techniques and Recent Applications of Remote Sensing to Landscape-Water Quality Studies. *Water, Air, and Soil Pollution*, *138*(1), 181–197. https://doi.org/10.1023/A:1015546915924

Griffith, J. A., Martinko, E. A., Whistler, J. L., & Price, K. P. (2002a). Interrelationships Among Landscapes, NDVI, and Stream Water Quality in the US Central Plains. *Ecological Applications*, *12*(6), 1702–1718. https://doi.org/10.1890/1051-0761(2002)012[1702:IALNAS]2.0.CO;2

Griffith, J. A., Martinko, E. A., Whistler, J. L., & Price, K. P. (2002b). Preliminary Comparison of Landscape Pattern–Normalized Difference Vegetation Index (NDVI) Relationships to Central Plains Stream Conditions. *Journal of Environmental Quality*, *31*(3), 846–859. https://doi.org/10.2134/jeq2002.8460

Grigg, N. S. (2008). Integrated water resources management: balancing views and improving practice. *Water International*, *33*(3), 279–292. https://doi.org/10.1080/02508060802272820

Grigg, N. S. (2016). *Integrated Water Resource Management: An Interdisciplinary Approach*. London: Palgrave Macmillan. https://doi.org/10.1057/978-1-137-57615-6

Grigg, N. S. (2021). Fifty years of water research: has it made a difference? *Water International*, *46*(7-8), 1087–1098. https://doi.org/10.1080/02508060.2021.1996968

Grimstead, J. P., Krynak, E. M., & Yates, A. G. (2018). Scale-specific land cover thresholds for conservation of stream invertebrate communities in agricultural landscapes. *Landscape Ecology*, *33*(12), 2239–2252. https://doi.org/10.1007/s10980-018-0738-5

Grison, C., Koop, S., Eisenreich, S., Hofman, J., Chang, I. S., Wu, J., Savic, D., & van Leeuwen, K. (2023). Integrated Water Resources Management in Cities in the World: Global Challenges. *Water Resources Management*. https://doi.org/10.1007/s11269-023-03475-3

Grizzetti, B., Lo Porto, A., Barkved, L. J., Joy, K. J., Paranjape, S., Deelstra, J., Bouraoui, F., & Manasi, S. (2010). The Science-Policy-Interface in Water Pollution Assessment. In G. D. Gooch & P. Stålnacke (Eds.), *Science, Policy and Stakeholders in Water Management: An Integrated Approach to River Basin Management* (pp. 67–82). London: Earthscan. https://doi.org/10.4324/9781849775151

Groffman, P. M., Baron, J. S., Blett, T., Gold, A. J., Goodman, I., Gunderson, L. H., Levinson, B. M., Palmer, M. A., Paerl, H. W., Peterson, G. D., Poff, N. L., Rejeski, D. W., Reynolds, J. F., Turner, M. G., Weathers, K. C., & Wiens, J. (2006). Ecological Thresholds: The Key to Successful Environmental Management or an Important Concept with No Practical Application? *Ecosystems*, *9*(1), 1–13. https://doi.org/10.1007/s10021-003-0142-z

Gule, T. T., Lemma, B., & Hailu, B. T. (2023). Implications of land use/land cover dynamics on urban water quality: Case of Addis Ababa city, Ethiopia. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e15665

Guntenspergen, G. R., & Gross, J. (2014). Threshold Concepts: Implications for the Management of Natural Resources. In G. R. Guntenspergen (Ed.), *Application of Threshold Concepts in Natural Resource Decision Making* (pp. 1–7). New York, NY: Springer New York. https://doi.org/10.1007/978-1-4899-8041-0_1

Gustafson, E. J. (1998). Quantifying Landscape Spatial Pattern: What Is the State of the Art? *Ecosystems*, *1*(2), 143–156. https://doi.org/10.1007/s100219900011

GWP. (1996). *Dublin-Rio principles*. Retrieved 11 September 2022 from https://www.gwptoolbox.org/resource/dublin-rio-principles

GWP. (2000). *Integrated Water Resources Management (Technical Advisory Committee, Background Paper No.4)*. Global Water Partnership. https://www.gwp.org/en/learn/KNOWLEDGE_RESOURCES/Global_Resources/background-papers/

GWP. (2004). *Catalyzing Change: A handbook for developing integrated water resources management (IWRM) and water efficiency strategies*. Global Water Partnership. https://www.gwp.org/en/learn/KNOWLEDGE_RESOURCES/Global_Resources/Catalyzing-Change-Handbook1/
GWP. (2013). *The Role of Decision Support Systems and Models in Integrated River Basin Management*. Global Water Partnership. https://www.gwp.org/en/learn/KNOWLEDGE_RESOURCES/Global_Resources/Technical-Focus-Papers/
GWP. (2017). *Modelling and Decision-making (C3)*. Global Water Partnership. Retrieved 2 September 2022 from https://www.gwp.org/en/learn/iwrm-toolbox/Management-Instruments/Modelling_and_decision_making/
GWP. (2018). *About the IWRM ToolBox*. Global Water Partnership. Retrieved 27 September 2022 from https://www.gwp.org/en/learn/iwrm-toolbox/About_IWRM_ToolBox/
GWP. (2020). *Why and How to Use the IWRM ToolBox*. Global Water Partnership. Retrieved 2 September 2020 from https://www.gwp.org/en/learn/iwrm-toolbox/About_IWRM_ToolBox/Why_and_How_to_Use_the_IWRM_ToolBox/
GWP. (2022a). *IWRM Explained*. Global Water Partnership. Retrieved 7 October 2022 from https://www.gwptoolbox.org/iwrm-explained
GWP. (2022b). *IWRM Tools*. Global Water Partnership. Retrieved 2 March 2022 from https://www.gwptoolbox.org/learn/iwrm-tools
GWP. (2022c). *Shared Vision Planning and Collaborative Modelling*. Global Water Partnership. Retrieved 7 October 2022 from https://www.gwptoolbox.org/learn/iwrm-tools/shared-vision-planning-and-collaborative-modelling
GWP. (2022d). *Socio-Hydrological Modelling*. Global Water Partnership. Retrieved 7 October 2022 from https://www.gwptoolbox.org/learn/iwrm-tools/socio-hydrological-modelling
GWPSA. (2009). *IWRM Survey and Status Report: Summary*. Global Water Partnership Southern Africa.
Gyamfi, C., Ndambuki, J. M., & Salim, R. W. (2016). Hydrological Responses to Land Use/Cover Changes in the Olifants Basin, South Africa. *Water*, *8*(12), 588. https://doi.org/10.3390/w8120588
Haddad, B. M., & Solomon, B. D. (2023). Integrated water resources management (IWRM). In *Dictionary of Ecological Economics* (pp. 299–300). Edward Elgar Publishing. https://doi.org/10.4337/9781788974912.I.43
Hagen-Zanker, A. (2016). A computational framework for generalized moving windows and its application to landscape pattern analysis. *International Journal of Applied Earth Observation and Geoinformation*, *44*, 205–216. https://doi.org/10.1016/j.jag.2015.09.010
Haith, D. A. (1976). Land Use and Water Quality in New York Rivers. *Journal of the Environmental Engineering Division*, *102*(1), 1–15. https://doi.org/doi:10.1061/JEEGAV.0000440
Halbe, J., Pahl-Wostl, C., Sendzimir, J., & Adamowski, J. (2013). Towards adaptive and integrated management paradigms to meet the challenges of water governance. *Water Science and Technology*, *67*(11), 2651–2660. https://doi.org/10.2166/wst.2013.146
Hallock, D. (2002). *A Water Quality Index for Ecology's Stream Monitoring Program*. Washington State Department of Ecology.
Halpern, A. B. W., & Meadows, M. E. (2013). Fifty years of land use change in the Swartland, Western Cape, South Africa: characteristics, causes and consequences. *South African Geographical Journal*, *95*(1), 38–49. https://doi.org/10.10520/EJC138420
Han, H., Yan, X., Xie, H., Qiu, J., Li, X., Zhao, D., Li, X., Yan, X., & Xia, Y. (2023). Incorporating a new landscape intensity indicator into landscape metrics to better understand controls of water quality and optimal width of riparian buffer zone. *Journal of Hydrology*, *625*, 130088. https://doi.org/10.1016/j.jhydrol.2023.130088
Hanna, D. E. L., Lehner, B., Taranu, Z. E., Solomon, C. T., & Bennett, E. M. (2021). The relationship between watershed protection and water quality: The case of Québec, Canada. *Freshwater Science*, *40*(2), 382–396. https://doi.org/10.1086/714598

Harding, J. S., Benfield, E. F., Bolstad, P. V., Helfman, G. S., & Jones, E. B. D. (1998). Stream biodiversity: The ghost of land use past. *Proceedings of the National Academy of Sciences*, *95*(25), 14843–14847. https://doi.org/10.1073/pnas.95.25.14843

Harris, G. (2002). Impacts of Agriculture on Water Quality Around the World. In P. M. Haygarth & S. C. Jarvis (Eds.), *Agriculture, Hydrology and Water Quality* (pp. 342–343). Wallingford: CABI International.

Hassan, Z., Shah, J. A., Kanth, T. A., & Pandit, A. K. (2015). Influence of land use/land cover on the water chemistry of Wular Lake in Kashmir Himalaya (India). *Ecological Processes*, *4*(1), 9. https://doi.org/10.1186/s13717-015-0035-z

Hassing, J., Ipsen, N., Clausen, T. J., Larsen, H., & Lindgaard-Jørgensen, P. (2009). *Integrated Water Resources Management in Action (Dialogue Paper)*. UNESCO.

Hawkins, C. P., Olson, J. R., & Hill, R. A. (2010). The reference condition: predicting benchmarks for ecological and water-quality assessments. *Journal of the North American Benthological Society*, *29*(1), 312–343. https://doi.org/10.1899/09-092.1

Hay, D. (2021). *The drought – crisis or opportunity?* International Water Security Network. Retrieved 16 September 2022 from http://www.watersecuritynetwork.org/the-drought-crisis-or-opportunity/

Haycock, N., Burt, T., Goulding, K., & Pinay, G. (2001). *Buffer Zones: Their Processes and Potential in Water Protection [Electronic Version]*. St. Albans: Haycock Associated Limited.

Haygarth, P. M., & Jarvis, S. C. (2002). *Agriculture, Hydrology and Water Quality*. Wallingford: CABI. https://doi.org/10.1079/9780851995458.0000

HDX. (2023). *The Humanitarian Data Exchange*. United Nations Office for the Coordination of Humanitarian Affairs. https://data.humdata.org/

He, H. S., DeZonia, B. E., & Mladenoff, D. J. (2000). An aggregation index (AI) to quantify spatial patterns of landscapes. *Landscape Ecology*, *15*(7), 591–601. https://doi.org/10.1023/A:1008102521322

Heidkamp, L. C., & Christian, A. D. (2022). A Case Study Evaluating Water Quality and Reach-, Buffer-, and Watershed-Scale Explanatory Variables of an Urban Coastal Watershed. *Urban Science*, *6*(1), 17. https://doi.org/10.3390/urbansci6010017

Helsel, D. R., Hirsch, R. M., Ryberg, K. R., Archfield, S. A., & Gilroy, E. J. (2020). *Statistical Methods in Water Resources*. USGS. https://doi.org/10.3133/tm4a3

Henderson, N. D., & Christian, A. D. (2022). Freshwater Invertebrate Assemblage Composition and Water Quality Assessment of an Urban Coastal Watershed in the Context of Land-Use Land-Cover and Reach-Scale Physical Habitat. *Ecologies*, *3*(3), 376-394. https://doi.org/10.3390/ecologies3030028

Hernández, S. (2013). *El Salvador: Development of community participation in the microbasin La Poza*. IWRM Action Hub. https://iwrmactionhub.org/case-study/el-salvador-development-community-participation-microbasin-la-poza

Herrfahrdt-Pähle, E. (2010). *Introducing catchment management: the case of South Africa (Discussion Paper)*. Bonn: German Development Institute.

Hilderbrand, R. H., Utz, R. M., Stranko, S. A., & Raesly, R. L. (2010). Applying thresholds to forecast potential biodiversity loss from human development. *Journal of the North American Benthological Society*, *29*(3), 1009–1016. https://doi.org/10.1899/09-138.1

Holzer, J., & Olson, L. J. (2021). Precautionary buffers and stochastic dependence in environmental policy. *Journal of Environmental Economics and Management*, *106*, 102406. https://doi.org/10.1016/j.jeem.2020.102406

Hooper, B. (2006). Integrated Water Resources Management: Governance, Best Practice, and Research Challenges. *Journal of Contemporary Water Research & Education*, *135*, 1–7.

Hooper, B. P., & Lloyd, G. J. (2011). *Report on IWRM in Transboundary Basins*. UNEP-DHI Centre for Water and Environment.

Horlemann, L., & Dombrowsky, I. (2010). *Institutionalizing IWRM in developing and transition countries: The case of Mongolia*, *UFZ Discussion Paper*, *No. 9/2010*. Helmholtz-Zentrum für Umweltforschung (UFZ).

Horning, N., Robinson, J. A., Sterling, E. J., Turner, W., & Spector, S. (2010). *Remote Sensing for Ecology and Conservation: A Handbook of Techniques*. Oxford University Press. https://doi.org/10.1093/oso/9780199219940.001.0001

Horton, P., Schaefli, B., & Kauzlaric, M. (2022). Why do we have so many different hydrological models? A review based on the case of Switzerland. *WIREs Water*, *9*(1), e1574. https://doi.org/10.1002/wat2.1574

Hua, A. K. (2017). Land Use Land Cover Changes in Detection of Water Quality: A Study Based on Remote Sensing and Multivariate Statistics. *Journal of Environmental and Public Health*, *2017*, 7515130. https://doi.org/10.1155/2017/7515130

Huang, J., & Klemas, V. (2012). Using Remote Sensing of Land Cover Change in Coastal Watersheds to Predict Downstream Water Quality. *Journal of Coastal Research*, *28*(4), 930–944. https://doi.org/10.2112/jcoastres-d-11-00176.1

Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, *32*(1), 1–6. https://doi.org/10.1007/s11676-020-01155-1

Huang, W., Mao, J., Zhu, D., & Lin, C. (2020). Impacts of Land Use and Land Cover on Water Quality at Multiple Buffer-Zone Scales in a Lakeside City. *Water*, *12*(1), 47. https://doi.org/10.3390/w12010047

Huggett, A. J. (2005). The concept and utility of 'ecological thresholds' in biodiversity conservation. *Biological Conservation*, *124*(3), 301–310. https://doi.org/10.1016/j.biocon.2005.01.037

Hughes, D. A. (2019). Facing a future water resources management crisis in sub-Saharan Africa. *Journal of Hydrology: Regional Studies*, *23*, 100600. https://doi.org/10.1016/j.ejrh.2019.100600

Hughes, D. A. (2022). Anatomy of an extended drought in part of the Eastern Cape Province, South Africa. *IAHS-AISH Scientific Assembly 2022, Montpellier, France, 29 May–3 Jun 2022, IAHS2022-147*.

Huizenga, J. M., Silberbauer, M., Dennis, R., & Dennis, I. (2013). An inorganic water chemistry dataset (1972–2011) of rivers, dams and lakes in South Africa. *Water SA*, *39*(2), 335–339. https://doi.org/10.4314/wsa.v39i2.18

Hunsaker, C. T., & Levine, D. A. (1995). Hierarchical Approaches to the Study of Water Quality in Rivers. *BioScience*, *45*(3), 193–203. https://doi.org/10.2307/1312558

Huynh, T., & Hobbs, D. (2019). *Deriving site-specific guideline values for physico-chemical parameters and toxicants*. Commonwealth of Australia: Independent Expert Scientific Committee on Coal Seam Gas and Large Coal Mining Development through the Department of the Environment and Energy. https://www.iesc.gov.au/publications/information-guidelines-explanatory-note-deriving-site-specific-guidelines-values

Hynes, H. B. N. (1975). The stream and its valley. *Internationale Vereinigung für theoretische und angewandte Limnologie: Verhandlungen*, *19*, 1–15. https://doi.org/10.1080/03680770.1974.11896033

Ibisch, R. B., Bogardi, J. J., & Borchardt, D. (2016). Integrated Water Resources Management: Concept, Research and Implementation. In D. Borchardt, J. J. Bogardi, & R. B. Ibisch (Eds.), *Integrated Water Resources Management: Concept, Research and Implementation* (pp. 3–32). Cham: Springer. https://doi.org/10.1007/978-3-319-25071-7_1

IBM. (2022). *SPSS Statistics 29.0.0.0*. IBM Corp.

Ide, J., Takeda, I., Somura, H., Mori, Y., Sakuno, Y., Yone, Y., & Takahashi, E. (2019). Impacts of Hydrological Changes on Nutrient Transport From Diffuse Sources in a Rural River Basin, Western Japan. *Journal of Geophysical Research: Biogeosciences*, *124*(8), 2565–2581. https://doi.org/10.1029/2018JG004513

Iñiguez-Armijos, C., Leiva, A., Frede, H.-G., Hampel, H., & Breuer, L. (2014). Deforestation and Benthic Indicators: How Much Vegetation Cover Is Needed to Sustain Healthy Andean Streams? *PLOS ONE*, *9*(8), e105869. https://doi.org/10.1371/journal.pone.0105869

IPCC. (2023). *Synthesis Report of the IPCC Sixth Assessment Report (AR6)*. Intergovernmental Panel on Climate Change. https://www.ipcc.ch/report/ar6/syr/

Ison, R. L., & Wallis, P. J. (2017). Mechanisms for Inclusive Governance. In *Fresh Water Governance for the 21st Century* (pp. 159–186). Switzerland: Springer / Water Research Commission.

IWA. (2022). *Integrated Water Resources Management: Basic Concepts*. International Water Association. Retrieved 5 October 2022 from https://www.iwapublishing.com/news/integrated-water-resources-management-basic-concepts

Jansen, L. J. M., & Gregorio, A. D. (2002). Parametric land cover and land-use classifications as tools for environmental change detection. *Agriculture, Ecosystems & Environment*, *91*(1), 89–100. https://doi.org/10.1016/S0167-8809(01)00243-2

Jarvie, H. P., Oguchi, T., & Neal, C. (2002). Exploring the linkages between river water chemistry and watershed characteristics using GIS-based catchment and locality analyses. *Regional Environmental Change*, *3*(1), 36–50. https://doi.org/10.1007/s10113-001-0036-6

Jeffrey, P., & Gearey, M. (2006). Integrated water resources management: lost on the road from ambition to realisation? *Water Science and Technology*, *53*(1), 1–8. https://doi.org/10.2166/wst.2006.001

Jellason, N. P., Robinson, E. J. Z., Chapman, A. S. A., Neina, D., Devenish, A. J. M., Po, J. Y. T., & Adolph, B. (2021). A Systematic Review of Drivers and Constraints on Agricultural Expansion in Sub-Saharan Africa. *Land*, *10*(3), 332. https://doi.org/10.3390/land10030332

Jewitt, G. (2005). Water and Forests. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 2894–2909). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa192

Jiménez Cisneros, B. E., Oki, T., Arnell, N. W., Benito, G., Cogley, J. G., Döll, P., Jiang, T., & Mwakalila, S. S. (2014). Freshwater resources. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, M. D. Mastrandrea, & L. L. White (Eds.), *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press.

Johnson, C. J. (2013). Identifying ecological thresholds for regulating human activity: Effective conservation or wishful thinking? *Biological Conservation*, *168*, 57–65. https://doi.org/10.1016/j.biocon.2013.09.012

Johnson, L., Richards, C., Host, G., & Arthur, J. (1997). Landscape influences on water chemistry in Midwestern stream ecosystems. *Freshwater Biology*, *37*(1), 193–208. https://doi.org/10.1046/j.1365-2427.1997.d01-539.x

Johnson, M., Anhaeusser, C., & Thomas, R. (2006). *The Geology of South Africa*. Pretoria: Geological Society of South Africa/Council for Geoscience.

Johnson, M., & Wolmarans, L. (2008). *Simplified Geological Map of the Republic of South Africa and Kingdoms of Lesotho and Swaziland*. Council for Geoscience. https://www.geoscience.org.za

Jolk, C., Zindler, B., Stolpe, H., Wössner, R., & Abecker, A. (2018). Planning and Decision Support Tools for Integrated Water Resource Management on River Basin Level in South Africa on the Example of the Middle Olifants Sub-Basin. In U. Freitag, F. Fuchs-Kittowski, F. Hosenfeld, A. Abecker, & A. Reineke (Eds.), *Umweltinformationssysteme 2018* (pp. 83–109). http://ceur-ws.org/Vol-2197/

Jønch-Clausen, T. (2016). Foreword. In D. Borchardt, J. J. Bogardi, & R. B. Ibisch (Eds.), *Integrated Water Resource Management: Concept, Research, and Implementation* (pp. v–vii). Cham: Springer. https://doi.org/10.1007/978-3-319-25071-7_1

Jønch-Clausen, T., & Fugl, J. (2001). Firming up the Conceptual Basis of Integrated Water Resources Management. *Water Resources Development*, *17*(4), 501–510. https://doi.org/10.1080/07900620120094055

Jones, E. R., Bierkens, M. F. P., van Puijenbroek, P. J. T. M., van Beek, L. P. H., Wanders, N., Sutanudjaja, E. H., & van Vliet, M. T. H. (2023). Sub-Saharan Africa will increasingly become the dominant hotspot of surface water pollution. *Nature Water*, *1*(7), 602–613. https://doi.org/10.1038/s44221-023-00105-5

Jonker, L. (2007). Integrated water resources management: The theory–praxis–nexus, a South African perspective. *Physics and Chemistry of the Earth, Parts A/B/C*, *32*(15), 1257–1263. https://doi.org/10.1016/j.pce.2007.07.031

Jonker, L. (2014). *Integrated Water Resource Management (IWRM): From Theory to Practice, From Policy to Outcomes [WRC Report No. 1975/1/14]*. Water Research Commission.

Judd, C. M., McCelland, G. H., & Ryan, C. S. (2017). *Data Analysis: A Model Comparison Approach to Regression, ANOVA, and Beyond* (3rd ed.). New York: Routledge.

Jump, A. S., Cavin, L., & Hunter, P. D. (2010). Monitoring and managing responses to climate change at the retreating range edge of forest trees. *Journal of Environmental Monitoring*, *12*(10), 1791–1798. https://doi.org/10.1039/B923773A

Kachroud, M., Trolard, F., Kefi, M., Jebari, S., & Bourrié, G. (2019). Water Quality Indices: Challenges and Application Limits in the Literature. *Water*, *11*(2), 361. https://doi.org/10.3390/w11020361

Kadi, M. A. (2014). Integrated Water Resources Management (IWRM): The International Experience. In P. Martínez-Santos, M. M. Aldaya, & M. Ramón Llamas (Eds.), *Integrated Water Resources Management in the 21st Century: Revisiting the Paradigm* (pp. 3–15). London: CRC Press.

Kadir, A., Ahmed, Z., Uddin, M. M., Xie, Z., & Kumar, P. (2022). Integrated Approach to Quantify the Impact of Land Use and Land Cover Changes on Water Quality of Surma River, Sylhet, Bangladesh. *Water*, *14*(1), 17. https://doi.org/10.3390/w14010017

Kahinda, J. M. M., & Boroto, J. R. (2009). *National IWRM Status Report: South Africa*. Global Water Partnership. https://www.gwp.org/globalassets/global/gwp-saf-files/south-africa-iwrm-report.pdf

Kajitvichyanukul, P., & D'Arcy, B. (2022). *Land Use and Water Quality: The Impacts of Diffuse Pollution*. London: IWA Publishing. https://doi.org/10.2166/9781789061123

Kändler, M., Blechinger, K., Seidler, C., Pavlů, V., Šanda, M., Dostál, T., Krása, J., Vitvar, T., & Štich, M. (2017). Impact of land use on water quality in the upper Nisa catchment in the Czech Republic and in Germany. *Science of The Total Environment*, *586*, 1316–1325. https://doi.org/10.1016/j.scitotenv.2016.10.221

Karakuş, C. B. (2020). Assessment of relationship between land use/cover and surface water quality trends within the riparian zone: A case study from Sivas, Turkey. *Desalination and Water Treatment*, *182*, 414–433. https://doi.org/10.5004/dwt.2020.25632

Karar, E. (2017). *Freshwater governance for the 21st century*. Switzerland: Springer Nature. https://doi.org/10.1007/978-3-319-43350-9

Kasbohm, J., Grothe, S., Steingrube, W., Lai, L., Ngan, L. D., Hong, N. T., Oanh, L. T. K., & Huong, N. (2009). Integrated water resources management (IWRM) - an introduction. *Journal of Geology, Series B*, *33*, 3–14.

Katusiime, J., & Schütt, B. (2020). Integrated Water Resources Management Approaches to Improve Water Resources Governance. *Water*, *12*(12), 3424. https://doi.org/10.3390/w12123424

Kearns, F. R., Kelly, N. M., Carter, J. L., & Resh, V. H. (2005). A method for the use of landscape metrics in freshwater research and management. *Landscape Ecology*, *20*(1), 113–125. https://doi.org/10.1007/s10980-004-2261-0

Kebede, W., Tefera, M., Habitamu, T., & Alemayehu, T. (2014). Impact of Land Cover Change on Water Quality and Stream Flow in Lake Hawassa Watershed of Ethiopia. *Agricultural Sciences*, *5*(8), 13, Article 47641. https://doi.org/10.4236/as.2014.58068

Kelly, R. P., Erickson, A. L., & Mease, L. A. (2014). How not to fall off a cliff, or, using tipping points to improve environmental management. *Ecology Law Quarterly*, *41*, 843–886. https://doi.org/10.15779/Z38FP1H

Kelly, R. P., Erickson, A. L., Mease, L. A., Battista, W., Kittinger, J. N., & Fujita, R. (2015). Embracing thresholds for better environmental management. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1659), 20130276. https://doi.org/10.1098/rstb.2013.0276

Kennet, S. (2006). *From Science-Based Thresholds to Regulatory Limits: Implementation Issues for Cumulative Effects Management [Report prepared for Environment Canada, Northern Division]*. Canadian Institute of Resources Law.

Khan, A. A., Tobin, A., Paterson, R., Khan, H., & Warren, R. (2005). Application of CCME Procedures for Deriving Site-Specific Water Quality Guidelines for the CCME Water Quality Index. *Water Quality Research Journal*, *40*(4), 448–456. https://doi.org/10.2166/wqrj.2005.047

Kidd, S., & Shaw, D. (2007). Integrated water resource management and institutional integration: realising the potential of spatial planning in England. *The Geographical Journal*, *173*(4), 312–329. https://doi.org/10.1111/j.1475-4959.2007.00260.x

Kikoyo, D. (2023). A harmonized characterization of drainage units on the African continent. *Physics and Chemistry of the Earth, Parts A/B/C*, *131*, 103449. https://doi.org/10.1016/j.pce.2023.103449

Kim, H., Jeong, H., Jeon, J., & Bae, S. (2016). The Impact of Impervious Surface on Water Quality and Its Threshold in Korea. *Water*, *8*(4), 111. https://doi.org/10.3390/w8040111

Kim, T., Kim, Y., Shin, J., Go, B., & Cha, Y. (2020). Assessing Land-Cover Effects on Stream Water Quality in Metropolitan Areas Using the Water Quality Index. *Water*, *12*(11), 3294. https://doi.org/10.3390/w12113294

King, N., Strydom, H., & Retief, F. (2018). *Environmental Management in South Africa* (3rd ed.). Cape Town: Juta.

King, R. S., Baker, M. E., Whigham, D. F., Weller, D. E., Jordan, T. E., Kazyak, P. F., & Hurd, M. K. (2005). Spatial considerations for linking watershed land cover to ecological indicators in streams. *Ecological Applications*, *15*(1), 137–153. https://doi.org/10.1890/04-0481

Kirchner, J., Moolman, J., Du Plessis, H., & Reynders, A. (1997). Causes and management of salinity in the Breede River Valley, South Africa. *Hydrogeology Journal*, *5*(1), 98–108. https://doi.org/10.1007/s100400050126

Klein, R. D. (1979). Urbanization and stream quality impairment. *JAWRA Journal of the American Water Resources Association*, *15*(4), 948–963. https://doi.org/10.1111/j.1752-1688.1979.tb01074.x

Kleynhans, C., Thirion, C., & Moolman, J. (2005). *A Level 1 Ecoregion Classification System for South Africa, Lesotho and Swaziland [Report No. N/0000/00/REQ0104]*. Resource Quality Services, Department of Water Affairs & Forestry.

Knight, J. (2019a). The Making of the South African Landscape. In J. Knight & C. M. Rogerson (Eds.), *The Geography of South Africa: Contemporary Changes and New Directions* (pp. 7–14). Cham, Switzerland: Springer Nature. https://doi.org/10.1007/978-3-319-94974-1

Knight, J. (2019b). Water Resources in South Africa. In J. Knight & C. M. Rogerson (Eds.), *The Geography of South Africa: Contemporary Changes and New Directions* (pp. 99–101). Cham, Switzerland: Springer Nature. https://doi.org/10.1007/978-3-319-94974-1

Knight, J., & Rogerson, C. M. (2019). *The Geography of South Africa: Contemporary Changes and New Directions*. Cham, Switzerland: Springer Nature. https://doi.org/10.1007/978-3-319-94974-1

Knowles, E. (2005). *The Oxford Dictionary of Phrase and Fable* (2nd ed.). Oxford University Press. https://www.oxfordreference.com

Koekemoer, L., Van Vuuren, S. J., & Levanets, A. (2021). The influence of land use–impacted tributaries on water quality and phytoplankton in the Mooi River, North West Province, South Africa. *Bothalia - African Biodiversity & Conservation*, *51*(1), 1–22. https://doi.org/10.38201/btha.abc.v51.i1.3

Koenker, R., Chernozhukov, V., He, X., & Peng, L. (2018). *Handbook of Quantile Regression*. Boca Raton, FL: CRC Press/Taylor & Francis.

Kőrösi, C. (2023). *Summary of Proceedings by the President of the General Assembly: United Nations Conference on The Midterm Comprehensive Review of the Implementation of the Objectives of the International Decade for Action "Water for Sustainable Development", 2018–2028*. United Nations. https://sdgs.un.org/conferences/water2023

Kreye, M. M., Adams, D. C., & Escobedo, F. J. (2014). The Value of Forest Conservation for Water Quality Protection. *Forests*, *5*(5), 862–884. https://doi.org/10.3390/f5050862

Kronvang, B., Wendland, F., Kovar, K., & Fraters, D. (2020). Land Use and Water Quality. *Water*, *12*(9), 2412. https://doi.org/10.3390/w12092412

Kumar, M. D., Batchelor, C., & James, A. J. (2019). Operationalizing IWRM concepts at the basin level: From theory to practice. In M. D. Kumar, V. R. Reddy, & A. J. James (Eds.), *Current Directions in Water Scarcity Research* (Vol. 1, pp. 299–329). Elsevier. https://doi.org/10.1016/B978-0-12-814851-8.00011-2

Kundu, P., Mathivha, F., & Nkuna, T. (2015). *The Use of GIS and Remote Sensing Techniques to Evaluate the Impact of Land Use and Land Cover Change on the Hydrology of Luvuvhu River Catchment in Limpopo Province: Report to the Water Research Commission [WRC Report No. 2246/1/15]* (1431207055). Water Research Commission.

Kuranchie, A., Anim, D. O., Harmer, A., & Brunton, D. H. (2022). The influence of season and landscape on the water quality of ponds at multiple spatial scales. *Inland Waters*, 1–27. https://doi.org/10.1080/20442041.2022.2077633

Lacher, I. L., Ahmadisharaf, E., Fergus, C., Akre, T., McShea, W. J., Benham, B. L., & Kline, K. S. (2019). Scale-dependent impacts of urban and agricultural land use on nutrients, sediment, and runoff. *Science of The Total Environment*, *652*, 611–622. https://doi.org/10.1016/j.scitotenv.2018.09.370

Ladson, A. R. (2000). *A Multi-Component Indicator of Stream Condition for Water Managers: Balancing Scientific Rigour with the Need for Utility* [Doctoral Thesis, University of Melbourne]. https://doi.org/10.31237/osf.io/fkvzn

Lammert, M., & Allan, J. D. (1999). Assessing biotic integrity of streams: effects of scale in measuring the influence of land use/cover and habitat structure on fish and macroinvertebrates. *Environmental Management*, *23*(2), 257–270. https://doi.org/10.1007/s002679900184

Lardizabal, C. C. (2015). Basin Comanagement Plans – A Participative Approach to Water Governance: A Case Study in Honduras, Central America. In S. G. Setegn & M. C. Donoso (Eds.), *Sustainability of Integrated Water Resources Management: Water Governance, Climate and Ecohydrology*. Cham: Springer. https://doi.org/10.1007/978-3-319-12194-9

Larned, S. T., Scarsbrook, M. R., Snelder, T. H., Norton, N. J., & Biggs, B. J. F. (2004). Water quality in low-elevation streams and rivers of New Zealand: Recent state and trends in contrasting land-cover classes. *New Zealand Journal of Marine and Freshwater Research*, *38*(2), 347–366. https://doi.org/10.1080/00288330.2004.9517243

Łaszewski, M., Fedorczyk, M., & Stępniewski, K. (2022). The Impact of Land Cover on Selected Water Quality Parameters in Polish Lowland Streams during the Non-Vegetative Period. *Water*, *14*(20), 3295. https://doi.org/10.3390/w14203295

Le Maitre, D. C., Seyler, H., Holland, M., Smith-Adao, L., Nel, J. L., Maherry, A., & Witthüser, K. (2018). *Identification, Delineation and Importance of the Strategic Water Source Areas of South Africa, Lesotho and Swaziland for Surface Water and Groundwater [Report No. TT 743/1/18]*. Water Research Commission.

Lee, J. H., Lee, J. Y., Cha, Y. S., Cho, S. J., Kim, T. H., Cha, Y. K., & Koo, J. Y. (2022a). Development of customized water quality index for medium- and long-term evaluation of urban river water quality. *Water Supply*, *22*(7), 6338–6355. https://doi.org/10.2166/ws.2022.238

Lee, M., Kim, H., Lee, J.-Y., Yang, J. E., & Lim, C. (2022b). A Shift Towards Integrated and Adaptive Water Management in South Korea: Building Resilience Against Climate Change. *Water Resources Management*, *36*(5), 1611–1625. https://doi.org/10.1007/s11269-022-03071-x

Lee, S.-W., Hwang, S.-J., Lee, S.-B., Hwang, H.-S., & Sung, H.-C. (2009). Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. *Landscape and Urban Planning*, *92*(2), 80–89. https://doi.org/10.1016/j.landurbplan.2009.02.008

Lehner, B., & Grill, G. (2013). Global river hydrography and network routing: baseline data and new approaches to study the world's large river systems. *Hydrological Processes*, *27*(15), 2171–2186. www.hydrosheds.org

Lenat, D. R., & Crawford, J. K. (1994). Effects of land use on water quality and aquatic biota of three North Carolina Piedmont streams. *Hydrobiologia*, *294*(3), 185–199. https://doi.org/10.1007/BF00021291

Lenton, R. (2011). Integrated Water Resource Management. In P. Wilderer (Ed.), *Treatise on Water Science* (pp. 9–21). Elsevier.

Lenton, R., & Muller, M. (2009). *Integrated Water Resources Management in Practice: Better water management for development*. London: Earthscan.

Lenton, T. M. (2013). Environmental Tipping Points. *Annual Review of Environment and Resources*, *38*(1), 1–29. https://doi.org/10.1146/annurev-environ-102511-084654

Li, H.-H., Huang, Y.-M., Guo, W., Hou, H.-Y., Fan, M.-Y., Qi, X.-P., Jia, P.-H., & Guo, Q.-B. (2022a). Influence of Land Use and Land Cover Patterns on Water Quality at Different Spatio-temporal Scales in Hehuang Valley. *Huan jing ke xue= Huanjing kexue*, *43*(8), 4042–4053. https://doi.org/10.13227/j.hjkx.202110065

Li, S., Gu, S., Liu, W., Han, H., & Zhang, Q. (2008). Water quality in relation to land use and land cover in the upper Han River Basin, China. *CATENA*, *75*(2), 216–222. https://doi.org/10.1016/j.catena.2008.06.005

Li, S., Gu, S., Tan, X., & Zhang, Q. (2009). Water quality in the upper Han River basin, China: The impacts of land use/land cover in riparian buffer zone. *Journal of Hazardous Materials*, *165*(1), 317–324. https://doi.org/10.1016/j.jhazmat.2008.09.123

Li, S., Zhang, J., Jiang, P., & Zhang, L. (2022b). Linking land use with riverine water quality: A multi-spatial scale analysis relating to various riparian strips [Article]. *Frontiers in Environmental Science*, *10*, Article 1013318. https://doi.org/10.3389/fenvs.2022.1013318

Li, Y., Boswell, E., & Thompson, A. (2021). Correlations between land use and stream nitrate-nitrite concentrations in the Yahara River Watershed in south-central Wisconsin. *Journal of Environmental Management*, *278*(2), 111535. https://doi.org/10.1016/j.jenvman.2020.111535

Liberoff, A. L., Flaherty, S., Hualde, P., García Asorey, M. I., Fogel, M. L., & Pascual, M. A. (2019). Assessing land use and land cover influence on surface water quality using a parametric weighted distance function. *Limnologica*, *74*, 28–37. https://doi.org/10.1016/j.limno.2018.10.003

Lintern, A., Webb, J. A., Ryu, D., Liu, S., Bende-Michl, U., Waters, D., Leahy, P., Wilson, P., & Western, A. W. (2018). Key factors influencing differences in stream water quality across space. *WIREs Water*, *5*(1), e1260. https://doi.org/10.1002/wat2.1260

Lipchin, C. (2014). Transboundary Wastewater Management Under Conditions of Inadequate Infrastructure and Political Complexity: the Need for Decentralized Approaches. *New Water Policy & Practice*, *1*(1), 40–44. https://doi.org/10.18278/nwpp.1.1.5

Liu, J., Xu, J., Zhang, X., Liang, Z., & Rao, K. (2021). Nonlinearity and threshold effects of landscape pattern on water quality in a rapidly urbanized headwater watershed in China. *Ecological Indicators*, *124*, 107389. https://doi.org/10.1016/j.ecolind.2021.107389

Liu, M., Wei, H., Dong, X., Wang, X. C., Zhao, B., & Zhang, Y. (2022). Integrating Land Use, Ecosystem Service, and Human Well-Being: A Systematic Review [Review]. *Sustainability (Switzerland)*, *14*(11), Article 6926. https://doi.org/10.3390/su14116926

Liu, W., Zhang, Q., & Liu, G. (2012). Influences of watershed landscape composition and configuration on lake-water quality in the Yangtze River basin of China. *Hydrological Processes*, *26*(4), 570–578. https://doi.org/10.1002/hyp.8157

Liu, X., Liu, H., Jing, J., Liu, Y., Xu, Z., Cao, X., Ma, L., Zhuo, Y., Wen, L., & Wang, L. (2023). How the land use/cover changes and environmental factors at different scales affect lake water quality in arid and semi-arid regions [Original Research]. *Frontiers in Ecology and Evolution*, *11*. https://doi.org/10.3389/fevo.2023.1188927

Liu, Z., Li, Y., & Peng, J. (2010). The landscape components threshold of stream water quality: A review [Article]. *Shengtai Xuebao/ Acta Ecologica Sinica*, *30*(21), 5983–5993.

Liu, Z., & Yang, H. (2018). The Impacts of Spatiotemporal Landscape Changes on Water Quality in Shenzhen, China. *International Journal of Environmental Research and Public Health*, *15*(5), 1038. https://doi.org/10.3390/ijerph15051038

Loague, K., & Corwin, D. L. (2005). Point and NonPoint Source Pollution. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 1427–1440). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa195

Lorion, C. M., & Kennedy, B. P. (2009). Relationships between deforestation, riparian forest buffers and benthic macroinvertebrates in neotropical headwater streams. *Freshwater Biology*, *54*(1), 165–180. https://doi.org/10.1111/j.1365-2427.2008.02092.x

Lötter, M. C., & Le Maitre, D. C. (2021). *Fine-scale delineation of Strategic Water Source Areas for surface water in South Africa using Empirical Bayesian Kriging Regression Prediction: Technical report.* South African National Biodiversity Institute. http://hdl.handle.net/20.500.12143/8521

Lu, J., Cai, H., Zhang, X., & Fu, Y. (2021). Water quality in relation to land use in the Junshan Lake watershed and water quality predictions. *Water Supply*, *21*(7), 3602–3613. https://doi.org/10.2166/ws.2021.123

Lubell, M., & Balazs, C. (2018). Integrated water resources management: Core research questions for governance. In K. Conca & E. Weinthal (Eds.), *The Oxford Handbook of Water Politics and*

Policy (pp. 569–593). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199335084.013.2

Lukat, E., Lenschow, A., Dombrowsky, I., Meergans, F., Schütze, N., Stein, U., & Pahl-Wostl, C. (2023). Governance towards coordination for water resources management: The effect of governance modes. *Environmental Science & Policy*, *141*, 50–60. https://doi.org/10.1016/j.envsci.2022.12.016

Lukat, E. C., Pahl-Wostl, C., & Lenschow, A. (2022a). Deficits in implementing integrated water resources management in South Africa: The role of institutional interplay. *Environmental Science & Policy*, *136*, 304–313. https://doi.org/10.1016/j.envsci.2022.06.010

Lukat, E. C., Schoderer, M., & Salvador, S. C. (2022b). When International Blueprints Hit Local Realities: Bricolage Processes in Implementing IWRM in South Africa, Mongolia and Peru. *Water Alternatives*, *15*(2), 473–500. https://www.water-alternatives.org/index.php/alldoc/articles/vol15/v15issue2/664-a15-2-6

Lukhabi, D. K., Mensah, P. K., Asare, N. K., Pulumuka-Kamanga, T., & Ouma, K. O. (2023). Adapted Water Quality Indices: Limitations and Potential for Water Quality Monitoring in Africa. *Water*, *15*(9), 1736. https://doi.org/10.3390/w15091736

Lumb, A., Halliwell, D., & Sharma, T. (2006). Application of CCME Water Quality Index to Monitor Water Quality: A Case Study of the Mackenzie River Basin, Canada. *Environmental Monitoring and Assessment*, *113*(1), 411–429. https://doi.org/10.1007/s10661-005-9092-6

Lumb, A., Sharma, T. C., & Bibeault, J.-F. (2011). A Review of Genesis and Evolution of Water Quality Index (WQI) and Some Future Directions. *Water Quality, Exposure and Health*, *3*, 11–24. https://doi.org/10.1007/s12403-011-0040-0

Lupi, F., Herriges, J. A., Kim, H., & Stevenson, R. J. (2023). Getting off the ladder: Disentangling water quality indices to enhance the valuation of divergent ecosystem services. *Proceedings of the National Academy of Sciences*, *120*(18), e2120261120. https://doi.org/10.1073/pnas.2120261120

Ma, B., Wu, C., Jia, X., Zhang, Y., & Zhou, Z. (2023). Predicting water quality using partial least squares regression of land use and morphology (Danjiangkou Reservoir, China). *Journal of Hydrology*, *624*, 129828. https://doi.org/10.1016/j.jhydrol.2023.129828

Ma, L., Engel, M., A, Ricketts, J., Soto-Montero, P., & Sullivan, P. L. (2022). Regional Drivers of Stream Chemical Behavior: Leveraging Lithology, Land Use, and Climate Gradients across the Colorado River, Texas USA. *Water Resources Research*, e2022WR032155. https://doi.org/10.1029/2022WR032155

Magierowski, R. H., Davies, P. E., Read, S. M., & Horrigan, N. (2012). Impacts of land use on the structure of river macroinvertebrate communities across Tasmania, Australia: spatial scales and thresholds. *Marine and Freshwater Research*, *63*(9), 762–776. https://doi.org/10.1071/MF11267

Mahabeer, P., & Tekere, M. (2021). Anthropogenic pollution influences on the physical and chemical quality of water and sediments of the Umdloti river system, Kwazulu-Natal. *Physics and Chemistry of the Earth, Parts A/B/C*, *123*, 103030. https://doi.org/10.1016/j.pce.2021.103030

Mainali, J., & Chang, H. (2018). Landscape and anthropogenic factors affecting spatial patterns of water quality trends in a large river basin, South Korea. *Journal of Hydrology*, *564*, 26–40. https://doi.org/10.1016/j.jhydrol.2018.06.074

Maine DEP. (2021). *Description of Nutrient Criteria for Class AA, A, B, and C Fresh Surface Waters (Chapter 583)*. Maine Department of Environmental Protection. https://www.maine.gov/dep/water/nutrient-criteria/index.html

Makgoale, M. M., Addo-Bediako, A., & Ayisi, K. K. (2022). Distribution Pattern of Macroinvertebrate Functional Feeding Groups in the Steelpoort River, South Africa. *Applied Ecology and Environmental Research*, *20*(1), 189–206. https://doi.org/10.15666/aeer/2001_189206

Malaza, N., & Mabuda, A. I. (2019). Challenges of integrated water resources management in the Western Cape Province, South Africa. *Journal of Water Resources and Ocean Science*, *8*(2), 9–20. https://doi.org/10.11648/j.wros.20190802.11

Malek, Ž., & Verburg, P. H. (2020). Mapping global patterns of land use decision-making. *Global Environmental Change*, *65*, 102170. https://doi.org/10.1016/j.gloenvcha.2020.102170

Malherbe, H., Le Maitre, D., Le Roux, J., Pauleit, S., & Lorz, C. (2019a). A simplified method to assess the impact of sediment and nutrient inputs on river water quality in two regions of the southern coast of South Africa. *Environmental Management*, *63*(5), 658–672.

Malherbe, H., Pauleit, S., & Lorz, C. (2019b). Mapping the loss of ecosystem services in a region under intensive land use along the southern coast of South Africa. *Land*, *8*(3), 51. https://doi.org/10.3390/land8030051

Mallya, C. L., & Rwiza, M. J. (2021). Influence of land use change on nitrate sources and pollutant enrichment in surface and groundwater of a growing urban area in Tanzania. *Environmental Earth Sciences*, *80*(3), 111. https://doi.org/10.1007/s12665-021-09386-z

Maloney, K. O., & Weller, D. E. (2011). Anthropogenic disturbance and streams: land use and land-use change affect stream ecosystems via multiple pathways. *Freshwater Biology*, *56*(3), 611–626. https://doi.org/10.1111/j.1365-2427.2010.02522.x

Manfrin, A., Bombic, P., Traversetti, L., Larsene, S., & Scalicid, M. (2016). A landscape-based predictive approach for running water quality assessment: A Mediterranean case study. *Journal for Nature Conservation*, *30*, 27–31. https://doi.org/10.1016/j.jnc.2016.01.002

Mararakanye, N., Le Roux, J. J., & Franke, A. C. (2022). Long-term water quality assessments under changing land use in a large semi-arid catchment in South Africa. *Science of The Total Environment*, *818*. https://doi.org/10.1016/j.scitotenv.2021.151670

Martin, J., Runge, M. C., Nichols, J. D., Lubow, B. C., & Kendall, W. L. (2009). Structured decision making as a conceptual framework to identify thresholds for conservation and management. *Ecological Applications*, *19*(5), 1079–1090. https://doi.org/10.1890/08-0255.1

Martin, S. L., Hayes, D. B., Kendall, A. D., & Hyndman, D. W. (2017). The land-use legacy effect: Towards a mechanistic understanding of time-lagged water quality responses to land use/cover. *Science of The Total Environment*, *579*, 1794–1803. https://doi.org/10.1016/j.scitotenv.2016.11.158

Martinez-Santos, P., Aldaya, M. M., & Llamas, M. R. (2014). *Integrated Water Resources Management in the 21st Century: Revisiting the paradigm*. London: CRC Press. https://doi.org/10.1201/b16591

Martínez-Santos, P., Aldaya, M. M., & Ramón Llamas, M. (2014). Integrated Water Resources Management: State of the art and the way forward. In P. Martínez-Santos, M. M. Aldaya, & M. Ramón Llamas (Eds.), *Integrated Water Resources Management in the 21st Century: Revisiting the Paradigm* (pp. 17–36). London: CRC Press. https://doi.org/10.1201/b16591

Mashala, M. J., Dube, T., Mudereri, B. T., Ayisi, K. K., & Ramudzuli, M. R. (2023). A Systematic Review on Advancements in Remote Sensing for Assessing and Monitoring Land Use and Land Cover Changes Impacts on Surface Water Resources in Semi-Arid Tropical Environments. *Remote Sensing*, *15*(16), 3926. https://doi.org/10.3390/rs15163926

Masocha, M., Murwira, A., Magadza, C. H., Hirji, R., & Dube, T. (2017). Remote sensing of surface water quality in relation to catchment condition in Zimbabwe. *Physics and Chemistry of the Earth*, *100*, 13–18. https://doi.org/10.1016/j.pce.2017.02.013

Mateo-Sagasta, J., Zadeh, S. M., & Turral, H. (2018). *More people, more food, worse water? A global review of water pollution from agriculture*. Rome/Colombo: Food and Agriculture Organization of the United Nations and the International Water Management Institute on behalf of the Water Land and Ecosystems research program of the CGIAR. http://www.fao.org/3/ca0146en/CA0146EN.pdf

Matz, M. (2008). Rethinking IWRM Under Cultural Considerations. In W. Scheumann, S. Neubert, & M. Kipping (Eds.), *Water Politics and Development Cooperation*. Berlin: Springer.

Mauck, G. E. (2012). *The Inclusion and Implementation of Integrated Water Resources Management Under South African Water Law and Policy* [Master's Thesis, University of Kwa-Zulu Natal]. http://hdl.handle.net/10413/9167

Maurya, P. K., Ali, S. A., Alharbi, R. S., Yadav, K. K., Alfaisal, F. M., Ahmad, A., Ditthakit, P., Prasad, S., Jung, Y.-K., & Jeon, B.-H. (2021). Impacts of Land Use Change on Water Quality Index in the Upper Ganges River near Haridwar, Uttarakhand: A GIS-Based Analysis. *Water*, *13*(24), 3572. https://doi.org/10.3390/w13243572

May, C. W., Horner, R. R., Karr, J. R., Mar, B. W., & Welch, E. B. (1998). *The cumulative effects of urbanization on small streams in the Puget Sound Lowland Ecoregion*. University of Washington.

McBride, G. (2005). *Using Statistical Methods for Water Quality Management: Issues, Problems and Solutions*. New Jersey: Wiley-Interscience/John Wiley & Sons.

McCutcheon, S. C., Martin, J. L., & Barnwell, T. O. (1993). Water Quality. In D. Maidment (Ed.), *Handbook of Hydrology*. New York: McGraw Hill.

McDonnell, R. A. (2008). Challenges for Integrated Water Resources Management: How Do We Provide the Knowledge to Support Truly Integrated Thinking? *International Journal of Water Resources Development*, *24*(1), 131–143. https://doi.org/10.1080/07900620701723240

McDowell, R. W., Snelder, T. H., & Cox, N. (2013). *Establishment of reference conditions and trigger values for chemical, physical and micro-biological indicators in New Zealand streams and rivers [Report prepared for the Ministry for the Environment]*. AgResearch Ltd.

McGarigal, K. (2001). Landscape Pattern Metrics. In *Encyclopedia of Environmetrics*. https://doi.org/doi.org/10.1002/9780470057339.val006.pub2

McGarigal, K., & Ene, E. (2023). *FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical Maps.* https://www.fragstats.org

Medema, W., & Jeffrey, P. (2005). IWRM and Adaptive Management: Synergy or Conflict? *NeWater Report Series No. 7*. https://www.newater.uni-osnabrueck.de/

Medema, W., McIntosh, B., & Jeffrey, P. (2008). From Premise to Practice: a Critical Assessment of Integrated Water Resources Management and Adaptive Management Approaches in the Water Sector. *Ecology and Society*, *13*(2), 29. https://www.jstor.org/stable/26268004

Medupin, C., Bark, R., & Owusu, K. (2020). Land Cover and Water Quality Patterns in an Urban River: A Case Study of River Medlock, Greater Manchester, UK. *Water*, *12*(3), 848. https://doi.org/10.3390/w12030848

Mehaffey, M. H., Nash, M. S., Wade, T. G., Ebert, D. W., Jones, K. B., & Rager, A. (2005). Linking Land Cover and Water Quality in New York City's Water Supply Watersheds. *Environmental Monitoring and Assessment*, *107*(1), 29–44. https://doi.org/10.1007/s10661-005-2018-5

Meissner, R., Stuart-Hill, S., & Nakhooda, Z. (2017). The Establishment of Catchment Management Agencies in South Africa with Reference to the Flussgebietsgemeinschaft Elbe: Some Practical Considerations. In E. Karar (Ed.), *Fresh Water Governance for the 21st Century* (pp. 15–28). Switzerland: Springer. https://doi.org/10.1007/978-3-319-43350-9

Meneses, B. M., Reis, R., Vale, M. J., & Saraiva, R. (2015). Land use and land cover changes in Zêzere watershed (Portugal) — Water quality implications. *Science of The Total Environment*, *527-528*, 439–447. https://doi.org/10.1016/j.scitotenv.2015.04.092

Meran, G., Siehlow, M., & von Hirschhausen, C. (2021). *The Economics of Water: Rules and Institutions*. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-48485-9

Merry, D. J. (2008). Is normative integrated water resources management implementable? Charting a practical course with lessons from Southern Africa. *Physics and Chemistry of the Earth, Parts A/B/C, 33*, 899–905. https://doi.org/10.1016/j.pce.2008.06.026

Meybeck, M., Peters, N. E., & Chapman, D. V. (2005). Water Quality. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 1373–1385). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa195

Michalak, A. M. (2016). Study role of climate change in extreme threats to water quality. *Nature*, *535*(7612), 349–350. https://doi.org/10.1038/535349a

Midway, S. R., Wagner, T., Tracy, B. H., Hogue, G. M., & Starnes, W. C. (2015). Evaluating changes in stream fish species richness over a 50-year time-period within a landscape context. *Environmental Biology of Fishes*, *98*(5), 1295–1309. https://doi.org/10.1007/s10641-014-0359-z

Miller, J. D., Schoonover, J. E., Williard, K. W. J., & Hwang, C. R. (2011). Whole Catchment Land Cover Effects on Water Quality in the Lower Kaskaskia River Watershed. *Water, Air, & Soil Pollution*, *221*(1), 337. https://doi.org/10.1007/s11270-011-0794-9

Mirzaei, M., Jafari, A., Gholamalifard, M., Azadi, H., Shooshtari, S. J., Moghaddam, S. M., Gebrehiwot, K., & Witlox, F. (2020). Mitigating environmental risks: Modeling the interaction of water quality parameters and land use cover. *Land Use Policy*, *95*, 103766. https://doi.org/10.1016/j.landusepol.2018.12.014

Miserendino, M. L., Casaux, R., Archangelsky, M., Di Prinzio, C. Y., Brand, C., & Kutschker, A. M. (2011). Assessing land-use effects on water quality, in-stream habitat, riparian ecosystems and biodiversity in Patagonian northwest streams. *Science of The Total Environment*, *409*(3), 612–624. https://doi.org/10.1016/j.scitotenv.2010.10.034

Mitchell, B. (2005). Integrated water resource management, institutional arrangements, and land-use planning. *Environment and Planning*, *37*, 1335–1352. https://doi.org/10.1068/a37224

Mladenović-Ranisavljević, I. I., Takić, L., & Nikolić, Đ. (2018). Water Quality Assessment Based on Combined Multi-Criteria Decision-Making Method with Index Method. *Water Resources Management*, *32*(7), 2261–2276. https://doi.org/10.1007/s11269-018-1927-3

Mo, W., Yang, N., Zhao, Y., & Xu, Z. (2023). Impacts of land use patterns on river water quality: the case of Dongjiang Lake Basin, China. *Ecological Informatics*, *75*, 102083. https://doi.org/10.1016/j.ecoinf.2023.102083

Molekoa, M. D., Avtar, R., Kumar, P., Thu Minh, H. V., Dasgupta, R., Johnson, B. A., Sahu, N., Verma, R. L., & Yunus, A. P. (2021). Spatio-Temporal Analysis of Surface Water Quality in Mokopane Area, Limpopo, South Africa. *Water*, *13*(2), 220. https://doi.org/10.3390/w13020220

Molle, F. (2006). *Planning and Managing Water Resources at the River-Basin Level: Emergence and Evolution of a Concept (IWMI Comprehensive Assessment Research Report 16)*. International Water Management Institute.

Molle, F. (2008). Nirvana concepts, narratives and policy models: Insight from the water sector. *Water Alternatives*, *1*(1), 131-156. https://www.water-alternatives.org/index.php/volume1/v1issue1/20-a-1-1-8

Montefiore, L. R., Nelson, N. G., Staudinger, M. D., & Terando, A. (2023). Vulnerability of Estuarine Systems in the Contiguous United States to Water Quality Change Under Future Climate and Land-Use. *Earth's Future*, *11*(3), e2022EF002884. https://doi.org/10.1029/2022EF002884

Moodley, K., Pillay, S., & Pather, K. (2015). Spatiotemporal characterization of water chemistry and pollution sources of the Umhlatuzana, Umbilo and Amanzimnyama River catchments of Durban, KwaZulu-Natal, South Africa. *Environmental Earth Sciences*, *74*(2), 1273–1289. https://doi.org/10.1007/s12665-015-4118-z

Morse, J., Welch, J. N., Weinberg, A., & Szabo, P. (2018). *Literature review: forest cover & water quality–implications for land conservation*. Open Space Institute. https://www.openspaceinstitute.org/what/land-for-clean-water

Movik, S., Mehta, L., & van Koppen, B. (2016). Emergence, interpretations and translations of IWRM [Integrated Water Resources Management] in South Africa. *Water Alternatives*, *9*(3), 456–472. https://hdl.handle.net/10568/78535

Mugejo, K., Ncube, B., & Mutsvangwa, C. (2022). Infrastructure Performance and Irrigation Water Governance in Genadendal, Western Cape, South Africa. *Preprints*, *2022080168*. https://doi.org/10.20944/preprints202208.0168.v1

Mukhtarov, F. G. (2008). Intellectual history and current status of Integrated Water Resources Management: A global perspective. In C. Pahl-Wostl, P. Kabat, & J. Möltgen (Eds.), *Adaptive and Integrated Water Management* (pp. 167–185). Berlin: Springer.

Muller, M. (2009). Attempting to Do it All: How a New South Africa has Harnessed Water to Address its Development Challenges. In R. Lenton & M. Muller (Eds.), *Integrated Water Resources Management in Practice: Better water management for development* (pp. 169–185). London: Earthscan/Global Water Partnership.

Muller, M. (2018). Cape Town’s drought: don’t blame climate change. *Nature*, *559*, 174–176. https://doi.org/10.1038/d41586-018-05649-1

Muller, M. (2019). Understanding South Africa’s real water crisis. *Farmer's Weekly*, *2019*(19046), 6–7. https://doi.org/10.10520/EJC-197e8b025e

Munnik, V. (2020). *The Reluctant Roll-Out of Catchment Management Agencies: Assessing Key Risks and Consequences of Delays in Finalising the Instituional Arrangements for Decentralised Water Resource Management [WRC Report No. 2943/1/20]*. Water Research Commission.

Munson, S. M., Reed, S. C., Peñuelas, J., McDowell, N. G., & Sala, O. E. (2018). Ecosystem thresholds, tipping points, and critical transitions. *The New Phytologist*, *218*(4), 1315–1317. https://doi.org/10.1111/nph.15145

Muradian, R. (2001). Ecological thresholds: a survey. *Ecological Economics*, *38*(1), 7–24. https://doi.org/10.1016/S0921-8009(01)00146-X

Musakwa, W., & Niekerk, A. V. (2013). Implications of land use change for the sustainability of urban areas: A case study of Stellenbosch, South Africa. *Cities*, *32*, 143–156. https://doi.org/10.1016/j.cities.2013.01.004

Mwaijengo, G. N., Msigwa, A., Njau, K. N., Brendonck, L., & Vanschoenwinkel, B. (2020). Where does land use matter most? Contrasting land use effects on river quality at different spatial scales. *Science of The Total Environment*, *715*, 134825. https://doi.org/10.1016/j.scitotenv.2019.134825

Namugize, J. N., Jewitt, G., & Graham, M. (2018). Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C*, *105*, 247–264. https://doi.org/10.1016/j.pce.2018.03.013

Namugize, J. N., & Jewitt, G. P. W. (2018). Sensitivity analysis for water quality monitoring frequency in the application of a water quality index for the uMngeni River and its tributaries, KwaZulu-Natal, South Africa. *Water SA*, *44*(4), 516–527. https://doi.org/10.4314/wsa.v44i4.01

Nash, M. S., Heggem, D. T., Ebert, D., Wade, T. G., & Hall, R. K. (2009). Multi-scale landscape factors influencing stream water quality in the state of Oregon. *Environmental Monitoring and Assessment*, *156*(1), 343–360. https://doi.org/10.1007/s10661-008-0489-x

Nath, S., Vyas, J. N., Deogade, R. B., & Chandra, P. (2023). Integrated Water Resources Management in Developing Nation: Status and Challenges Toward Water Sustainability. In P. Singh, Y. Milshina, A. Batalhão, S. Sharma, & M. M. Hanafiah (Eds.), *The Route Towards Global Sustainability: Challenges and Management Practices* (pp. 367–378). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-10437-4_18

National Research Council. (2001). Water Availability: Quantity and Quality. In *Envisioning the Agenda for Water Resources Research in the Twenty-First Century* (pp. 70). Washington, DC: The National Academies Press. https://doi.org/doi:10.17226/10140

Nava-López, M. Z., Diemont, S. A. W., Hall, M., & Ávila-Akerberg, V. (2016). Riparian Buffer Zone and Whole Watershed Influences on River Water Quality: Implications for Ecosystem Services near Megacities. *Environmental Processes*, *3*(2), 277–305. https://doi.org/10.1007/s40710-016-0145-3

Nde, S. C., Bett, S., Okpara, E. C., Olagbaju, P. O., Fayemi, O. E., & Mathuthu, M. (2021). An Assessment of Land Use and Land Cover Changes and Its Impact on the Surface Water Quality of the Crocodile River Catchment, South Africa. In *River Deltas-Recent Advances*. IntechOpen. https://doi.org/10.5772/intechopen.95753

Nde, S. C., & Mathuthu, M. (2018). Assessment of Potentially Toxic Elements as Non-Point Sources of Contamination in the Upper Crocodile Catchment Area, North-West Province, South Africa. *International Journal of Environmental Research and Public Health*, *15*(4), 576. https://doi.org/10.3390/ijerph15040576

Nel, J. L., Driver, A., Strydom, W. F., Maherry, A., Petersen, C., Hill, L., Roux, D. J., Nienaber, S., van Deventer, H., Swartz, E., & Smith-Adao, L. B. (2011a). *Atlas of Freshwater Ecosystem Priority Areas in South Africa: Maps to Support Sustainable Development of Water Resources [WRC Report No. TT 500/11]*. Water Research Commission.

Nel, J. L., Murray, K. M., Maherry, A. M., Petersen, C. P., Roux, D. J., Driver, A., Hill, L., van Deventer, H., Funke, N., Swartz, E. R., Smith-Adao, L. B., Mbona, N., Downsborough, L., & Nienaber, S. (2011b). *Technical Report for the National Freshwater Ecosystem Priority Areas Project [WRC Report No. 1801/2/11]*. Water Research Commission.

Nemerow, N. L. (1991). *Stream, lake, estuary, and ocean pollution* (2nd ed.). New York: Van Nostrand Reinhold.

Nemerow, N. L., & Sumitomo, H. (1970). *Benefits of Water Quality Enhancement*. U.S. Environmental Protection Agency.

Ngoye, E., & Machiwa, J. F. (2004). The influence of land-use patterns in the Ruvu river watershed on water quality in the river system. *Physics and Chemistry of the Earth, Parts A/B/C*, *29*(15), 1161–1166. https://doi.org/10.1016/j.pce.2004.09.002

Nguvulu, A., Shane, A., Mwale, C. S., Tena, T. M., Mwaanga, P., Siame, J., Chirambo, B., Lungu, M., Mudenda, F., Mwelwa, D., Chinyanta, S., Kawala, J., Bowa, V. M., Mutambo, L. S., & Okell, N. (2021). Surface Water Quality Response to Land Use Land Cover Change in an Urbanizing Catchment: A Case of Upper Chongwe River Catchment, Zambia. *Journal of Geographic Information System*, *13*(5). https://doi.org/10.4236/jgis.2021.135032

Nielsen, A., Trolle, D., Sondergaard, M., Lauridsen, T. L., Bjerring, R., Olesen, J. E., & Jeppensen, E. (2012). Watershed land use effects on lake water quality in Denmark. *Ecological Applications*, *22*(4), 1187–1200. https://doi.org/10.1890/11-1831.1

Nkosi, M., Mathivha, F. I., & Odiyo, J. O. (2021). Impact of Land Management on Water Resources, a South African Context. *Sustainability*, *13*(2), 701. https://doi.org/10.3390/su13020701

Nobre, R. L. G., Caliman, A., Cabral, C. R., Araújo, F. d. C., Guérin, J., Dantas, F. d. C. C., Quesado, L. B., Venticinque, E. M., Guariento, R. D., Amado, A. M., Kelly, P., Vanni, M. J., & Carneiro, L. S. (2020). Precipitation, landscape properties and land use interactively affect water quality of tropical freshwaters. *Science of The Total Environment*, *716*, 137044. https://doi.org/10.1016/j.scitotenv.2020.137044

Nomquphu, W. (2005). *Overview of the Situation and Challenges for Water Quality Monitoring and Reporting in South Africa*. United Nations Intersecretariat Working Group on Environment Statistics, Work Session on Water Statistics, 20-22 June, Vienna. http://mdgs.un.org/unsd/ENVIRONMENT/envpdf/pap_wasess5a4sa.pdf

Norris, V. (1993). The use of buffer zones to protect water quality: A review. *Water Resources Management*, *7*(4), 257–272. https://doi.org/10.1007/BF00872284

Nusantara, D. P., Sutjiningsih, D., & Anggraheni, E. (2020). Water Quality Index Response of UI Cascade-Pond System on Catchment Imperviousness Temporal Variation. *IOP Conference Series: Earth and Environmental Science*, *426*(1), 012044. https://doi.org/10.1088/1755-1315/426/1/012044

O'Keeffe, J. (2012). Environmental Flow Allocation as a Practical Aspect of IWRM. In *River Conservation and Management* (pp. 45–57). https://doi.org/10.1002/9781119961819.ch4

Obeng, L. A. (2009). Foreward. In R. Lenton & M. Muller (Eds.), *Integrated Water Resources Management in Practice: Better water management for development* (pp. xiii). London: Earthscan/Global Water Partnership.

Obubu, J. P., Mengistou, S., Odong, R., Fetahi, T., & Alamirew, T. (2022). Determination of the Connectedness of Land Use, Land Cover Change to Water Quality Status of a Shallow Lake: A Case of Lake Kyoga Basin, Uganda. *Sustainability*, *14*(1), 372. https://doi.org/10.3390/su14010372

OECD. (2017). *Diffuse Pollution, Degraded Waters: Emerging Policy Solutions*. OECD Studies on Water. https://doi.org/10.1787/9789264269064-en

Ogbozige, F. J., & Alfa, M. I. (2019). Land Use-Land Cover Effects on Surface Flowing Water Quality: A Statistical Approach. *Nigerian Journal of Technological Development*, *16*(1), 25–35. https://doi.org/10.4314/njtd.v16i1.4

Olander, L., Polasky, S., Kagan, J. S., Johnston, R. J., Wainger, L., Saah, D., Maguire, L., Boyd, J., & Yoskowitz, D. (2017). So you want your research to be relevant? Building the bridge between ecosystem services research and practice. *Ecosystem Services*, *26*, 170–182. https://doi.org/10.1016/j.ecoser.2017.06.003

Oliver, K., & Cairney, P. (2019). The dos and don’ts of influencing policy: a systematic review of advice to academics. *Palgrave Communications*, *5*(1), 21. https://doi.org/10.1057/s41599-019-0232-y

Omernik, J. M., Abernathy, A. R., & Male, L. M. (1981). Stream nutrient levels and proximity of agricultural and forest land to streams: Some relationships. *Journal of Soil and Water Conservation*, *36*(4), 227-231. https://www.jswconline.org/

Oosterbaan, R. J. (2021). Analysis of Different Curved Regressions using Free Software and Selection of the Appropriate Type Based on Statistical Tests for Goodness of Fit and Analysis of

Variance. *International Journal of Mathematical and Computational Methods*, *6*, 56–68. https://www.waterlog.info/segreg.htm
Open Space Institute. (2018). *Measuring the Connection Between Land Protection and Clean Water*. Retrieved 27 March 2023 from https://www.openspaceinstitute.org/research/measuring-the-connection-between-land-protection-and-clean-water
Oqubay, A., Tregenna, F., & Valodia, I. (2021). *The Oxford Handbook of the South African Economy*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780192894199.001.0001
Osborne, J. W., & Overbay, A. (2004). The power of outliers (and why researchers should ALWAYS check for them). *Practical Assessment, Research, and Evaluation*, *9*. https://doi.org/10.7275/qf69-7k43
Osborne, L. L., & Kovacic, D. A. (1993). Riparian vegetated buffer strips in water-quality restoration and stream management. *Freshwater Biology*, *29*(2), 243–258. https://doi.org/10.1111/j.1365-2427.1993.tb00761.x
Ott, R. L., & Longnecker, M. T. (2016). *An Introduction to Statistical Methods and Data Analysis* (7th ed.). Cengage Learning.
Ott, W. (1978). *Environmental indices: theory and practice*. Michigan: Ann Arbor Science.
Otto, F. E. L., Wolski, P., Lehner, F., Tebaldi, C., van Oldenborgh, G. J., Hogesteeger, S., Singh, R., Holden, P., Fučkar, N. S., & Odoulami, R. C. (2018). Anthropogenic influence on the drivers of the Western Cape drought 2015–2017. *Environmental Research Letters*, *13*(124010). https://doi.org/10.1088/1748-9326/aae9f9
Ou, Y., Wang, X., Wang, L., & Rousseau, A. N. (2016). Landscape influences on water quality in riparian buffer zone of drinking water source area, Northern China. *Environmental Earth Sciences*, *75*(2), 114. https://doi.org/10.1007/s12665-015-4884-7
Pahl-Wostl, C., Jeffrey, P., Isendahl, N., & Brugnach, M. (2011a). Maturing the New Water Management Paradigm: Progressing from Aspiration to Practice. *Water Resources Management*, *25*, 837–856. https://doi.org/10.1007/s11269-010-9729-2
Pahl-Wostl, C., Jeffrey, P., & Sendzimir, J. (2011b). Adaptive and integrated management of water resources. In K. Hussey & R. Q. Grafton (Eds.), *Water Resources Planning and Management* (pp. 292–310). Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511974304.016
Pahl-Wostl, C., & Sendzimir, J. (2005). The relationship between IWRM and Adaptive Water Management. *NeWater Report Series No. 3*. https://www.newater.uni-osnabrueck.de/
Palma, P., Fialho, S., Lima, A., Mourinha, C., Penha, A., Novais, M. H., Rosado, A., Morais, M., Potes, M., Costa, M. J., & Alvarenga, P. (2020). Land-Cover Patterns and Hydrogeomorphology of Tributaries: Are These Important Stressors for the Water Quality of Reservoirs in the Mediterranean Region? *Water*, *12*(10), 2665. https://doi.org/10.3390/w12102665
Palmer, C. G., & Munnik, V. (2018). *Practising Adaptive IWRM (Integrated Water Resources Management) in South Africa*. Water Research Commission.
Paná, S., Ferral, A., Marinelli, M. V., Petrosillo, I., Asís, I. d. V., Roqué, M., & Bonansea, M. (2022). Study of the impacts of Land Use-Land Cover on surface water quality based on field data and satellite information. 2022 IEEE Biennial Congress of Argentina (7-9 Sept. 2022), San Juan.
Pandey, P. K., Soupir, M. L., Haddad, M., & Rothwell, J. J. (2012). Assessing the impacts of watershed indexes and precipitation on spatial in-stream E. coli concentrations. *Ecological Indicators*, *23*, 641–652. https://doi.org/10.1016/j.ecolind.2012.05.023
Pandey, S., Kumari, N., & Al Nawajish, S. (2023). Land Use Land Cover (LULC) and Surface Water Quality Assessment in and around Selected Dams of Jharkhand using Water Quality Index (WQI) and Geographic Information System (GIS). *Journal of the Geological Society of India*, *99*(2), 205–218. https://doi.org/10.1007/s12594-023-2288-y
Pardo, I., Gómez-Rodríguez, C., Wasson, J.-G., Owen, R., van de Bund, W., Kelly, M., Bennett, C., Birk, S., Buffagni, A., Erba, S., Mengin, N., Murray-Bligh, J., & Ofenböeck, G. (2012). The European reference condition concept: A scientific and technical approach to identify minimally-impacted river ecosystems. *Science of The Total Environment*, *420*, 33–42. https://doi.org/10.1016/j.scitotenv.2012.01.026
Parece, T. E., & Campbell, J. B. (2015). Land Use/Land Cover Monitoring and Geospatial Technologies: An Overview. In T. Younos & T. E. Parece (Eds.), *Advances in Watershed*

Science and Assessment (pp. 1–32). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-14212-8_1

Park, S.-R., Kim, S., & Lee, S.-W. (2021). Evaluating the Relationships between Riparian Land Cover Characteristics and Biological Integrity of Streams Using Random Forest Algorithms. *International Journal of Environmental Research and Public Health*, *18*(6), 3182. https://doi.org/10.3390/ijerph18063182

Park, S.-R., & Lee, S.-W. (2020). Spatially Varying and Scale-Dependent Relationships of Land Use Types with Stream Water Quality. *International Journal of Environmental Research and Public Health*, *17*(5), 1673. https://doi.org/10.3390/ijerph17051673

Parween, M. (2022). Integrated Water Resource Management for Future Water Security. In *Urban Ecology and Global Climate Change* (pp. 73–84). https://doi.org/10.1002/9781119807216.ch4

Pascale, S., Kapnick, S. B., Delworth, T. L., & Cooke, W. F. (2020). Increasing risk of another Cape Town "Day Zero" drought in the 21st century. *Proceedings of the National Academy of Sciences*, *117*(47), 29495–29503. https://doi.org/10.1073/pnas.2009144117

Patrício, J., Elliott, M., Mazik, K., Papadopoulou, K.-N., & Smith, C. J. (2016). DPSIR—two decades of trying to develop a unifying framework for marine environmental management? *Frontiers in Marine Science*, *3*, 177. https://doi.org/10.3389/fmars.2016.00177

Patterson, J. J., Smith, C., & Bellamy, J. (2013). Understanding enabling capacities for managing the 'wicked problem' of nonpoint source water pollution in catchments: A conceptual framework. *Journal of Environmental Management*, *128*, 441–452. https://doi.org/10.1016/j.jenvman.2013.05.033

Paul, M. J., & Meyer, J. L. (2001). Streams in the Urban Landscape. *Annual Review of Ecology and Systematics*, *32*(1), 333–365. https://doi.org/10.1146/annurev.ecolsys.32.081501.114040

Pegram, G. C., & Görgens, A. H. M. (2000). *A Guide to Non-Point Source Pollution: To Support Water Quality Management of Surface Water Resources in South Africa [WRC Report No. TT 142/01]*. Water Research Commission.

Pei, W., Lei, Q., Zhao, Y., Xu, Q., Du, X., Luo, J., An, M., Ma, H., Fan, B., Qiu, W., & Liu, H. (2023). Effect of landscape pattern on river water quality under different regional delineation methods: A case study of Northwest Section of the Yellow River in China. *Journal of Hydrology: Regional Studies*, *50*, 101536. https://doi.org/10.1016/j.ejrh.2023.101536

Pengelly, S., & Fishburn, G. (2002). Land, Water and People: Complex Interactions in the Murrumbidgee River Catchment, New South Wales, Australia. In P. M. Haygarth & S. C. Jarvis (Eds.), *Agriculture, Hydrology and Water Quality* (pp. 395–416). Wallingford: CABI. https://doi.org/10.1079/9780851995458.0395

Peters, N. E., & Meybeck, M. (2000). Water Quality Degradation Effects on Freshwater Availability: Impacts of Human Activities. *Water International*, *25*(2), 185–193. https://doi.org/10.1080/02508060008686817

Peters, N. E., Meybeck, M., & Chapman, D. V. (2005). Effects of Human Activities on Water Quality. In M. G. Anderson & J. J. McDonnell (Eds.), *Encyclopedia of Hydrological Sciences* (pp. 1409–1425). Chichester: John Wiley & Sons Ltd. https://doi.org/10.1002/0470848944.hsa195

Petersen, C. R., Jovanovic, N. Z., & Grenfell, M. C. (2020). The effectiveness of riparian zones in mitigating water quality impacts in an agriculturally dominated river system in South Africa. *African Journal of Aquatic Science*, *45*(3), 336–349. https://doi.org/10.2989/16085914.2019.1685451

Petersen, C. R., Jovanovic, N. Z., Le Maitre, D. C., & Grenfell, M. C. (2017). Effects of land use change on streamflow and stream water quality of a coastal catchment. *Water SA*, *43*(1), 139–152. https://doi.org/10.4314/wsa.v43i1.16

Piffer, P. R., Tambosi, L. R., Ferraz, S. F. d. B., Metzger, J. P., & Uriarte, M. (2021). Native forest cover safeguards stream water quality under a changing climate. *Ecological Applications*, *31*(7), e02414. https://doi.org/10.1002/eap.2414

Pilgrim, D. H., Cordery, I., & Baron, B. C. (1982). Effects of catchment size on runoff relationships. *Journal of Hydrology*, *58*(3), 205–221. https://doi.org/10.1016/0022-1694(82)90035-X

Pitman, W. V., Midgley, B. J., & Middleton, D. C. (1998). Surface water resources of South Africa 1990. *Civil Engineering*, *1998*(9), 16–19. https://doi.org/10.10520/AJA10212019_22385

Polasky, S., Carpenter, S. R., Folke, C., & Keeler, B. (2011). Decision-making under great uncertainty: environmental management in an era of global change. *Trends in Ecology & Evolution*, *26*(8), 398–404. https://doi.org/10.1016/j.tree.2011.04.007

Pollard, S. (2002). Operationalising the new Water Act: contributions from the Save the Sand Project – an integrated catchment management initiative. *Physics and Chemistry of the Earth, Parts A/B/C*, *27*, 941–948. https://doi.org/10.1016/S1474-7065(02)00097-9

Pollard, S., & du Toit, D. (2008). Integrated water resource management in complex systems: How the catchment management strategies seek to achieve sustainability and equity in water resources in South Africa. *Water SA*, *34*(6). https://doi.org/10.4314/wsa.v34i6.183668

Pond, G. J., Krock, K. J. G., Cruz, J. V., & Ettema, L. F. (2017). Effort-based predictors of headwater stream conditions: comparing the proximity of land use pressures and instream stressors on macroinvertebrate assemblages. *Aquatic Sciences*, *79*(3), 765–781. https://doi.org/10.1007/s00027-017-0534-3

Prakoso, S. B., Miyake, Y., Ueda, W., & Suryatmojo, H. (2023). Impact of land use on water quality and invertebrate assemblages in Indonesian streams. *Limnologica*, *101*, 126082. https://doi.org/10.1016/j.limno.2023.126082

Pratt, B., & Chang, H. (2012). Effects of land cover, topography, and built structure on seasonal water quality at multiple spatial scales. *Journal of Hazardous Materials*, *209-210*, 48–58. https://doi.org/10.1016/j.jhazmat.2011.12.068

Procopio, N. A., & Zampella, R. A. (2022). Assessing land-use/water-quality relationships across contrasting geologic areas in New Jersey. *JAWRA Journal of the American Water Resources Association*. https://doi.org/10.1111/1752-1688.13074

Prosser, I. P., Chiew, F. H., & Stafford Smith, M. (2021). Adapting water management to climate change in the Murray–Darling Basin, Australia. *Water*, *13*(18), 2504. https://doi.org/10.3390/w13182504

Qiu, J., & Turner, M. G. (2015). Importance of landscape heterogeneity in sustaining hydrologic ecosystem services in an agricultural watershed. *Ecosphere*, *6*(11), art229. https://doi.org/10.1890/ES15-00312.1

Qiu, M., Wei, X., Hou, Y., Spencer, S. A., & Hui, J. (2023). Forest cover, landscape patterns, and water quality: a meta-analysis. *Landscape Ecology*. https://doi.org/10.1007/s10980-023-01593-2

Rahaman, M. M., & Varis, O. (2005). Integrated water resources management: evolution, prospects and future challenges. *Sustainability: Science, Practice and Policy*, *1*(1), 15–21. https://doi.org/10.1080/15487733.2005.11907961

Rahmatillah, H. M., & Ramli, I. (2021). Water quality index and the sediment criteria due to anthropogenic activity in West Aceh District, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *922*(1), 012042. https://doi.org/10.1088/1755-1315/922/1/012042

Ramião, J. P., Cássio, F., & Pascoal, C. (2020). Riparian land use and stream habitat regulate water quality. *Limnologica*, *82*, 125762. https://doi.org/10.1016/j.limno.2020.125762

Ramjukadh, C.-L., Silberbauer, M., & Taljaard, S. (2018). An anomaly in pH data in South Africa's national water quality monitoring database – implications for future use. *Water SA*, *44*(4), 760–673. https://doi.org/10.4314/wsa.v

Ramsey, E. W., & Rangoonwala, A. (2017). *Mapping the change of Phragmites australis live biomass in the lower Mississippi River Delta marshes [Open-File Report 2017-1098]*. USGS. http://pubs.er.usgs.gov/publication/ofr20171098

Reed, M. S., Stringer, L. C., Fazey, I., Evely, A. C., & Kruijsen, J. H. J. (2014). Five principles for the practice of knowledge exchange in environmental management. *Journal of Environmental Management*, *146*, 337–345. https://doi.org/10.1016/j.jenvman.2014.07.021

Republic of South Africa. (1996). *Constitution of the Republic of South Africa (No. 7 of 1996)*. Pretoria.

Rhodes, A. L., Newton, R. M., & Pufall, A. (2001). Influences of Land Use on Water Quality of a Diverse New England Watershed. *Environmental Science & Technology*, *35*(18), 3640–3645. https://doi.org/10.1021/es002052u

Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S. E., Donges, J. F., Drüke, M., Fetzer, I., Bala, G., von Bloh, W., Feulner, G., Fiedler, S., Gerten, D., Gleeson, T., Hofmann, M., Huiskamp, W., Kummu, M., Mohan, C., Nogués-Bravo, D., . . . Rockström, J. (2023). Earth

beyond six of nine planetary boundaries. *Science Advances*, *9*(37), eadh2458. https://doi.org/10.1126/sciadv.adh2458
Riddell, E. S., Boyd, L., Petersen, R. M., & Heath, R. G. M. (2022). Protected areas and the diffuse pollution problem: rivers of the Kruger National Park, South Africa. In P. Kajitvichyanukul & B. D'Arcy (Eds.), *Land Use and Water Quality: The Impacts of Diffuse Pollution* (pp. 169–186). IWA Publishing. https://doi.org/10.2166/9781789061123_169
Riseng, C. M., Wiley, M. J., Seelbach, P. W., & Stevenson, R. J. (2010). An ecological assessment of Great Lakes tributaries in the Michigan Peninsulas. *Journal of Great Lakes Research*, *36*(3), 505–519. https://doi.org/10.1016/j.jglr.2010.04.008
Rockström, J., Falkenmark, M., Allan, T., Folke, C., Gordon, L., Jägerskog, A., Kummu, M., Lannerstad, M., Meybeck, M., Molden, D., Postel, S., Savenije, H. H. G., Svedin, U., Turton, A., & Varis, O. (2014). The unfolding water drama in the Anthropocene: towards a resilience-based perspective on water for global sustainability. *Ecohydrology*, *7*(5), 1249–1261. https://doi.org/10.1002/eco.1562
Rockström, J., Richardson, K., Steffen, W., & Mace, G. (2018). Planetary Boundaries: Separating Fact from Fiction. A Response to Montoya et al. *Trends in Ecology and Evolution*, *33*(4), 233–234. https://doi.org/10.1016/j.tree.2018.01.010
Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., . . . Foley, J. (2009). Planetary Boundaries Exploring the Safe Operating Space for Humanity. *Ecology and Society*, *14*(2). http://www.jstor.org/stable/26268316
Rodríguez-Romero, A. J., Rico-Sánchez, A. E., Mendoza-Martínez, E., Gómez-Ruiz, A., Sedeño-Díaz, J. E., & López-López, E. (2018). Impact of Changes of Land Use on Water Quality, from Tropical Forest to Anthropogenic Occupation: A Multivariate Approach. *Water*, *10*(11), 1518. https://doi.org/10.3390/w10111518
Rogers, K., Roux, D., & Biggs, H. (2000). Challenges for catchment management agencies: Lessons from bureaucracies, business and resource management. *Water SA*, *26*(4). https://doi.org/10.10520/AJA03784738_1607
Roldán-Arias, A., García-Ávila, F., Pesántez-Quintuña, K., Cabello-Torres, R., & Valdiviezo-Gonzales, L. (2023). Spatiotemporal dynamics of a peri-urban stream water quality and its relationship with land use. *Case Studies in Chemical and Environmental Engineering*, *8*, 100420. https://doi.org/10.1016/j.cscee.2023.100420
Rosemond, S. d., Duro, D. C., & Dubé, M. (2009). Comparative analysis of regional water quality in Canada using the Water Quality Index. *Environmental Monitoring and Assessment*, *156*(1), 223–240. https://doi.org/10.1007/s10661-008-0480-6
Roth, N. E., Allan, J. D., & Erickson, D. L. (1996). Landscape influences on stream biotic integrity assessed at multiple spatial scales. *Landscape Ecology*, *11*(3), 141–156. https://doi.org/10.1007/BF02447513
Rothenberger, M. B., Burkholder, J. M., & Brownie, C. (2009). Long-Term Effects of Changing Land Use Practices on Surface Water Quality in a Coastal River and Lagoonal Estuary. *Environmental Management*, *44*(3), 505–523. https://doi.org/10.1007/s00267-009-9330-8
Rothwell, J. J., Dise, N. B., Taylor, K. G., Allott, T. E. H., Scholefield, P., Davies, H., & Neal, C. (2010). A spatial and seasonal assessment of river water chemistry across North West England. *Science of The Total Environment*, *408*(4), 841–855. https://doi.org/10.1016/j.scitotenv.2009.10.041
Roy, A. H., Rosemond, A. D., Paul, M. J., Leigh, D. S., & Wallace, J. B. (2003). Stream macroinvertebrate response to catchment urbanisation (Georgia, U.S.A.). *Freshwater Biology*, *48*(2), 329–346. https://doi.org/10.1046/j.1365-2427.2003.00979.x
Roy, D., Barr, J., & Venema, H. D. (2011). *Ecosystem Approaches in Integrated Water Resources Management (IWRM): A Review of Transboundary Basins*. International Institute for Sustainable Development. https://www.iisd.org/publications/report/ecosystem-approaches-integrated-water-resources-management-iwrm-review

Rutledge, D. (2003). *Landscape indices as measures of the effects of fragmentation: can pattern reflect process? [DOC Science Internal Series 98]*. New Zealand Department of Conservation. https://www.doc.govt.nz/

Salimi, M., Esrafili, A., Gholami, M., Jonidi Jafari, A., Rezaei Kalantary, R., Farzadkia, M., Kermani, M., & Sobhi, H. R. (2017). Contaminants of emerging concern: a review of new approach in AOP technologies. *Environmental Monitoring and Assessment*, *189*(8), 414. https://doi.org/10.1007/s10661-017-6097-x

SANSA. (2015). *South African Remote Sensing Atlas*. South African Space Agency. http://atlas.sansa.org.za/atlas-geology.html

Sarhat, A. R., Mohsin, M., & Mohammed, A. H. (2022). Investigation of Groundwater Quality for Drinking Usage in Kifri District (Iraq) by using NPI and WQI Indices: Investigation of groundwater quality for drinking usage in Kifri District. *Proceedings of the Pakistan Academy of Sciences: A. Physical and Computational Sciences*, *59*(4), 67–77. https://doi.org/10.53560/PPASA(59-4)802

Sayers, M., Fahnenstiel, G. L., Shuchman, R. A., & Whitley, M. (2016). Cyanobacteria blooms in three eutrophic basins of the Great Lakes: a comparative analysis using satellite remote sensing. *International Journal of Remote Sensing*, *37*(17), 4148–4171. https://doi.org/10.1080/01431161.2016.1207265

Scanlon, B. R., Fakhreddine, S., Rateb, A., de Graaf, I., Famiglietti, J., Gleeson, T., Grafton, R. Q., Jobbagy, E., Kebede, S., Kolusu, S. R., Konikow, L. F., Long, D., Mekonnen, M., Schmied, H. M., Mukherjee, A., MacDonald, A., Reedy, R. C., Shamsudduha, M., Simmons, C. T., . . . Zheng, C. (2023). Global water resources and the role of groundwater in a resilient water future. *Nature Reviews Earth & Environment*, *4*(2), 87–101. https://doi.org/10.1038/s43017-022-00378-6

Scheffer, M. (2009). *Critical Transitions in Nature and Society*. Princeton University Press. https://doi.org/10.2307/j.ctv173f1g1

Scheffer, M., Carpenter, S., Foley, J. A., Folke, C., & Walker, B. (2001). Catastrophic shifts in ecosystems. *Nature*, *413*(6856), 591–596. https://doi.org/10.1038/35098000

Schiff, R., & Benoit, G. (2007). Effects of Impervious Cover at Multiple Spatial Scales on Coastal Watershed Streams. *Journal of the American Planning Association*, *43*(3), 712–730. https://doi.org/10.1111/j.1752-1688.2007.00057.x

Schneider, P., Nilius, U., Gottschalk, N., Süß, A., Schaffrath, M., Löser, R., & Lange, T. (2017). Determination of the Geogenic Metal Background in Surface Water: Benchmarking Methodology for the Rivers of Saxony-Anhalt, Germany. *Water*, *9*(2), 75. https://doi.org/10.3390/w9020075

Schoonover, J. E., & Lockaby, B. G. (2006). Land cover impacts on stream nutrients and fecal coliform in the lower Piedmont of West Georgia. *Journal of Hydrology*, *331*(3), 371–382. https://doi.org/10.1016/j.jhydrol.2006.05.031

Schreiner, B. (2013). Viewpoint - Why Has the South African National Water Act Been so Difficult to Implement? *Water Wheel*, *15*(5). https://hdl.handle.net/10520/EJC142540

Schueler, T. (1994). The Importance of Imperviousness. *Watershed protection techniques*, *1*(3), 100–101. https://owl.cwp.org/mdocs-posts/elc_pwp1/

Schueler, T. R., Fraley-McNeal, L., & Cappiella, K. (2009). Is Impervious Cover Still Important? Review of Recent Research. *Journal of Hydrologic Engineering*, *14*(4), 309–315. https://doi.org/doi:10.1061/(ASCE)1084-0699(2009)14:4(309)

Schultze, R. (2012). Water Resources and Hydrological Challenges in South Africa within a Climate Change Context. In R. Schultze (Ed.), *A 2011 Perspective on Climate Change and the South African Water Sector [WRC Report No. TT 518/12]* (pp. 127–138). Pretoria: Water Research Commission.

Schulze, R. E. (2000). Modelling Hydrological Responses to Land Use and Climate Change: A Southern African Perspective. *Ambio*, *29*(1), 12–22. http://www.jstor.org/stable/4314988

Schumaker, N. H. (1996). Using Landscape Indices to Predict Habitat Connectivity. *Ecology*, *77*(4), 1210–1225. https://doi.org/10.2307/2265590

Scott, D. F., & Gush, M. B. (2017). Forest management and water in the Republic of South Africa. In P. García Chevesich, D. Neary, G., D. F. Scott, R. G. Benyon, & T. Reyna (Eds.), *Forest*

management and the impact on water resources: A review of 13 countries. UNESCO. http://hdl.handle.net/10204/9160
Senbore, S., & Oke, S. A. (2021). Urban development impact on climate variability and surface water quality in part of Mangaung metropolis of South Africa. *Development Southern Africa*. https://doi.org/10.1080/0376835X.2021.1993794
Setegen, S. G. (2015). Introduction: Sustainability of Integrated Water Resources Management (IWRM). In S. G. Setegn & M. C. Donoso (Eds.), *Sustainability of Integrated Water Resources Management: Water Governance, Climate and Ecohydrology* (pp. 1–6). Cham: Springer. https://doi.org/10.1007/978-3-319-12194-9
Sheeder, S. A., & Evans, B. M. (2007). Estimating Nutrient and Sediment Threshold Criteria for Biological Impairment In Pennsylvania Watersheds. *JAWRA Journal of the American Water Resources Association*, *40*(4), 881–888. https://doi.org/https://doi.org/10.1111/j.1752-1688.2004.tb01052.x
Shen, Z., Hou, X., Li, W., & Aini, G. (2014). Relating landscape characteristics to non-point source pollution in a typical urbanized watershed in the municipality of Beijing. *Landscape and Urban Planning*, *123*, 96–107. https://doi.org/10.1016/j.landurbplan.2013.12.007
Shen, Z., Hou, X., Li, W., Aini, G., Chen, L., & Gong, Y. (2015). Impact of landscape pattern at multiple spatial scales on water quality: A case study in a typical urbanised watershed in China. *Ecological Indicators*, *48*, 417–427. https://doi.org/10.1016/j.ecolind.2014.08.019
Shi, P., Zhang, Y., Li, Z., Li, P., & Xu, G. (2017). Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales. *CATENA*, *151*, 182–190. https://doi.org/10.1016/j.catena.2016.12.017
Shiels, D. R. (2010). Implementing landscape indices to predict stream water quality in an agricultural setting: An assessment of the Lake and River Enhancement (LARE) protocol in the Mississinewa River watershed, East-Central Indiana. *Ecological Indicators*, *10*(6), 1102–1110. https://doi.org/10.1016/j.ecolind.2010.03.007
Shivoga, W. A., Muchiri, M., Kibichi, S., Odanga, J., Miller, S. N., Baldyga, T. J., Enanga, E. M., & Gichaba, M. C. (2007). Influences of land use/cover on water quality in the upper and middle reaches of River Njoro, Kenya. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use*, *12*(2), 97–105. https://doi.org/10.1111/j.1440-1770.2007.00325.x
Shukla, A. K., Ojha, C. S. P., Mijic, A., Buytaert, W., Pathak, S., Garg, R. D., & Shukla, S. (2018). Population growth, land use and land cover transformations, and water quality nexus in the Upper Ganga River basin. *Hydrology and Earth System Sciences*, *22*(9), 4745–4770. https://doi.org/10.5194/hess-22-4745-2018
Shupe, S. (2013). Statistical and Spatial Analysis of Land Cover Impact on Selected Metro Vancouver, British Columbia Watersheds. *Environmental Management*, *51*(1), 18–31. https://doi.org/10.1007/s00267-012-9955-x
Simedo, M., Martins, A., Pissarra, T., Lopes, M., Costa, R., Valle-Junior, R., Campanelli, L., Rojas, N., & Finoto, E. (2018). Effect of watershed land use on water quality: a case study in Córrego da Olaria Basin, São Paulo State, Brazil. *Brazilian Journal of Biology*, *78*, 625–635. https://doi.org/10.1590/1519-6984.168423
Simpson, I. M., Winston, R. J., & Brooker, M. R. (2022). Effects of land use, climate, and imperviousness on urban stormwater quality: A meta-analysis. *Science of The Total Environment*, *809*, 152206. https://doi.org/10.1016/j.scitotenv.2021.152206
Siqueira, T. d. S., Pessoa, L. A., Vieira, L., Cionek, V. d. M., Singh, S. K., Benedito, E., & do Couto, E. V. (2023). Evaluating land use impacts on water quality: perspectives for watershed management. *Sustainable Water Resources Management*, *9*(6), 192. https://doi.org/10.1007/s40899-023-00968-2
Skowno, A. L., Jewitt, D., & Slingsby, J. A. (2021). Rates and patterns of habitat loss across South Africa's vegetation biomes. *South African Journal of Science*, *117*, 1–5. http://dx.doi.org/10.17159/sajs.2021/8182
Skowno, A. L., Poole, C. J., Raimondo, D. C., Sink, K. J., Van Deventer, H., Van Niekerk, L., Harris, L. R., Smith-Adao, L. B., Tolley, K. A., Zengeya, T. A., Foden, W. B., Midgley, G. F., & Driver, A. (2019). *National Biodiversity Assessment 2018: The status of South Africa's*

ecosystems and biodiversity. Synthesis Report. South African National Biodiversity Institute, Department of Environment, Forestry & Fisheries. http://hdl.handle.net/20.500.12143/6362
Slaughter, A. R., & Mantel, S. K. (2013). A simple and rapid method to relate land cover and river flow rate to river nutrient concentration. *Physics and Chemistry of the Earth, Parts A/B/C, 66*, 131–138. https://doi.org/10.1016/j.pce.2013.08.001
Slaughter, A. R., & Mantel, S. K. (2017). Land cover models to predict non-point nutrient inputs for selected biomes in South Africa. *Water SA*, *43*(3), 499–508. https://doi.org/10.4314/wsa.v43i3.15
Sliva, L., & Williams, D. D. (2001). Buffer Zone versus Whole Catchment Approaches to Studying Land Use Impact on River Water Quality. *Water Research*, *35*(14), 3462–3472. https://doi.org/10.1016/S0043-1354(01)00062-8
Smith, M., & Jønch-Clausen, T. (2015). *Integrated Water Resource Management: A New Way Forward (A Discussion Paper of the World Water Council Task Force on IWRM)*. World Water Council. https://www.fsnnetwork.org/resource/integrated-water-resource-management-new-way-forward
Smith, M., & Jønch-Clausen, T. (2018). *Revitalising IWRM for the 2030 Agenda: World Water Council Challenge Paper for the High Level Panel on IWRM at the 8th World Water Forum, Brasilia, Brazil*. World Water Council. https://www.worldwatercouncil.org/en/publications/revitalizing-iwrm-2030-agenda
Snellen, W., & Schrevel, A. (2004). *IWRM: for sustainable use of water; 50 years of international experience with the concept of integrated water resources management; background document to the FAO/Netherlands conference on water for food an ecosystems, The Hague, 31 January - 5 February 2005*. Alterra. https://edepot.wur.nl/30428
Snyder, M. N., Goetz, S. J., & Wright, R. K. (2005). Stream Health Rankings Predicted by Satellite Derived Land Cover Metrics. *JAWRA Journal of the American Water Resources Association*, *41*(3), 659–677. https://doi.org/10.1111/j.1752-1688.2005.tb03762.x
Song, M., Jiang, Y., Liu, Q., Tian, Y., Liu, Y., Xu, X., & Kang, M. (2021). Catchment versus Riparian Buffers: Which Land Use Spatial Scales Have the Greatest Ability to Explain Water Quality Changes in a Typical Temperate Watershed? *Water*, *13*(13), 1758. https://doi.org/10.3390/w13131758
Song, Y., Song, X., Shao, G., & Hu, T. (2020). Effects of Land Use on Stream Water Quality in the Rapidly Urbanized Areas: A Multiscale Analysis. *Water*, *12*(4), 1123. https://doi.org/10.3390/w12041123
Soranno, P. A., Wagner, T., Martin, S. L., McLean, C., Novitski, L. N., Provence, C. D., & Rober, A. R. (2011). Quantifying regional reference conditions for freshwater ecosystem management: A comparison of approaches and future research needs. *Lake and Reservoir Management*, *27*, 138–148. https://doi.org/10.1080/07438141.2011.573614
Sponseller, R. A., Benfield, E. F., & Valett, H. M. (2001). Relationships between land use, spatial scale and stream macroinvertebrate communities. *Freshwater Biology*, *46*(10), 1409–1424. https://doi.org/10.1046/j.1365-2427.2001.00758.x
Sprugel, D. G. (1991). Disturbance, equilibrium, and environmental variability: What is 'Natural' vegetation in a changing environment? *Biological Conservation*, *58*(1), 1-18. https://doi.org/10.1016/0006-3207(91)90041-7
Stärz, C., Kaden, S., Klauer, B., & Leben, L. (2016). Decision Support in the Context of IWRM: Lessons Learnt from Research Projects in Developing and Emerging Countries. In D. Borchardt, J. J. Bogardi, & R. B. Ibisch (Eds.), *Integrated Water Resource Management: Concept, Research, and Implementation* (pp. 435–455). Cham: Springer. https://doi.org/10.1007/978-3-319-25071-7_1
Stats SA. (2019a). *South Africa's Voluntary National Review (VNR) Report 2019*. Statistics South Africa.
Stats SA. (2019b). *Sustainable Development Goals: Country Report 2019*. Statistics South Africa.
Stats SA. (2023). *Natural Capital Series 3: Accounts for Strategic Water Source Areas, 1990 to 2020. Discussion document D0401.3*. Statistics South Africa/South African National Biodiversity Institute/Department of Forestry, Fisheries & the Environment.

Steedman, R. J. (1988). Modification and Assessment of an Index of Biotic Integrity to Quantify Stream Quality in Southern Ontario. *Canadian Journal of Fisheries and Aquatic Sciences*, *45*(3), 492–501. https://doi.org/10.1139/f88-059

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223), 1259855. https://doi.org/doi:10.1126/science.1259855

Stehman, S. V., & Foody, G. M. (2019). Key issues in rigorous accuracy assessment of land cover products. *Remote Sensing of Environment*, *231*, 111199. https://doi.org/10.1016/j.rse.2019.05.018

Stein, E. D., & Yoon, V. K. (2007). *Assessment of Water Quality Concentrations and Loads from Natural Landscapes. Technical Report 500*. Southern California Coastal Water Research Project.

Strayer, D. L., Beighley, R. E., Thompson, L. C., Brooks, S., Nilsson, C., Pinay, G., & Naiman, R. J. (2003). Effects of Land Cover on Stream Ecosystems: Roles of Empirical Models and Scaling Issues. *Ecosystems*, *6*(5), 407–423. https://doi.org/10.1007/PL00021506

Struyf, E., Bal, K. D., Backx, H., Vrebos, D., Casteleyn, A., De Deckere, E., Schoelynck, J., Brendonck, L., Raitt, L. M., & Meire, P. (2012). Nitrogen, phosphorus and silicon in riparian ecosystems along the Berg River (South Africa): the effect of increasing human land use. *Water SA*, *38*(4), 597–606. https://doi.org/10.4314/wsa.v38i4.15

Stuart-Hill, S., Lukat, E., Pringle, C., & Pahl-Wostl, C. (2020). *Coordination beyond the state to solve complex water problems: Insights from South Africa, Briefing Paper, No. 21/2020* (21/2020). Deutsches Institut für Entwicklungspolitik (DIE). http://hdl.handle.net/10419/242604

Stutter, M. I., Chardon, W. J., & Kronvang, B. (2012). Riparian Buffer Strips as a Multifunctional Management Tool in Agricultural Landscapes: Introduction. *Journal of Environmental Quality*, *41*(2), 297–303. https://doi.org/10.2134/jeq2011.0439

Su, K., Wang, Q., Li, L., Cao, R., & Xi, Y. (2022). Water quality assessment of Lugu Lake based on Nemerow pollution index method. *Scientific Reports*, *12*(1), 13613. https://doi.org/10.1038/s41598-022-17874-w

Sugam, R. K., Kabir, M. H., George, S. S., & Phukan, M. (2023). Integrated Water Resources Management and Flood risk Management. In V. Oladokun, D. Proverbs, O. Adebimpe, & T. Adedeji (Eds.), *Handbook of Flood Risk Management in Developing Countries*. Routledge. https://doi.org/10.1201/9781003160823

Sun, G., Bishop, K., Ferraz, S., & Jones, J. (2020). Managing Forests and Water for People under a Changing Environment. *Forests*, *11*(3), 331. https://doi.org/10.3390/f11030331

Sun, S., Wang, Y., Liu, J., Cai, H., Wu, P., Geng, Q., & Xu, L. (2016). Sustainability assessment of regional water resources under the DPSIR framework. *Journal of Hydrology*, *532*, 140–148. https://doi.org/10.1016/j.jhydrol.2015.11.028

Sutadian, A. D., Muttil, N., Yilmaz, A. G., & Perera, B. J. C. (2016). Development of river water quality indices—a review. *Environmental Monitoring and Assessment*, *188*(58), 58. https://doi.org/10.1007/s10661-015-5050-0

Sutjiningsih, D. (2017). Water Quality Index for Determining the Development Threshold of Urbanized Catchment Area in Indonesia. *International Journal of Technology*, *8*(1), 145–159. https://doi.org/10.14716/ijtech.v8i1.3971

Swatuk, L., & Qader, A. I. A. (2023). IWRM: Ideology or Methodology? https://doi.org/10.1093/acrefore/9780199389414.013.620

Sweeney, B. W., & Newbold, J. D. (2014). Streamside Forest Buffer Width Needed to Protect Stream Water Quality, Habitat, and Organisms: A Literature Review. *JAWRA Journal of the American Water Resources Association*, *50*(3), 560–584. https://doi.org/10.1111/jawr.12203

Sykes, M. T., Prentice, I. C., & Laarif, F. (1999). Quantifying the Impact of Global Climate Change on Potential Natural Vegetation. *Climatic Change*, *41*(1), 37-52. https://doi.org/10.1023/A:1005435831549

Szymańska-Walkiewicz, M., Matela, M., & Obolewski, K. (2023). Patterns of effects of land-use structure on lake water quality in coastal lake catchments of the southern Baltic Sea. *Ecohydrology & Hydrobiology*. https://doi.org/10.1016/j.ecohyd.2023.07.004

Tabassum, S., Kotnala, C. B., Masih, R. K., Shuaib, M., Alam, S., & Alar, T. M. (2023). Performance Analysis of Machine Learning Techniques for Predicting Water Quality Index using Physiochemical Parameters. 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS) (14-16 June 2023), Coimbatore.

Tahiru, A. A., Doke, D. A., & Baatuuwie, B. N. (2020). Effect of land use and land cover changes on water quality in the Nawuni Catchment of the White Volta Basin, Northern Region, Ghana. *Applied Water Science*, *10*(8), 198. https://doi.org/10.1007/s13201-020-01272-6

Taylor, C. A., & Rising, J. (2021). Tipping point dynamics in global land use. *Environmental Research Letters*, *16*(12), 125012. https://doi.org/10.1088/1748-9326/ac3c6d

Tayyebi, A., Pijanowski, B. C., & Pekin, B. K. (2015). Land use legacies of the Ohio River Basin: Using a spatially explicit land use change model to assess past and future impacts on aquatic resources. *Applied Geography*, *57*, 100–111. https://doi.org/10.1016/j.apgeog.2014.12.020

Tejada-Guibert, J. A. (2015). Integrated Water Resources Management (IWRM) in a Changing World. In S. G. Setegn & M. C. Donoso (Eds.), *Sustainability of Integrated Water Resources Management: Water Governance, Climate and Ecohydrology* (pp. 65–86). Cham: Springer. https://doi.org/10.1007/978-3-319-12194-9

Tejada-Guibert, J. A., Setegn, S. G., & Stoa, R. B. (2015). Sustainable Development and Integrated Water Resources Management. In S. G. Setegn & M. C. Donoso (Eds.), *Sustainability of Integrated Water Resources Management: Water Governance, Climate and Ecohydrology* (pp. 197–214). Cham: Springer. https://doi.org/10.1007/978-3-319-12194-9

Thenkabail, P. S. (2015). *Remote Sensing Handbook: Remote Sensing of Water Resources, Disasters, and Urban Studies*. CRC Press. https://doi.org/10.1201/b19321

Thomas, A., Masante, D., Jackson, B., Cosby, B., Emmett, B., & Jones, L. (2020). Fragmentation and thresholds in hydrological flow-based ecosystem services. *Ecological Applications*, *30*(2), e02046. https://doi.org/10.1002/eap.2046

Thompson, M. (1996). A standard land-cover classification scheme for remote-sensing applications in South Africa. *South African Journal of Science*, *92*(1), 34–42. https://doi.org/doi:10.10520/AJA00382353_7698

Tiner, R. W. (2004). Remotely-sensed indicators for monitoring the general condition of “natural habitat” in watersheds: an application for Delaware’s Nanticoke River watershed. *Ecological Indicators*, *4*(4), 227–243. https://doi.org/10.1016/j.ecolind.2004.04.002

Tinoco, C., Julio, N., Meirelles, B., Pineda, R., Figueroa, R., Urrutia, R., & Parra, Ó. (2022). Water Resources Management in Mexico, Chile and Brazil: Comparative Analysis of Their Progress on SDG 6.5.1 and the Role of Governance. *Sustainability*, *14*(10), 5814. https://doi.org/10.3390/su14105814

Tollefson, J. (2023). *World recommits to 2030 plan to save humanity — despite falling short so far*. Nature. Retrieved 22 September 2023 from https://www.nature.com/articles/d41586-023-02970-2

Tomal, J. H., & Ciborowski, J. J. H. (2020). Ecological models for estimating breakpoints and prediction intervals. *Ecology and Evolution*, *10*(23), 13500–13517. https://doi.org/10.1002/ece3.6955

Toms, J. D., & Lesperance, M. L. (2003). Piecewise Regression: A Tool for Identifying Ecological Thresholds. *Ecology*, *85*(8), 2034–2041.

Toms, J. D., & Villard, M. (2015). Threshold detection: matching statistical methodology to ecological questions and conservation planning objectives [Détection des seuils : choix de la méthode statistique en fonction des questions écologiques et des objectifs de planification de la conservation]. *Avian Conservation and Ecology*, *10*(1), Article 2. https://doi.org/10.5751/ACE-00715-100102

Tong, S. T. Y., & Chen, W. (2002). Modeling the relationship between land use and surface water quality. *Journal of Environmental Management*, *66*(4), 377–393. https://doi.org/10.1006/jema.2002.0593

Torres-Bejarano, F., Torregroza-Espinosa, A. C., Martínez-Mera, E., & González-Márquez, L. C. (2022). Impact of land cover changes on water quality: an application to the Guájaro reservoir, Colombia. *International Journal of Environmental Science and Technology*. https://doi.org/10.1007/s13762-022-04535-8

Tozer, L. (2023). Water pollution 'timebomb' threatens global health. *Nature News*. https://doi.org/10.1038/d41586-023-02337-7

Tran, C. P., Bode, R. W., Smith, A. J., & Kleppel, G. S. (2010). Land-use proximity as a basis for assessing stream water quality in New York State (USA). *Ecological Indicators*, *10*(3), 727–733. https://doi.org/10.1016/j.ecolind.2009.12.002

Tromboni, F., & Dodds, W. K. (2017). Relationships Between Land Use and Stream Nutrient Concentrations in a Highly Urbanized Tropical Region of Brazil: Thresholds and Riparian Zones. *Environmental Management*, *60*(1), 30–40. https://doi.org/10.1007/s00267-017-0858-8

Tsegaye, T. D., Sheppard, D., Islam, K. R., Johnson, A., Tadesse, W., Atalay, A., & Marzen, L. (2006). Development of Chemical Index as a Measure of In-Stream Water Quality in Response to Land-use and Land Cover Changes. *Water, Air and Soil Pollution*, *174*, 161–179. https://doi.org/10.1007/s11270-006-9090-5

Tu, J. (2011a). Spatial and temporal relationships between water quality and land use in northern Georgia, USA. *Journal of Integrative Environmental Sciences*, *8*(3), 151–170. https://doi.org/10.1080/1943815X.2011.577076

Tu, J. (2011b). Spatially varying relationships between land use and water quality across an urbanization gradient explored by geographically weighted regression. *Applied Geography*, *31*(1), 376–392. https://doi.org/10.1016/j.apgeog.2010.08.001

Tundisi, J. G., Matsumura-Tundisi, T., Ciminelli, V. S., & Barbosa, F. A. (2015). Water availability, water quality water governance: the future ahead. *Proc. IAHS*, *366*, 75–79. https://doi.org/10.5194/piahs-366-75-2015

Turner, M. G. (2005). Landscape Ecology in North America: Past, Present and Future. *Ecology*, *86*(8), 1967–1974. https://doi.org/https://doi.org/10.1890/04-0890

Turton, A. R., Hattingh, J., Maree, G. A., D.J., R., & M., C. (2007). Towards a Model for Ecosystem Governance: An Integrated Water Resource Management Example. In A. R. Turton, H. J. Hattingh, G. A. Maree, D. J. Roux, M. Claassen, & W. F. Strydom (Eds.), *Governance as a trialogue: Government-society-science in transition* (pp. 1–28). Berlin: Springer.

Twesigye, C. K., Onywere, S. M., Getenga, Z. M., Mwakalila, S. S., & Nakiranda, J. K. (2011). The Impact of Land Use Activities on Vegetation Cover and Water Quality in the Lake Victoria Watershed. *The Open Environmental Engineering Journal*, *4*, 66–77. http://ir.mksu.ac.ke/handle/123456780/4173

Uddin, M. G., Nash, S., & Olbert, A. (2021). A review of water quality index models and their use for assessing surface water quality. *Ecological Indicators*, *122*. https://doi.org/10.1016/j.ecolind.2020.107218

Ullah, K. A., Jiang, J., & Wang, P. (2018). Land use impacts on surface water quality by statistical approaches. *Global Journal of Environmental Science and Management*, *4*(2), 231–250. https://doi.org/10.22034/gjesm.2018.04.02.010

Umwali, E. D., Kurban, A., Isabwe, A., Mind'je, R., Azadi, H., Guo, Z., Udahogora, M., Nyirarwasa, A., Umuhoza, J., Nzabarinda, V., Gasirabo, A., & Sabirhazi, G. (2021). Spatio-seasonal variation of water quality influenced by land use and land cover in Lake Muhazi. *Scientific Reports*, *11*(1), 17376. https://doi.org/10.1038/s41598-021-96633-9

UNDP. (2013). *User's guide on assessing water governance*. United Nations Development Programme/Water Integrity Network. Retrieved 17 September 2022 from https://www.undp.org/publications/users-guide-assessing-water-governance

UNEP-DHI. (2020). *Implementation of Integrated Water Resources Management (IWRM): South Africa*. http://iwrmdataportal.unepdhi.org/countrydatabase

UNEP-DHI. (2023). *IWRM Data Portal Country Reports*. UNEP-DHI Centre on Water and Environment. Retrieved 23 August 2023 from http://iwrmdataportal.unepdhi.org/country-reports

UNEP. (1992). *International Conference on Water and the Environment: Development Issues for the 2lst century*. United Nations Environment Programme & World Meteorological Organization. https://wedocs.unep.org/20.500.11822/30961
UNEP. (2012). *UN-Water Status Report on the Application of Integrated Approaches to Water Resources Management*. United Nations Environment Programme. https://www.unwater.org/publications/un-water-status-report-application-integrated-approaches-water-resources-management-0
UNEP. (2014). *Towards Integrated Water Resources Management: International experience in development of river basin organisations*. United Nations Environment Programme. https://wedocs.unep.org/20.500.11822/22452
UNEP. (2021). *Progress on Integrated Water Resources Management. Tracking SDG 6 series: global indicator 6.5.1 updates and acceleration needs*. United Nations Environmental Programme.
UNEP. (2023a). *GOAL 6: Clean water and sanitation*. United Nations Environment Programme. Retrieved 29 August 2023 from https://www.unep.org/explore-topics/sustainable-development-goals/why-do-sustainable-development-goals-matter/goal-6
UNEP. (2023b). *What is Integrated Water Resources Management?* United Nations Environment Programme. Retrieved 29 March 2023 from https://www.unep.org/explore-topics/disasters-conflicts/where-we-work/sudan/what-integrated-water-resources-management
UNESCO. (2009). *IWRM Guidelines at River Basin Level – Part 1: Principles*. United Nations Educational, Scientific, and Cultural Organization. https://unesdoc.unesco.org/ark:/48223/pf0000186417
UNICEF. (2022). *Children's lives and rights at risk due to KwaZulu-Natal floods* Retrieved 31 May 2022 from https://www.unicef.org/southafrica/press-releases/childrens-lives-and-rights-risk-due-kwazulu-natal-floods
United Nations. (2015). *Transforming our world: the 2030 agenda for sustainable development*. United Nations Department of Economic and Social Affairs. https://sustainabledevelopment.un.org/post2015/transformingourworld/publication
United Nations. (2023a). *Progress towards the Sustainable Development Goals: towards a rescue plan for people and planet [Report of the Secretary-General (special edition)]*. United Nations General Assembly. https://www.un.org/en/conferences/SDGSummit2023/documentation
United Nations. (2023b). *The Sustainable Development Goals Report 2023: Special Edition*. https://unstats.un.org/sdgs/report/2023/
United Nations. (2023c). *UN-Water SDG 6 Data Portal*. Retrieved 23 August 2023 from https://www.sdg6data.org/en/country-or-area/South%20Africa#anchor_6.5.1
Urbanič, G., Mihaljević, Z., Petkovska, V., & Pavlin Urbanič, M. (2021). Back to Ecology: Reference Conditions as a Basis for Assessment, Restoration and Sustainable Management of Large Rivers. *Water*, *13*(18), 2596. https://doi.org/10.3390/w13182596
Uriarte, M., Yackulic, C. B., Lim, Y., & Arce-Nazario, J. A. (2011). Influence of land use on water quality in a tropical landscape: a multi-scale analysis. *Landscape Ecology*, *26*(8), 1151. https://doi.org/10.1007/s10980-011-9642-y
USEPA. (1986). *Quality Criteria for Water, 1986 ("Gold Book")*. U.S. Environmental Protection Agency. https://www.epa.gov/wqc/historical-water-quality-criteria-documents
USEPA. (2000). *Nutrient Criteria Technical Guidance Manual Rivers and Streams (EPA-822-B-00-002)*. U.S. Environmental Protection Agency. https://www.epa.gov/nutrient-policy-data/nutrient-criteria-development-document-rivers-and-streams
USEPA. (2022a). *Indicators: Conductivity*. U.S. Environmental Protection Agency,. https://www.epa.gov/national-aquatic-resource-surveys/indicators-conductivity
USEPA. (2022b). *National Recommended Water Quality Criteria - Aquatic Life Criteria Table* U.S. Environmental Protection Agency. Retrieved 27 June 2023 from https://www.epa.gov/wqc/national-recommended-water-quality-criteria-aquatic-life-criteria-table
USEPA. (2023). *Factsheets on Water Quality Parameters*. U.S. Environmental Protection Agency. Retrieved 27 June 2023 from https://www.epa.gov/awma/factsheets-water-quality-parameters
USGS. (2023). *Earth Explorer*. United States Geological Survey. https://earthexplorer.usgs.gov/

Uuemaa, E., Antrop, M., Roosaare, J., Marja, R., & Mander, Ü. (2009). Landscape metrics and indices : an overview of their use in landscape research. *Living Reviews in Landscape Research*, *1*, 1–18. http://hdl.handle.net/1854/LU-695518

Uuemaa, E., & Oja, T. (2017). Mapping the Abstractions of Forest Landscape Patterns. In T. K. Remmel & A. H. Perera (Eds.), *Mapping Forest Landscape Patterns* (pp. 213–261). New York, NY: Springer New York. https://doi.org/10.1007/978-1-4939-7331-6_6

Uuemaa, E., Roosaare, J., & Mander, Ü. (2007). Landscape metrics as indicators of river water quality at catchment scale. *Hydrology Research*, *38*(2), 125–138. https://doi.org/10.2166/nh.2007.002

Valera, C. A., Pissarra, T. C. T., Filho, M. V. M., Valle Júnior, R. F. d., Oliveira, C. F., Moura, J. P., Sanches Fernandes, L. F., & Pacheco, F. A. L. (2019). The Buffer Capacity of Riparian Vegetation to Control Water Quality in Anthropogenic Catchments from a Legally Protected Area: A Critical View over the Brazilian New Forest Code. *Water*, *11*(3), 549. https://doi.org/10.3390/w11030549

van Dam, R. A., Hogan, A. C., Harford, A. J., & Humphrey, C. L. (2019). How Specific Is Site-Specific? A Review and Guidance for Selecting and Evaluating Approaches for Deriving Local Water Quality Benchmarks. *Integrated Environmental Assessment and Management*, *15*(5), 683–702. https://doi.org/10.1002/ieam.4181

van Dam, R. A., Humphrey, C. L., Harford, A. J., Sinclair, A., Jones, D. R., Davies, S., & Storey, A. W. (2014). Site-specific water quality guidelines: 1. Derivation approaches based on physicochemical, ecotoxicological and ecological data. *Environmental Science and Pollution Research*, *21*(1), 118–130. https://doi.org/10.1007/s11356-013-1780-0

van der Hoven, C., Ubomba-Jaswa, E., van der Merwe, B., Loubser, M., & Abia, A. L. K. (2017). The impact of various land uses on the microbial and physicochemical quality of surface water bodies in developing countries: Prioritisation of water resources management areas. *Environmental Nanotechnology, Monitoring & Management*, *8*, 280–289. https://doi.org/10.1016/j.enmm.2017.10.006

van der Keur, P., Henriksen, H. J., Refsgaard, J. C., Brugnach, M., Pahl-Wostl, C., Dewulf, A., & Buiteveld, H. (2008). Identification of Major Sources of Uncertainty in Current IWRM Practice. Illustrated for the Rhine Basin. *Water Resources Management*, *22*(11), 1677–1708. https://doi.org/10.1007/s11269-008-9248-6

van der Zaag, P. (2005). Integrated Water Resources Management: Relevant concept or irrelevant buzzword? A capacity building and research. *Physics and Chemistry of the Earth, Parts A/B/C*, *30*, 867–871. https://doi.org/10.1016/j.pce.2005.08.032

van Deventer, H., Smith-Adao, L., Petersen, C., Mbona, N., Skowno, A., & Nel, J. L. (2018). Review of available data for a South African Inventory of Inland Aquatic Ecosystems (SAIIAE). *Water SA*, *44*. https://doi.org/10.4314/wsa.v44i2.05

van Deventer, R., Morris, C. D., Hill, T. R., & Rivers-Moore, N. A. (2022). Use of biological and water quality indices to evaluate conditions of the Upper uMngeni Catchment, KwaZulu-Natal, South Africa. *African Journal of Aquatic Science*, *47*, 1–12. https://doi.org/10.2989/16085914.2021.1941743

van Koppen, B., & Schreiner, B. (2014). Moving beyond integrated water resource management: developmental water management in South Africa. *International Journal of Water Resources Development*, *30*(3), 543–558. https://doi.org/10.1080/07900627.2014.912111

van Koppen, B., Tarimo, A. K. P. R., van Eeden, A., Manzungu, E., & Sumuni, P. M. (2016). Winners and losers of IWRM [Integrated Water Resources Management] in Tanzania. *Water Alternatives*, *9*(3), 588–607. https://hdl.handle.net/10568/78545

van Nes, E. H., Arani, B. M. S., Staal, A., van der Bolt, B., Flores, B. M., Bathiany, S., & Scheffer, M. (2016). What Do You Mean, 'Tipping Point'? *Trends in Ecology & Evolution*, *31*(12), 902–904. https://doi.org/10.1016/j.tree.2016.09.011

van Niekerk, A. (2016). *Stellenbosch University Digital Elevation Model (SUDEM) 2016 Edition*. Centre for Geographical Analysis, Stellenbosch University. http://146.232.21.108/Downloads/sudem/SUDEM_Product_Description.pdf

van Tonder, D. M. (2022). *Investigation of the drivers for water quality decline and risks thereof to agricultural activities in the Breede River catchment* [Master's Thesis, North-West University]. http://hdl.handle.net/10394/39599

Varadharajan, C., Appling, A. P., Arora, B., Christianson, D. S., Hendrix, V. C., Kumar, V., Lima, A. R., Müller, J., Oliver, S., Ombadi, M., Perciano, T., Sadler, J. M., Weierbach, H., Willard, J. D., Xu, Z., & Zwart, J. (2022). Can machine learning accelerate process understanding and decision-relevant predictions of river water quality? *Hydrological Processes*, *36*(4), e14565. https://doi.org/10.1002/hyp.14565

Venkateswarlu, T., & Anmala, J. (2023). Importance of land use factors in the prediction of water quality of the Upper Green River watershed, Kentucky, USA, using random forest. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-03630-1

Vera Mercado, J. A., & Engel, B. (2021). Multi-Scale Analysis of the Dependence of Water Quality on Land Use Using Linear and Mixed Models. *Water*, *13*(19), 2618. https://doi.org/10.3390/w13192618

Vigil, K. M. (2003). *Clean Water: An Introduction to Water Quality and Water Pollution Control*. Corvallis: Oregon State University Press.

Visscher, J. T., Bury, P., Gould, T., & Moriarty, P. (1999). *Integrated water resource management in water and sanitation projects: Lessons from projects in Africa, Asia and South America*. IRC International Water and Sanitation Centre.

Vollmer, D., Abell, R., Bezerra, M., Harrison, I., Hauck, S., Shaad, K., & Souter, N. (2023). A watershed moment for healthy watersheds. *Nature Sustainability*, *6*(3), 233–235. https://doi.org/10.1038/s41893-022-01027-y

Vrebos, D., Beauchard, O., & Meire, P. (2017). The impact of land use and spatial mediated processes on the water quality in a river system. *Science of The Total Environment*, *601-602*, 365–373. https://doi.org/10.1016/j.scitotenv.2017.05.217

Wade, A. J., Skeffington, R. A., Couture, R. M., Erlandsson Lampa, M., Groot, S., Halliday, S. J., Harezlak, V., Hejzlar, J., Jackson-Blake, L. A., Lepistö, A., & Papastergiadou, E. (2022). Land Use Change to Reduce Freshwater Nitrogen and Phosphorus will Be Effective Even with Projected Climate Change. *Water*, *14*(5), 829. https://doi.org/10.3390/w14050829

Waite, I. R. (2014). Agricultural disturbance response models for invertebrate and algal metrics from streams at two spatial scales within the U.S. *Hydrobiologia*, *726*(1), 285–303. https://doi.org/10.1007/s10750-013-1774-4

Waite, I. R., Brown, L. R., Kennen, J. G., May, J. T., Cuffney, T. F., Orlando, J. L., & Jones, K. A. (2010). Comparison of watershed disturbance predictive models for stream benthic macroinvertebrates for three distinct ecoregions in western US. *Ecological Indicators*, *10*(6), 1125–1136. https://doi.org/10.1016/j.ecolind.2010.03.011

Walker, B., & Meyers, J. A. (2004). Thresholds in Ecological and Social–Ecological Systems a Developing Database. *Ecology and Society*, *9*(2). http://www.jstor.org/stable/26267674

Walsh, G., & Wepener, V. (2009). The influence of land use on water quality and diatom community structures in urban and agriculturally stressed rivers. *Water SA*, *35*(5), 579–594. https://doi.org/10.4314/wsa.v35i5.49184

Wan, R., Cai, S., Li, H., Yang, G., Li, Z., & Nie, X. (2014). Inferring land use and land cover impact on stream water quality using a Bayesian hierarchical modeling approach in the Xitiaoxi River Watershed, China. *Journal of Environmental Management*, *133*, 1–11. https://doi.org/10.1016/j.jenvman.2013.11.035

Wang, H., Wang, J., Ni, J., Cui, Y., & Yan, S. (2023a). Spatial scale effects of integrated landscape indicators on river water quality in Chaohu Lake basin, China. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-023-29482-w

Wang, L., Han, X., Zhang, Y., Zhang, Q., Wan, X., Liang, T., Song, H., Bolan, N., Shaheen, S. M., White, J. R., & Rinklebe, J. (2023b). Impacts of land uses on spatio-temporal variations of seasonal water quality in a regulated river basin, Huai River, China. *Science of The Total Environment*, *857*, 159584. https://doi.org/10.1016/j.scitotenv.2022.159584

Wang, L., Lyons, J., Kanehl, P., & Gatti, R. (1997). Influences of Watershed Land Use on Habitat Quality and Biotic Integrity in Wisconsin Streams. *Fisheries*, *22*(6), 6–12. https://doi.org/10.1577/1548-8446(1997)022<0006:IOWLUO>2.0.CO;2

Wang, L., Lyons, J., Rasmussen, P., Seelbach, P., Simon, T., Wiley, M., Kanehl, P., Baker, E., Niemela, S., & Stewart, P. M. (2003). Watershed, reach, and riparian influences on stream fish assemblages in the Northern Lakes and Forest Ecoregion, U.S.A. *Canadian Journal of Fisheries and Aquatic Sciences*, *60*(5), 491–505. https://doi.org/10.1139/f03-043

Wang, Q., Liu, R., Jiao, L., Li, L., Wang, Y., & Cao, L. (2022). Significance of using dynamic land-use data and its threshold in hydrology and water quality simulation models. *Environmental Monitoring and Assessment*, *194*(2), 108. https://doi.org/10.1007/s10661-022-09761-8

Wang, T., Kumwimba, M., Zhu, B., Wang, X., & Tang, J. (2017). Nutrient distribution and risk assessment in drainage ditches with different surrounding land uses. *Nutrient Cycling in Agroecosystems*, *107*(3), 381–394. https://doi.org/10.1007/s10705-017-9840-3

Wang, W., Yang, P., Xia, J., Huang, H., & Li, J. (2023c). Impact of land use on water quality in buffer zones at different scales in the Poyang Lake, middle reaches of the Yangtze River basin. *Science of The Total Environment*, *896*, 165161. https://doi.org/10.1016/j.scitotenv.2023.165161

Wang, X. (2001). Integrating water-quality management and land-use planning in a watershed context. *Journal of Environmental Management*, *61*(1), 25–36. https://doi.org/10.1006/jema.2000.0395

Wang, X., Blanchet, F. G., & Koper, N. (2014). Measuring habitat fragmentation: An evaluation of landscape pattern metrics. *Methods in Ecology and Evolution*, *5*(7), 634–646. https://doi.org/10.1111/2041-210X.12198

Wang, X., & Yin, Z.-Y. (1997). Using GIS to assess the relationship between land use and water quality at a watershed level. *Environment International*, *23*(1), 103–114. https://doi.org/10.1016/S0160-4120(96)00081-5

Wang, X., & Zhang, F. (2018). Multi-scale analysis of the relationship between landscape patterns and a water quality index (WQI) based on a stepwise linear regression (SLR) and geographically weighted regression (GWR) in the Ebinur Lake oasis. *Environmental Science and Pollution Research*, *25*(7), 7033–7048. https://doi.org/10.1007/s11356-017-1041-8

Wang, Y., Li, B., & Yang, G. (2023d). Stream water quality optimized prediction based on human activity intensity and landscape metrics with regional heterogeneity in Taihu Basin, China. *Environmental Science and Pollution Research*, *30*(2), 4986–5004. https://doi.org/10.1007/s11356-022-22536-5

Wang, Y., Liu, X., Wang, T., Zhang, X., Feng, Y., Yang, G., & Zhen, W. (2021). Relating land-use/land-cover patterns to water quality in watersheds based on the structural equation modeling. *CATENA*, *206*, 105566. https://doi.org/10.1016/j.catena.2021.105566

Wang, Z., Zhang, S., Peng, Y., Wu, C., Lv, Y., Xiao, K., Zhao, J., & Qian, G. (2020). Impact of rapid urbanization on the threshold effect in the relationship between impervious surfaces and water quality in Shanghai, China. *Environmental Pollution*, *267*, 115569. https://doi.org/10.1016/j.envpol.2020.115569

Waturu, M., Sitoki, L., Lalah, J., Chasia, S., & Mbao, E. (2023). Effect of land use/land cover changes on water quality in the Upper Athi River sub-catchment in Kenya. *African Journal of Aquatic Science*, 1–14. https://doi.org/10.2989/16085914.2023.2207098

Wear, D. N., Turner, M. G., & Naiman, R. J. (1998). Land Cover Along an Urban-Rural Gradient: Implications for Water Quality. *Ecological Applications*, *8*(3), 619–630. https://doi.org/10.1890/1051-0761(1998)008[0619:LCAAUR]2.0.CO;2

Wei, X., Xiao, Z., Li, Q., Li, P., & Xiang, C. (2017). Evaluating the effectiveness of landscape configuration metrics from landscape composition metrics. *Landscape and Ecological Engineering*, *13*(1), 169–181. https://doi.org/10.1007/s11355-016-0314-6

Weiner, E. R. (2013). *Applications of Environmental Aquatic Chemistry* (3rd ed.). Florida: CRC Press. https://doi.org/10.1201/b12963

Wepener, V., Euler, N., van Vuren, J. H. J., du Preez, H. H., & Köhler, A. (1992). The development of an aquatic toxicity index as a tool in the operational management of water quality in the Olifants River (Kruger National Park). *Koedoe: African Protected Area Conservation and Science*, *35*(2). https://doi.org/10.4102/koedoe.v35i2.400

Wepener, V., Malherbe, W., & Smit, N. J. (2018). Water Resources in South Africa. In N. King, H. Strydom, & F. Retief (Eds.), *Environmental Management in South Africa* (3rd ed., pp. 351–400). Cape Town: Juta.

White, C. (2013). *Integrated Water Resources Management: What is it and why is it used?* Global Water Forum. Retrieved 5 October 2022 from https://globalwaterforum.org/2013/06/10/integrated-water-resources-management-what-is-it-and-why-is-it-used/

Wilson, C., & Weng, Q. (2010). Assessing Surface Water Quality and Its Relation with Urban Land Cover Changes in the Lake Calumet Area, Greater Chicago. *Environmental Management*, *45*(5), 1096–1111. https://doi.org/10.1007/s00267-010-9482-6

Wilson, C. O. (2015). Land use/land cover water quality nexus: quantifying anthropogenic influences on surface water quality. *Environmental Monitoring and Assessment*, *187*(7), 1–23. https://doi.org/10.1007/s10661-015-4666-4

Winter, K. (2018). *Crisis proofing South Africa's water security*. The Conversation. Retrieved 1 September 2022 from https://theconversation.com/crisis-proofing-south-africas-water-security-106261

Winton, R. S., Teodoru, C. R., Calamita, E., Kleinschroth, F., Banda, K., Nyambe, I., & Wehrli, B. (2021). Anthropogenic influences on Zambian water quality: hydropower and land-use change. *Environmental Science: Processes & Impacts*, *23*(7), 981–994. https://doi.org/10.1039/D1EM00006C

WMO. (2021). *2021 State of Climate Services: Water*. World Meteorological Organisation.

WMO. (2022). *State of Global Water Resources 2021*. World Meteorological Organisation.

Woodhouse, P., & Muller, M. (2017). Water Governance—An Historical Perspective on Current Debates. *World Development*, *92*, 225–241. https://doi.org/10.1016/j.worlddev.2016.11.014

World Bank Group. (2018). *Overcoming Poverty and Inequality in South Africa: An Assessment of Drivers, Constraints and Opportunities*. World Bank. https://openknowledge.worldbank.org/handle/10986/29614

World Bank Group. (2021). *Climate Change Knowledge Portal*. Retrieved 6 January 2023 from https://climateknowledgeportal.worldbank.org/country/south-africa/climate-data-historical

World Weather Attribution. (2022). *Climate change-exacerbated rainfall causing devastating flooding in Eastern South Africa*. Retrieved 31 May 2022 from https://www.worldweatherattribution.org/climate-change-exacerbated-rainfall-causing-devastating-flooding-in-eastern-south-africa/

Woznicki, S. A., Kraynick, G., Wickham, J., Nash, M., & Sohl, T. (2023). Modeling future land cover and water quality change in Minneapolis, MN, USA to support drinking water source protection decisions. *JAWRA Journal of the American Water Resources Association*, *59*(4), 726-742. https://doi.org/10.1111/1752-1688.13109

Wu, J., & Lu, J. (2021). Spatial scale effects of landscape metrics on stream water quality and their seasonal changes. *Water Research*, *191*, 116811. https://doi.org/10.1016/j.watres.2021.116811

Wu, W., Yin, S., Liu, H., & Chen, H. (2014). Groundwater Vulnerability Assessment and Feasibility Mapping Under Reclaimed Water Irrigation by a Modified DRASTIC Model. *Water Resources Management*, *28*(5), 1219–1234. https://doi.org/10.1007/s11269-014-0536-z

WWF. (2013). *An Introduction to South Africa's Water Source Areas*. WWF South Africa/CSIR. https://water.cer.org.za/resources

WWF. (2017). *Scenarios for the Future of Water in South Africa*. WWF South Africa/Boston Consulting Group.

Xiao, H., & Ji, W. (2007). Relating landscape characteristics to non-point source pollution in mine waste-located watersheds using geospatial techniques. *Journal of Environmental Management*, *82*(1), 111–119. https://doi.org/10.1016/j.jenvman.2005.12.009

Xie, M. (2006). *Integrated Water Resources Management (IWRM) – Introduction to Principles and Practices [Paper prepared for the Africa Regional Workshop on IWRM, Nairobi, Oct. 29-Nov. 2006]*. World Bank Institute.

Xu, G., Xie, J., Zhang, Y., Zhao, C., & Wu, Q. (2010). Application of Nemerow Pollution Index in Landscape River Water Quality Assessment of Tianjin. *2010 4th International Conference on Bioinformatics and Biomedical Engineering*. https://doi.org/10.1109/ICBBE.2010.5514830

Xu, H., Zheng, H., Chen, X., Ren, Y., & Ouyang, Z. (2016). Relationships between river water quality and landscape factors in Haihe River Basin, China: Implications for environmental management. *Chinese Geographical Science*, *26*(2), 197–207. https://doi.org/10.1007/s11769-016-0799-9

Xu, J., & Xiao, P. (2022). A Bibliometric Analysis on the Effects of Land Use Change on Ecosystem Services: Current Status, Progress, and Future Directions [Review]. *Sustainability (Switzerland)*, *14*(5), Article 3079. https://doi.org/10.3390/su14053079

Xu, M., Xu, G., Li, Z., Dang, Y., Li, Q., Min, Z., Gu, F., Wang, B., Liu, S., & Zhang, Y. (2023a). Effects of comprehensive landscape patterns on water quality and identification of key metrics thresholds causing its abrupt changes. *Environmental Pollution*, *333*, 122097. https://doi.org/10.1016/j.envpol.2023.122097

Xu, Q., Yan, T., Wang, C., Hua, L., & Zhai, L. (2023b). Managing landscape patterns at the riparian zone and sub-basin scale is equally important for water quality protection. *Water Research*, *229*, 119280. https://doi.org/10.1016/j.watres.2022.119280

Yang, D., Jayawardena, A. W., & Cong, Z. (2017). Watersheds, River Basins, and Land Use. In V. P. Sing (Ed.), *Handbook of Applied Hydrology* (2nd ed.). McGraw-Hill Education.

Yang, S., & Berdine, G. (2016). Outliers. *The Southwest Respiratory and Critical Care Chronicles*, *4*(13), 52–56. https://doi.org/10.12746/swrccc2016.0413.178

Yao, S., Chen, C., He, M., Cui, Z., Mo, K., Pang, R., & Chen, Q. (2023). Land use as an important indicator for water quality prediction in a region under rapid urbanization. *Ecological Indicators*, *146*, 109768. https://doi.org/10.1016/j.ecolind.2022.109768

Ye, Y., Xingyuan, H., Wei, C., Jing, Y., Shuai, Y., & Lian, J. (2014). Seasonal Water Quality Upstream of Dahuofang Reservoir, China – the Effects of Land Use Type at Various Spatial Scales. *Clean – Soil, Air, Water*, *42*(10), 1423–1432. https://doi.org/10.1002/clen.201300600

Yirigui, Y., Lee, S.-W., Nejadhashemi, A. P., Herman, M. R., & Lee, J.-W. (2019). Relationships between Riparian Forest Fragmentation and Biological Indicators of Streams. *Sustainability*, *11*(10), 2870. https://doi.org/10.3390/su11102870

Young, R. G., Quarterman, A. J., Eyles, R. F., Smith, R. A., & Bowden, W. B. (2005). Water quality and thermal regime of the Motueka River: Influences of land cover, geology and position in the catchment. *New Zealand Journal of Marine and Freshwater Research*, *39*(4), 803–825. https://doi.org/10.1080/00288330.2005.9517354

Yu, D., Shi, P., Liu, Y., & Xun, B. (2013). Detecting land use-water quality relationships from the viewpoint of ecological restoration in an urban area. *Ecological Engineering*, *53*, 205–216. https://doi.org/10.1016/j.ecoleng.2012.12.045

Yu, S., Xu, Z., Wu, W., & Zuo, D. (2016). Effect of land use types on stream water quality under seasonal variation and topographic characteristics in the Wei River basin, China. *Ecological Indicators*, *60*, 202–212. https://doi.org/0.1016/j.ecolind.2015.06.029

Yuan, L., Sinshaw, T., & Forshay, K. J. (2020). Review of Watershed-Scale Water Quality and Nonpoint Source Pollution Models. *Geosciences*, *10*(1), 25. https://doi.org/10.3390/geosciences10010025

Zaccarelli, N., Petrosillo, I., & Zurlini., G. (2008). Retrospective Analysis. In S. E. Jørgensen & B. D. Fath (Eds.), *Systems Ecology. Vol. [4] of Encyclopedia of Ecology, 5 vols.* (pp. 3020–3029). Oxford: Elsevier.

Zampella, R. A., Procopio, N. A., Lathrop, R. G., & Dow, C. L. (2007). Relationship of Land-Use/Land-Cover Patterns and Surface-Water Quality in The Mullica River Basin. *JAWRA Journal of the American Water Resources Association*, *43*(3), 594–604. https://doi.org/10.1111/j.1752-1688.2007.00045.x

Zhang, F., Chen, Y., Wang, W., Jim, C. Y., Zhang, Z., Tan, M. L., Liu, C., Chan, N. W., Wang, D., Wang, Z., & Rahman, H. A. (2022a). Impact of land-use/land-cover and landscape pattern on seasonal in-stream water quality in small watersheds. *Journal of Cleaner Production*, *357*, 131907. https://doi.org/10.1016/j.jclepro.2022.131907

Zhang, J., Li, S., Dong, R., Jiang, C., & Ni, M. (2019). Influences of land use metrics at multi-spatial scales on seasonal water quality: A case study of river systems in the Three Gorges Reservoir Area, China. *Journal of Cleaner Production*, *206*, 76–85. https://doi.org/10.1016/j.jclepro.2018.09.179

Zhang, J., Mengting, L., Hui, Y., Xiyun, C., & Chong, F. (2018). Critical thresholds in ecological restoration to achieve optimal ecosystem services: An analysis based on forest ecosystem restoration projects in China. *Land Use Policy*, *76*, 675–678. https://doi.org/10.1016/j.landusepol.2018.02.050

Zhang, Y., Zhao, Y., Zhang, H., Cao, J., Chen, J., Su, C., & Chen, Y. (2023a). The Impact of Land-Use Composition and Landscape Pattern on Water Quality at Different Spatial Scales in the Dan River Basin, Qin Ling Mountains. *Water*, *15*(18), 3276. https://doi.org/10.3390/w15183276

Zhang, Z., Huang, J., Duan, S., Huang, Y., Cai, J., & Bian, J. (2022b). Use of interpretable machine learning to identify the factors influencing the nonlinear linkage between land use and river water quality in the Chesapeake Bay watershed. *Ecological Indicators*, *140*, 108977. https://doi.org/10.1016/j.ecolind.2022.108977

Zhang, Z., Li, J., Hu, Z., Zhang, W., Ge, H., & Li, X. (2023b). Impact of Land Use/Land Cover and Landscape Pattern on Water Quality in Dianchi Lake Basin, Southwest of China. *Sustainability*, *15*(4), 3145. https://doi.org/10.3390/su15043145

Zhang, Z., Zhang, F., Du, J., Chen, D., & Zhang, W. (2021). Impacts of land use at multiple buffer scales on seasonal water quality in a reticular river network area. *PLOS ONE*, *16*(1), e0244606. https://doi.org/10.1371/journal.pone.0244606

Zhong, X., Xu, Q., Yi, J., & Jin, L. (2022). Study on the threshold relationship between landscape pattern and water quality considering spatial scale effect—a case study of Dianchi Lake Basin in China. *Environmental Science and Pollution Research*, *29*(29), 44103–44118. https://doi.org/10.1007/s11356-022-18970-0

Zhou, J., Chuyu, L., Ma, D., Shi, W., Lanying, W., Guo, Z., Tang, H., Wang, X., Wang, J., Chunfang, L., Wei, W., & Wang, C. (2022). The impact of land use landscape pattern on river hydrochemistry at multi-scale in an inland river basin, China. *Ecological Indicators*, *143*, 109334. https://doi.org/10.1016/j.ecolind.2022.109334

Zhou, T., Wu, J., & Peng, S. (2012). Assessing the effects of landscape pattern on river water quality at multiple scales: A case study of the Dongjiang River watershed, China. *Ecological Indicators*, *23*, 166–175. https://doi.org/10.1016/j.ecolind.2012.03.013

Ziervogel, G. (2019). *Unpacking the Cape Town Drought: Lessons Learned*. Cities Support Programme, African Centre for Cities. https://www.africancentreforcities.net/unpacking-cape-town-drought-lessons-learned/

Appendices

Appendix 1: Parameters and Pollutants Derived From and/or Influenced by LULC

Note: The nomenclature and taxonomies used to categorise these parameters/pollutants vary from text to text. An attempt is made in the table below to unify the various classification approaches.

Water Quality Parameter/Pollutant	**Nature/Description**	**Sources/Causes**	**Impacts/Effects**
Biocides	Technically a sub-category of Persistent Organic Pollutants (POPs), these include pesticides, herbicides, and fungicides.	While typically present in agricultural runoff, urban stormwater may also include biocides when used for pest and weed control in built-up areas.	Biocides are directly toxic to many aquatic species but may also affect other organisms indirectly by altering the species diversity/community structure of aquatic ecosystems. They also tend to bioaccumulate and are often toxic to humans.
Dissolved Oxygen (DO)	Measured in mg/l, or expressed as a percentage of saturation, DO levels of unpolluted freshwater are normally close to saturation point (i.e., 100% or around 10 mg/l). An adequate concentration of DO is critical for the survival of aquatic life. Concentrations of DO are directly affected by chemical and biological oxygen demand, as well as the temperature and salinity of the water.	Reduced DO levels are usually due to the aerobic respiration of aquatic organisms (e.g., bacteria or phytoplankton) and are thus typically associated with eutrophication and/or organic enrichment from domestic and agricultural effluents which contain nutrients and/or organic material. Salinisation and increases in water temperature also reduce oxygen solubility.	Low concentrations of DO (i.e., hypoxic conditions) will place aquatic organisms under stress and may be fatal (less than 80% saturation is problematic). Reductions in DO may also trigger the release of toxic substances (such as ammonia, nitrite, and hydrogen sulphide) from the anaerobic decomposition of organic matter. Toxic substances (including heavy metals) also become increasingly harmful to aquatic organisms due to the higher respiration rates induced by hypoxic conditions.

Water Quality Parameter/Pollutant	Nature/Description	Sources/Causes	Impacts/Effects
Dissolved Solids (Salts)	Dissolved solids refer to the combined concentration of mineral salts/ions in solution (e.g., calcium, magnesium, sodium, potassium, carbonate, chloride, sulphate). They are typically derived from the dissolution of minerals from soils and geologic formations. The nature and availability of dissolved solids are largely dependent on the geological characteristics of the catchment.	Dissolved solids are usually leached into waterways from areas where the ground has been disturbed and/or irrigated (e.g., agricultural activities, mining operations, and construction sites).	High concentrations of dissolved solids (i.e., salinisation) may cause osmoregulatory difficulties in aquatic organisms. Excessive concentrations may also make water unsuitable for domestic use, irrigation, or industrial use. Increased salinity further decreases the concentration of dissolved oxygen.
Emerging Pollutants (i.e., Contaminants of Emerging Concern)	So-called "emerging pollutants" include pharmaceutical products, hormones, solvents, and nanomaterials (e.g., microplastics).	Pharmaceuticals and veterinary medicines are often present in domestic and agricultural wastewater. Industrial effluents and landfill leachate are two other common sources of emerging pollutants.	The impacts of emerging pollutants remain uncertain, but they are assumed to be toxic to aquatic life (and possibly humans). Declining fertility of aquatic organisms has also been reported.
Microorganisms	These are typically bacterial in nature but may also include species of phytoplankton/algae. Bacteria are responsible for the decomposition of organic matter, while phytoplankton photosynthesise and act as primary producers.	Bacteria are primarily contained in untreated domestic wastewater which may enter water bodies through direct end-of-pipe discharges, leaks from poorly maintained treatment works and sewerage systems, or as diffuse runoff from informal settlements that lack sanitation infrastructure. Bacteria are also found in animal waste and thus agricultural runoff in cases where manure is used as fertiliser or from fields where livestock graze. Increases in phytoplankton are usually associated with eutrophication due to nutrient loading from agricultural and/or urban runoff as described above.	Bacterial decomposition of organic matter can reduce dissolved oxygen concentrations. Some bacteria are also pathogenic. Blooms of phytoplankton can lead to reductions in dissolved oxygen concentrations through nocturnal respiration and/or the decomposition of dead phytoplankton. Cyanobacteria (blue-green algae) are toxic.

Water Quality Parameter/Pollutant	Nature/Description	Sources/Causes	Impacts/Effects
Nutrients	These include species of nitrogen and phosphorous, both of which are essential for aquatic plant growth but are harmful in excess.	Nutrients are usually found in agricultural runoff (either owing to the intentional application of inorganic fertilisers and/or manure, or from excreta deposited by grazing livestock). Runoff from animal feed lots may also contain high levels of nutrients. Domestic wastewater and runoff from informal settlements are also common sources of nutrients in urban settings. Some industrial effluents (such as those from food processing operations) may also contain nutrients.	Excess nutrients cause eutrophication and associated problems, including hypoxic conditions. Nitrite (NO_2) and ammonia (NH_3) are highly toxic to aquatic organisms. High concentrations of nitrate (NO_3) are toxic to humans.
Oils and Grease	Oils and fats of biological origin (e.g., animal and vegetable fats and oils) as well as mineral oils (e.g., petroleum-based hydrocarbons).	Oils and grease are typically found in urban runoff (from roads, parking lots, and domestic wastewater) and industrial effluent.	Oils and grease may be toxic to aquatic organisms and may impair the respiration and mobility of aquatic organisms.
Organic Matter	This includes any biodegradable organic material, typically containing carbon, which may be decomposed by bacteria.	Organic matter may originate from animal waste or plant detritus from agricultural activities, animal feedlots, as well as from domestic wastewater and urban runoff. Discharges from food processing plants, breweries, and some industries may also contain organic matter.	Organic enrichment typically causes eutrophication and a depletion of DO due to the decomposition of organic material by bacteria. Suspended organic matter may also lead to turbid conditions.
Persistent Organic Pollutants (POPs)	POPs include compounds manufactured by humans such as polychlorinated biphenyls (PCBs) and polycyclic aromatic hydrocarbons (PAHs) and are typically used in industrial processes. POPs are toxic and persist in the environment for a long time.	POPs are typically found in urban runoff and industrial effluent. Agricultural runoff may also contain POPs in the form of pesticides.	Many POPs are directly toxic to aquatic life. Bioaccumulation is common, causing a build-up of toxic compounds along the food chain.

Water Quality Parameter/Pollutant	Nature/Description	Sources/Causes	Impacts/Effects
pH	pH relates to the concentration of dissolved hydrogen ions and determines the acidity of water. Natural or "background" pH levels are typically determined by catchment geology. Variations in pH are buffered by alkalinity (the concentration of calcium carbonate, $CaCO_3$, in solution).	Acidification of surface waters is primarily due to acid mine drainage (AMD). Acid rain from urban or industrial atmospheric emissions will also lower the pH of receiving waters. Depending on their composition, industrial discharges may also affect pH.	Extremes in pH generally reduce aquatic productivity and biodiversity. Changes in pH affect the ionic and biotic balance of aquatic organisms. Low pH levels may affect gill function in fish, while extremes in pH may be fatal to aquatic organisms. The rates of many chemical reactions are also controlled by pH and fluctuations in pH can influence the form, solubility, and availability of potentially toxic trace elements. Low pH can also lead to the release of toxic substances and phosphorous from sediments due to changes in the surface charges of the adsorbing molecules.
Suspended Solids and Sediments	Mainly eroded material, silt, and soil particles, as well as vegetative debris, held in suspension. Increased levels of suspended solids will affect turbidity and reduce water clarity. These particles may subsequently settle out (i.e., sedimentation).	Suspended solids and sediments mainly derive from ground disturbance and subsequent erosion. They are thus typically associated with construction sites, quarrying and mining operations, agricultural activities, and vegetation removal. They may also derive from domestic sewage releases and industrial discharges.	While suspended, these particles increase the turbidity of water, reduce light penetration, and thus lower photosynthetic potential and primary production. Reduced light penetration may also influence the temperature of the water. Reduced visibility may negatively affect predatory species. In addition, suspended solids may impair the gill function of fish, while sediments may smother benthic habitats and breeding grounds. Suspended particles and sediments also adsorb and transport nutrients (especially phosphorous) and toxins (such as POPs).

Water Quality Parameter/Pollutant	Nature/Description	Sources/Causes	Impacts/Effects
Temperature	Fluctuations in the temperature of surface water bodies.	Heated water from power stations and other industries will increase the temperature of the water bodies into which they are discharged. Losses of riverine vegetation which shade water bodies may also result in increased water temperatures. Changes in turbidity will affect water temperature due to increased (or decreased) light penetration. Return flow from irrigation may also increase the temperature of receiving waters.	The temperature of water determines its capacity to contain many dissolved substances in solution. Increased water temperature may therefore lead to reductions in DO. Water temperature also influences the availability of nutrients and toxins. All organisms have a temperature (or range of temperatures) that are optimal for growth, reproduction and general health. Temperature also influences the metabolism and lifecycle processes (such as breeding and migration patterns) of aquatic organisms. These processes may thus be unnaturally altered due to changes in water temperature.
Trace Elements and Heavy Metals	Non- and semi-metallic trace elements include antimony (Sb), boron (B), and selenium (Se). Metallic elements include arsenic (As), cadmium (Cd), cobalt (Co), copper (Cu), iron (Fe), manganese (Mn), mercury (Hg), molybdenum (Mo), nickel (Ni), lead (Pb), vanadium (V), and zinc (Zn). Some of these metals are essential in trace amounts for plants and animals, while others are toxic.	Heavy metal contamination may originate from mines, the urban environment (usually in industrial effluent, in runoff from roads, or from weathering of metals and paints on buildings), or agricultural activity (usually from the excreta of animals fed with enriched feedstuffs).	Even trace amounts of certain elements can be toxic to aquatic ecosystems.

Sources: Calder (1993); Haygarth & Jarvis (2002); CWP (2003); Vigil (2003); Dallas & Day (2004); Anderson & McDonnell (2005); Day and Dallas (2011); Weiner (2013); King et al. (2018); Boyd (2020); Chapman et al. (2020); Bohenek and Sulliván (2022); Kajitvichyanukul and D'Arcy (2022)

Appendix 2: Water Quality Indicators Used as Response Variables

Water Quality Indicator	Examples of Publications
Physiochemical and/or Microbiological Water Quality Parameters	Haith (1976); Detenbeck et al. (1993); Osborne and Kovacic (1993); Lenat and Crawford (1994); Hunsaker and Levine (1995); Johnson et al. (1997); Wang and Yin (1997); Basnyat et al. (1999); Dauer et al. (2000); Gove et al. (2001); Rhodes et al. (2001); Sliva and Williams (2001); Sponseller et al. (2001); Wang (2001); Griffith et al. (2002a); Jarvie et al. (2002); Tong and Chen (2002); Strayer et al. (2003); Buck et al. (2004); Larned et al. (2004); Ngoye and Machiwa (2004); Ahearn et al. (2005); Carle et al. (2005); King et al. (2005); Mehaffey et al. (2005); Snyder et al. (2005); Young et al. (2005); Amiri and Nakane (2006); Donohue et al. (2006); Schoonover and Lockaby (2006); Galbraith and Burns (2007); Schiff and Benoit (2007); Shivoga et al. (2007); Uuemaa et al. (2007); Zampella et al. (2007); Amiri and Nakane (2008); Li et al. (2008); Li et al. (2009); Nash et al. (2009); Rothenberger et al. (2009); Walsh and Wepener (2009); Rothwell et al. (2010); Shiels (2010); Tran et al. (2010); Carpio and Fath (2011); Maloney and Weller (2011); Miller et al. (2011); Tu (2011a); Tu (2011b); Twesigye et al. (2011); Uriarte et al. (2011); Clapcott et al. (2012); Nielsen et al. (2012); Pandey et al. (2012); Pratt and Chang (2012); Zhou et al. (2012); Aighewi et al. (2013); Bateni et al. (2013); Chu et al. (2013); Dabrowski and de Klerk (2013); Firdaus and Nakagoshi (2013); Shupe (2013); Slaughter and Mantel (2013); Attua et al. (2014); Bu et al. (2014); du Plessis et al. (2014); Kebede et al. (2014); Wan et al. (2014); Calijuri et al. (2015); Ding et al. (2015); du Plessis et al. (2015); Hassan et al. (2015); Meneses et al. (2015); Moodley et al. (2015); Shen et al. (2015); Wilson (2015); Bonansea et al. (2016); Chen et al. (2016); Chidamba et al. (2016); Ding et al. (2016); Kim et al. (2016); Nava-López et al. (2016); Ou et al. (2016); Dai et al. (2017); de Oliveira et al. (2017); Hua (2017); Kändler et al. (2017); Martin et al. (2017); Petersen et al. (2017); Shi et al. (2017); Tromboni and Dodds (2017); van der Hoven et al. (2017); Vrebos et al. (2017); Asare et al. (2018); de Mello et al. (2018); Liu and Yang (2018); Mainali and Chang (2018); Namugize et al. (2018); Nde and Mathuthu (2018); Ide et al. (2019); Liberoff et al. (2019); Ogbozige and Alfa (2019); Zhang et al. (2019); Dunea et al. (2020); Gorgoglione et al. (2020); Huang et al. (2020); Karakuş (2020); Medupin et al. (2020); Mirzaei et al. (2020); Mwaijengo et al. (2020); Park and Lee (2020); Petersen et al. (2020); Ramião et al. (2020); Barnard et al. (2021); Chiang et al. (2021); Crooks et al. (2021); Ding et al. (2021); Dlamini et al. (2021); du Plessis (2021); Dymek et al. (2021); Koekemoer et al. (2021); Li et al. (2021); Liu et al. (2021); Mahabeer and Tekere (2021); Mallya and Rwiza (2021); Nde et al. (2021); Nguvulu et al. (2021); Vera Mercado and Engel (2021); Wang et al. (2021); Winton et al. (2021); Wu and Lu (2021); Zhang et al. (2021); Aalipour et al. (2022); Allafta and Opp (2022); Clark et al. (2022); Dębska et al. (2022); de Mello et al. (2022); Kadir et al. (2022); Kuranchie et al. (2022); Łaszewski et al. (2022); Li et al. (2022b); Makgoale et al. (2022); Obubu et al. (2022); Procopio and Zampella (2022); Simpson et al. (2022); Torres-Bejarano et al. (2022); van Deventer et al. (2022); Zhong et al. (2022); Zhou et al. (2022); Bowes et al. (2023); Caldwell et al. (2023); Deng et al. (2023); Feng et al. (2023b); Goswami et al. (2023); Liu et al. (2023); Prakoso et al. (2023); Roldán-Arias et al. (2023); Waturu et al. (2023); Xu et al. (2023a); Xu et al. (2023b); Yao et al. (2023)

Water Quality Indicator	**Examples of Publications**
Biological Indices	Klein (1979); Steedman (1988); Lenat and Crawford (1994); Roth et al. (1996); Allan et al. (1997); Lammert and Allan (1999); Dauer et al. (2000); Fitzpatrick et al. (2001); Wang (2001); Griffith et al. (2002a); Griffith et al. (2002b); Roy et al. (2003); Strayer et al. (2003); Black et al. (2004); Tiner (2004); King et al. (2005); Snyder et al. (2005); Donohue et al. (2006); Schiff and Benoit (2007); Walsh and Wepener (2009); Death and Collier (2010); Riseng et al. (2010); Tran et al. (2010); Maloney and Weller (2011); Miserendino et al. (2011); Clapcott et al. (2012); Magierowski et al. (2012); Feld (2013); Waite (2014); Farrell et al. (2015); Midway et al. (2015); Manfrin et al. (2016); Clément et al. (2017); Grimstead et al. (2018); Yirigui et al. (2019); Mwaijengo et al. (2020); Barnard et al. (2021); Chen and Olden (2020); Dymek et al. (2021); Koekemoer et al. (2021); Dalu et al. (2022); Heidkamp and Christian (2022); Henderson and Christian (2022); Makgoale et al. (2022); van Deventer et al. (2022); Bowes et al. (2023); Prakoso et al. (2023)
Water Quality Indices	Tsegaye et al. (2006); Schiff and Benoit (2007); Firdaus and Nakagoshi (2013); Yu et al. (2013); Iñiguez-Armijos et al. (2014); Rodríguez-Romero et al. (2018); Shukla et al. (2018); Wang and Zhang (2018); Gossweiler et al. (2019); Kim et al. (2020); Sutjiningsih (2017); Karakuş (2020); Hanna et al. (2021); Molekoa et al. (2021); Senbore and Oke (2021); Umwali et al. (2021); Paná et al. (2022); Zhang et al. (2022a); Pandey et al. (2023); Gani et al. (2023); Ma et al. (2023); Roldán-Arias et al. (2023); Wang et al. (2023b); Zhang et al. (2023b); Wang et al. (2023a); Maurya et al. (2021); Gule et al. (2023); Siqueira et al. (2023)
Spectral Indices Derived from Remote-Sensing Platforms	Bonansea et al. (2021); Baltodano et al. (2022)

Appendix 3: Common Statistical Methods Used to Analyse the Influence of LULC on Water Quality

Statistical Method	**Examples of Publications**
Analysis of Variance (ANOVA) OR Kruskal-Wallis Tests	Lammert and Allan (1999); Sliva and Williams (2001); Booth et al. (2002); Tong and Chen (2002); Larned et al. (2004); Ngoye and Machiwa (2004); Young et al. (2005); Schoonover and Lockaby (2006); Galbraith and Burns (2007); Shivoga et al. (2007); Zampella et al. (2007); Li et al. (2008); Tran et al. (2010); Miller et al. (2011); Miserendino et al. (2011); Firdaus and Nakagoshi (2013); Zhou et al. (2012); Attua et al. (2014); Bu et al. (2014); Kebede et al. (2014); Ding et al. (2015); Bonansea et al. (2016); Chen et al. (2016); Chidamba et al. (2016); Ding et al. (2016); Yu et al. (2016); Hua (2017); Kändler et al. (2017); Shi et al. (2017); van der Hoven et al. (2017); Mainali and Chang (2018); Rodríguez-Romero et al. (2018); Zhang et al. (2019); Kim et al. (2020); Petersen et al. (2020); Ramião et al. (2020); Tahiru et al. (2020); Barnard et al. (2021); Crooks et al. (2021); Koekemoer et al. (2021); Mahabeer and Tekere (2021); Wu and Lu (2021); Zhang et al. (2021); Clark et al. (2022); Dalu et al. (2022); Dębska et al. (2022); de Souza et al. (2022); Li et al. (2022b); Roldán-Arias et al. (2023); Simpson et al. (2022); Waturu et al. (2023); Xu et al. (2023a); Xu et al. (2023b)
Pearson's Correlation Analysis OR Spearman's Rank Correlation Analysis	Wang and Yin (1997); Lammert and Allan (1999); Fitzpatrick et al. (2001); Wang (2001); Griffith et al. (2002a, 2002b); Tong and Chen (2002); Buck et al. (2004); Donohue et al. (2006); Schiff and Benoit (2007); Zampella et al. (2007); Li et al. (2009); Rothenberger et al. (2009); Uuemaa et al. (2009); Rothwell et al. (2010); Tu (2011a); Magierowski et al. (2012); Pandey et al. (2012); Aighewi et al. (2013); Bateni et al. (2013); Feld (2013); Shupe (2013); du Plessis et al. (2014); Waite (2014); Ding et al. (2015); du Plessis et al. (2015); Hassan et al. (2015); Bonansea et al. (2016); Chen et al. (2016); Gyamfi et al. (2016); Nava-López et al. (2016); Yu et al. (2016); Dai et al. (2017); de Oliveira et al. (2017); Tromboni and Dodds (2017); Namugize et al. (2018); Nde and Mathuthu (2018); Shukla et al. (2018); Wang and Zhang (2018); Ide et al. (2019); Karakuş (2020); Palma et al. (2020); Park and Lee (2020); Song et al. (2020); Tahiru et al. (2020); Crooks et al. (2021); Fernandes et al. (2021); Li et al. (2021); Nguvulu et al. (2021); Umwali et al. (2021); Aalipour et al. (2022); Dalu et al. (2022); Kadir et al. (2022); Kuranchie et al. (2022); Łaszewski et al. (2022); Obubu et al. (2022); Procopio and Zampella (2022); Torres-Bejarano et al. (2022); Zhong et al. (2022); Gani et al. (2023); Gobry et al. (2023); Prakoso et al. (2023); Roldán-Arias et al. (2023); Szymańska-Walkiewicz et al. (2023); Wang et al. (2023a); Xu et al. (2023b); Zhang et al. (2023a); Zhang et al. (2023b)
Principal Component Analysis (PCA)	Walsh and Wepener (2009); Nielsen et al. (2012); Aighewi et al. (2013); Dabrowski and de Klerk (2013); Slaughter and Mantel (2013); Moodley et al. (2015); Petersen et al. (2017); Rodríguez-Romero et al. (2018); Gorgoglione et al. (2020); Palma et al. (2020); Petersen et al. (2020); Ramião et al. (2020); Nguvulu et al. (2021); Umwali et al. (2021); de Mello et al. (2022); de Souza et al. (2022); Heidkamp and Christian (2022); Ma et al. (2022); Torres-Bejarano et al. (2022); van Deventer et al. (2022); Bowes et al. (2023); Gani et al. (2023); Siqueira et al. (2023); Waturu et al. (2023)

Statistical Method	Examples of Publications
Redundancy Analysis (RDA)	Johnson et al. (1997); Fitzpatrick et al. (2001); Sliva and Williams (2001); Galbraith and Burns (2007); Schiff and Benoit (2007); Feld (2013); Iñiguez-Armijos et al. (2014); Ding et al. (2015); Farrell et al. (2015);Shen et al. (2015); Chen et al. (2016); Ding et al. (2016); Nava-López et al. (2016); Xu et al. (2016); Kändler et al. (2017); Shi et al. (2017); Vrebos et al. (2017); de Mello et al. (2018); Huang et al. (2020); Mwaijengo et al. (2020); Song et al. (2020); Dymek et al. (2021); Wang et al. (2021); Wu and Lu (2021); Zhang et al. (2021); Kuranchie et al. (2022); Li et al. (2022b); Zhang et al. (2022a); Zhou et al. (2022); Bowes et al. (2023); Deng et al. (2023); Wang et al. (2023a); Wang et al. (2023c); Xu et al. (2023a); Zhang et al. (2023a); Zhang et al. (2023b)
Cluster Analysis (CA)	Uuemaa et al. (2009); Walsh and Wepener (2009); Calijuri et al. (2015); Ding et al. (2015); Meneses et al. (2015); Kändler et al. (2017); Liu and Yang (2018); Rodríguez-Romero et al. (2018); Gorgoglione et al. (2020); Kim et al. (2020); Palma et al. (2020); Ramião et al. (2020); Nguvulu et al. (2021); Umwali et al. (2021); Łaszewski et al. (2022); Makgoale et al. (2022); Obubu et al. (2022); Paná et al. (2022)
Regression Analysis (all forms)	Haith (1976); Steedman (1988); Detenbeck et al. (1993); Hunsaker and Levine (1995); Basnyat et al. (1999); Lammert and Allan (1999); Schulze (2000); Sliva and Williams (2001); Sponseller et al. (2001); Wang (2001); Booth et al. (2002); Jarvie et al. (2002); Roy et al. (2003); Ahearn et al. (2005); Carle et al. (2005); King et al. (2005); Young et al. (2005); Uuemaa et al. (2007); Amiri and Nakane (2008); Li et al. (2008); Nash et al. (2009); Rothenberger et al. (2009); Dodds et al. (2010); Shiels (2010); Maloney and Weller (2011); Tu (2011a); Uriarte et al. (2011); Huang and Klemas (2012); Magierowski et al. (2012); Nielsen et al. (2012); Pandey et al. (2012); Zhou et al. (2012); Aighewi et al. (2013); Bateni et al. (2013); Chu et al. (2013); Firdaus and Nakagoshi (2013); Yu et al. (2013); Shupe (2013); Attua et al. (2014); Bu et al. (2014); Iñiguez-Armijos et al. (2014); Ye et al. (2014); du Plessis et al. (2014, 2015); Bonansea et al. (2016); Chen et al. (2016); Ding et al. (2016); Gyamfi et al. (2016); Kim et al. (2016); Manfrin et al. (2016); de Oliveira et al. (2017); Masocha et al. (2017); Asare et al. (2018); de Mello et al. (2018); Grimstead et al. (2018); Liu and Yang (2018); Mainali and Chang (2018); Shukla et al. (2018); Wang and Zhang (2018); Ide et al. (2019); Mwaijengo et al. (2020); Nusantara et al. (2020); Park and Lee (2020); Petersen et al. (2020); Thomas et al. (2020); Chiang et al. (2021); du Plessis (2021); Li et al. (2021); Liu et al. (2021); Nguvulu et al. (2021); Vera Mercado and Engel (2021); Aalipour et al. (2022); Allafta and Opp (2022); Clark et al. (2022); Heidkamp and Christian (2022); Kadir et al. (2022); Li et al. (2022b); Zhong et al. (2022); Bowes et al. (2023); Caldwell et al. (2023); Prakoso et al. (2023); Wang et al. (2023a); Waturu et al. (2023); Zhang et al. (2023b)

Appendix 4: Land Use/Land Cover Classes and Their Typical Relationship with Water Quality as Determined by Statistical Methods

Land Use/Land Cover Class	Statistical Relationship with Water Quality	Examples of Publications
Urban	Negative correlation (i.e., as the proportion of urban land increases, water quality decreases)	Haith (1976); Steedman (1988); Lenat and Crawford (1994); Wang and Yin (1997); Basnyat et al. (1999); Dauer et al. (2000); Rhodes et al. (2001); Sliva and Williams (2001); Jarvie et al. (2002); Tong and Chen (2002); Larned et al. (2004); Ngoye and Machiwa (2004); Ahearn et al. (2005); Carle et al. (2005); Mehaffey et al. (2005); Amiri and Nakane (2006); Donohue et al. (2006); Tsegaye et al. (2006); Uuemaa et al. (2007); Li et al. (2008); Nash et al. (2009); Rothenberger et al. (2009); Riseng et al. (2010); Tran et al. (2010); Waite et al. (2010); Carpio and Fath (2011); Maloney and Weller (2011); Miller et al. (2011); Miserendino et al. (2011); Tu (2011b, 2011a); Huang and Klemas (2012); Zhou et al. (2012); Shupe (2013); Attua et al. (2014); Bu et al. (2014); du Plessis et al. (2014); Wan et al. (2014); Ding et al. (2015); Hassan et al. (2015); Meneses et al. (2015); Moodley et al. (2015); Bonansea et al. (2016); Manfrin et al. (2016); Ou et al. (2016); Yu et al. (2016); Dai et al. (2017); de Oliveira et al. (2017); Kändler et al. (2017); Shi et al. (2017); Tromboni and Dodds (2017); Vrebos et al. (2017); de Mello et al. (2018); Shukla et al. (2018); Gossweiler et al. (2019); Liberoff et al. (2019); Ogbozige and Alfa (2019); Zhang et al. (2019); Gorgoglione et al. (2020); Karakuş (2020); Kim et al. (2020); Palma et al. (2020); Ramião et al. (2020); Song et al. (2020); Tahiru et al. (2020); Ding et al. (2021); Chiang et al. (2021); Fernandes et al. (2021); Hanna et al. (2021); Lu et al. (2021); Molekoa et al. (2021); Nguvulu et al. (2021); Senbore and Oke (2021); Umwali et al. (2021); Wang et al. (2021); Zhang et al. (2021); Baltodano et al. (2022); Dębska et al. (2022); Kadir et al. (2022); Łaszewski et al. (2022); Li et al. (2022b); Obubu et al. (2022); Procopio and Zampella (2022); Zhang et al. (2022a); Zhou et al. (2022); Bowes et al. (2023); Caldwell et al. (2023); Gani et al. (2023); Gobry et al. (2023); Prakoso et al. (2023); Roldán-Arias et al. (2023); Szymańska-Walkiewicz et al. (2023); Wang et al. (2023a); Wang et al. (2023b); Waturu et al. (2023); Xu et al. (2023a); Yao et al. (2023); Zhang et al. (2023a); Zhang et al. (2023b)
Impervious surfaces	Negative correlation (i.e., as the proportion of impervious cover increases, water quality decreases)	Klein (1979); Arnold and Gibbons (1996); Booth and Jackson (1997); Brabec et al. (2002); Tong and Chen (2002); Roy et al. (2003); Snyder et al. (2005); Schoonover and Lockaby (2006); Galbraith and Burns (2007); Schiff and Benoit (2007); Chen et al. (2016); Kim et al. (2016); Sutjiningsih (2017); Vrebos et al. (2017); Medupin et al. (2020); Wang et al. (2020); Winton et al. (2021); Heidkamp and Christian (2022); Simpson et al. (2022); Liu et al. (2023)

Land Use/Land Cover Class	Statistical Relationship with Water Quality	Examples of Publications
Agriculture	Negative correlation (i.e., as the proportion of agricultural land increases, water quality decreases)	Haith (1976); Detenbeck et al. (1993); Lenat and Crawford (1994); Johnson et al. (1997); Allan and Johnson (1997); Wang and Yin (1997); Basnyat et al. (1999); Cuffney et al. (2000); Dauer et al. (2000); Rhodes et al. (2001); Brabec et al. (2002); Jarvie et al. (2002); Tong and Chen (2002); Foley et al. (2004); Larned et al. (2004); Ngoye and Machiwa (2004); Ahearn et al. (2005); Mehaffey et al. (2005); Young et al. (2005); Donohue et al. (2006); Tsegaye et al. (2006); Galbraith and Burns (2007); Li et al. (2008); Nash et al. (2009); Rothenberger et al. (2009); Walsh and Wepener (2009); Riseng et al. (2010); Waite et al. (2010); Maloney and Weller (2011); Miller et al. (2011); Miserendino et al. (2011); Magierowski et al. (2012); Aighewi et al. (2013); Shupe (2013); Attua et al. (2014); Bu et al. (2014); du Plessis et al. (2014); Waite (2014); Wan et al. (2014); Ye et al. (2014); Hassan et al. (2015); Meneses et al. (2015); Qiu and Turner (2015); Bonansea et al. (2016); Chen et al. (2016); Ou et al. (2016); Xu et al. (2016); Yu et al. (2016); de Oliveira et al. (2017); Kändler et al. (2017); Shi et al. (2017); de Mello et al. (2018); Shukla et al. (2018); Simedo et al. (2018); Ide et al. (2019); Liberoff et al. (2019); Ogbozige and Alfa (2019); Zhang et al. (2019); Gorgoglione et al. (2020); Karakuş (2020); Kim et al. (2020); Palma et al. (2020); Park and Lee (2020); Petersen et al. (2020); Ramião et al. (2020); Tahiru et al. (2020); Chiang et al. (2021); Crooks et al. (2021); Ding et al. (2021); Dymek et al. (2021); Fernandes et al. (2021); Hanna et al. (2021); Li et al. (2021); Lu et al. (2021); Mallya and Rwiza (2021); Nguvulu et al. (2021); Senbore and Oke (2021); Umwali et al. (2021); Wang et al. (2021); Winton et al. (2021); Zhang et al. (2021); Allafta and Opp (2022); Dębska et al. (2022); Kadir et al. (2022); Łaszewski et al. (2022); Li et al. (2022b); Obubu et al. (2022); Procopio and Zampella (2022); Zhang et al. (2022a); (Zhou et al., 2022); Bowes et al. (2023); Caldwell et al. (2023); Gobry et al. (2023); Liu et al. (2023); Roldán-Arias et al. (2023); Wang et al. (2023b); Xu et al. (2023a); Zhang et al. (2023a)

Land Use/Land Cover Class	Statistical Relationship with Water Quality	Examples of Publications
Natural Vegetation (Typically classified as forested land, but may include shrubland, grassland, and wetlands).	Positive correlation (i.e., as the proportion of natural vegetation cover increases, water quality improves OR as the proportion of natural vegetation cover decreases, water quality decreases)	Haith (1976); Detenbeck et al. (1993); Lenat and Crawford (1994); Hunsaker and Levine (1995); Wang and Yin (1997); Basnyat et al. (1999); Dauer et al. (2000); Sliva and Williams (2001); Tong and Chen (2002); Roy et al. (2003); Larned et al. (2004); Ngoye and Machiwa (2004); Ahearn et al. (2005); Young et al. (2005); Amiri and Nakane (2006); Donohue et al. (2006); Galbraith and Burns (2007); Li et al. (2008); Nash et al. (2009); Rothenberger et al. (2009); Death and Collier (2010); Tran et al. (2010); Maloney and Weller (2011); Miserendino et al. (2011); Tu (2011b, 2011a); Clapcott et al. (2012); Magierowski et al. (2012); Shupe (2013); Yu et al. (2013); Attua et al. (2014); Bu et al. (2014); Iñiguez-Armijos et al. (2014); Kebede et al. (2014); Ye et al. (2014); Ding et al. (2015); Meneses et al. (2015); Midway et al. (2015); Qiu and Turner (2015); Chen et al. (2016); Manfrin et al. (2016); Ou et al. (2016); Xu et al. (2016); Clément et al. (2017); Dai et al. (2017); de Oliveira et al. (2017); Kändler et al. (2017); Shi et al. (2017); Tromboni and Dodds (2017); de Mello et al. (2018); Liu and Yang (2018); Shukla et al. (2018); Simedo et al. (2018); Ide et al. (2019); Lacher et al. (2019); Ogbozige and Alfa (2019); Yirigui et al. (2019); Zhang et al. (2019); Gorgoglione et al. (2020); Huang et al. (2020); Karakuş (2020); Kim et al. (2020); Medupin et al. (2020); Park and Lee (2020); Ramião et al. (2020); Song et al. (2020); Tahiru et al. (2020); Ding et al. (2021); Dymek et al. (2021); Fernandes et al. (2021); Hanna et al. (2021); Nguvulu et al. (2021); Umwali et al. (2021); Wang et al. (2021); Wu and Lu (2021); Allafta and Opp (2022); Dębska et al. (2022); Łaszewski et al. (2022); Li et al. (2022b); Paná et al. (2022); Zhang et al. (2022a); (Zhou et al., 2022); Bowes et al. (2023); Caldwell et al. (2023); Deng et al. (2023); Gobry et al. (2023); Liu et al. (2023); Prakoso et al. (2023); Roldán-Arias et al. (2023); Szymańska-Walkiewicz et al. (2023); Wang et al. (2023a); Wang et al. (2023b); Xu et al. (2023a); Zhang et al. (2023a)

Appendix 5: Existing South African Research Pertaining to the Impacts of LULC on Water Quality

Publication	**Location**	**Study Objective and Outline**	**Results and Findings**	**Remarks**
Walsh and Wepener (2009)	Crocodile and Magalies Rivers (Gauteng and North West Provinces)	The objective of the study was to compare and relate changes in water quality (using diatom species assemblages as proxy indicators) to differences in land cover/land use among groups of sites that ranged from minimally impacted (reference sites) to highly impacted (urban and agricultural sites). Using multivariate statistical techniques, the authors tested for spatial and temporal patterns in the relationship between land use, diatom communities, and water quality data.	Statistically significant differences were found between urban, agricultural, and reference groups. Agricultural sites showed elevated levels of conductivity, suspended inorganic matter, sulphate, and chloride. Urban sites showed elevated levels of nutrients and chemical oxygen demand. An analysis of diatom community assemblages showed that, in terms of water quality, agricultural areas were more severely impacted than urban areas, and that both had poorer water quality than the reference sites.	The study confirms the usefulness of diatom species as indicators of water quality. The study likewise confirms that agricultural and urban land use negatively affect water quality in the study area. However, the study offers little practical guidance for the management of water resources beyond confirming what now amounts to common knowledge regarding the influence of urban and agricultural areas as sources of diffuse pollution.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Dabrowski and de Klerk (2013)	Olifants River (Mpumalanga Province)	The study investigated spatial trends in water quality across the selected study area and related these to patterns in land use. Routine water quality sampling was conducted at 10 sites across the study area over a 10-month period. Sub-catchments for each site were delineated and the land use activities in each were identified. Thirty-two additional sites were selected for once-off water quality sampling. Land use activities upstream of each site were identified. The sites were classified as current mining (10 sites), abandoned mining (6 sites), agriculture (9 sites), wastewater treatment works (WWTWs) (5 sites), and industry (2 sites). Principal Component Analysis (PCA) was used to evaluate correlations between sites (representative of different land use activities) and median measurements of water quality variables collected during both routine and once-off sampling.	The PCA grouped sites according to their water quality signatures. From the once-off monitoring samples, three groups of sites could be clearly distinguished: (1) abandoned mining sites (characterised by high concentrations of aluminium, iron, manganese, zinc, and low pH), (2) current mining and industry sites (characterised by high pH and very high TDS), and (3) a combination of agriculture, WWTWs, and current mining sites (which had relatively low TDS and metal concentrations). A descriptive analysis of the spatial distribution of water quality trends across the sites also revealed probable (i.e., plausible) links between land use and water quality.	The study confirmed correlations between land use activities (such as mining) and water quality trends (such as elevated TDS and metal concentrations) but did not quantify these relationships or provide specific management guidelines.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Slaughter and Mantel (2013)	Multiple locations in the Limpopo and Mpumalanga Provinces	The study aimed to develop a simple model that could relate in-stream diffuse-source nutrient concentrations to land cover categories within a catchment. Across sixteen sites, a previously developed model was used to distinguish between proportions of in-stream nutrient concentrations originating from point and diffuse sources. Principal Component Analysis (PCA) was used to test for correlations between fifteen different land cover categories and the diffuse pollution signatures. Regression models were constructed for diffuse-source nitrogen and phosphorous using the land cover categories identified by the PCA.	The regression models indicated a complex mix of both positive and negative relationships between diffuse nutrient signatures and land cover classes. Influential land cover classes included urban land, cropland, and vegetated areas. The mixed results required some speculative explanation, although the authors claimed that "most of the correlations between the diffuse signature parameters and the land cover categories were expected" (p. 137).	The complex results of this study are particularly difficult to interpret and do not offer a great deal of practical insight that would be of direct use to resource managers and policymakers. However, the study does confirm that the relationship between LULC and water quality is complex and likely to be influenced by a variety of additional variables that can confound the results of simple analyses.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
du Plessis et al. (2014)	Blesbok Spruit Catchment (Gauteng Province)	In this study a regression model was developed to predict water quality responses to LULC change in the study area. Regression analysis was conducted between the average annual concentrations of selected water quality parameters and five classes of cover for the years 2000, 2005, and 2009. Model equations were consequently used to predict the concentration of water quality parameters according to future land use scenarios, based on observed trends in land cover change (a 0.5% per year increase in the extent of urban land over 35 years).	Regression equations were produced for 16 water quality variables, such that predictions could be made for each parameter based on land cover. Using the forecast land use change scenario, concentrations for each parameter were calculated for the years 2015, 2020, 2030, and 2050. Future LULC changes were predicted to have a negative impact on water quality in the study area. It was established that urban, mining, and cultivated land cover would have the greatest negative impact on the catchment's water quality. These predictions were compared to South African water quality guidelines, demonstrating the likelihood that predicted land use changes would result in unacceptable changes in water quality.	The study demonstrates the usefulness of regression analysis and the predictive power of models developed using this approach. It also confirms the negative impact of urban, agricultural, and mining land on water quality.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
du Plessis et al. (2015)	Grootdraai Dam Catchment (Mpumalanga Province)	Essentially a replication of the methods of du Plessis et al. (2014) above, regression analysis was performed on water quality and land cover data from the study area. The resultant equations enabled the prediction of selected water quality parameters in relation to changes in land cover. Using the equations, water quality predictions were made for the years 2015, 2020, 2030, and 2050, based on a 1% per year increase in urban/built-up land cover.	Very few significant relationships were found between water quality variables and land cover in the catchment. Notable were negative relationships between calcium and urban land, as well as magnesium and forestry and plantations. Positive relationships of significance were established between chemical oxygen demand and urban land, as well as between dissolved oxygen and forestry and plantations. Regression equations were modelled for 14 water quality parameters. The results of the predictions showed that increases in urban land cover, based on the 1% per annum scenario, may result in unacceptable impacts on water quality over time.	A comparison between this study and the previous one (du Plessis et al., 2014), wherein the methods were replicated but the results were different, demonstrates possible regional differences in the relationship between LULC and water quality. Despite the lack of significant relationships found, the results do confirm the negative influence of urban land cover and the positive influence of forestry on water quality.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Farrell et al. (2015)	Wilge River (Mpumalanga Province)	The study aimed to investigate the response of aquatic macroinvertebrate communities to the effects of various land uses, while taking in situ water quality, habitat, and season into consideration Biological response was measured in terms of taxa richness (using the South African Scoring System, SASS5) and differences in the predominant functional feeding groups (FFGs) between sites. Seven sites along the river were sampled between March 2010 and May 2013 in wet and dry seasons. At each site a limited number of physiochemical water quality parameters were measured. Habitat scores were also calculated according to the Integrated Habitat Assessment System (IHAS v2). Land use for each site, within a 1 km radius, was also determined. Among other methods, Redundancy Analysis (RDA) and Principal Component Analysis (PCA) were used to determine which explanatory variables (i.e., water quality, habitat, or land use) corresponded to different taxonomic groups and/or FFGs.	Water quality varied both spatially (i.e., between sites) and temporally (i.e., between seasons). Dissolved oxygen levels were reported to be the main limiting factor for aquatic organisms, as all other variables were within guideline limits. Habitat availability varied according to season, with better habitat availability in the wet season. Macroinvertebrate taxa and FFGs likewise varied spatially and temporally. It was anticipated that FFGs would reflect land use conditions, with scraper/grazer groups expected to dominate due to eutrophic conditions from local agricultural runoff. However, this was not the case, leading the authors to conclude that land use was not a significant explanatory variable. Based on the results of the RDA and PCA, the authors reported that “a combination of habitat availability, good water quality and flow conditions/velocities at a particular site were the primary driving variables that supported a diverse aquatic macroinvertebrate community” (p. 171).	While the authors did not report clear relationships between macroinvertebrate indicators and land use, they did observe correlations between water quality variables (e.g., dissolved oxygen) and macroinvertebrate indicators. However, they did not attempt to attribute variations in the former (i.e., water quality) to land use. Logically, however, the impact of land use on macroinvertebrate communities is likely to be indirect, with water quality mediating the impact. Only in passing did the authors speculate that low dissolved oxygen levels (which were a limiting factor for macroinvertebrate organisms) may be linked to eutrophication and nutrient enrichment from agricultural sources. Nevertheless, the study does demonstrate that multiple explanatory variables (including habitat availability and season) may be responsible for changes in the condition of aquatic ecosystems. The study affirms the fact that the relationships between multiple system variables can be complex and difficult to measure.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Moodley et al. (2015)	Tributaries of the Bayhead Canal, Durban (KwaZulu-Natal Province)	Physiochemical and microbiological samples were taken at 25 sites along three separate tributaries during wet and dry seasons between December 2011 and September 2012. The monitoring points were systematically sited at the interface of different land use types along the river systems, in order to reflect the potential influence of land use on water quality. Principal Component Analysis (PCA) was used to detect spatiotemporal variation between sites using water quality measurements from both seasons.	Nutrient concentrations frequently exceeded prescribed standards and often rendered the rivers hypertrophic. High dissolved mineral concentrations were also detected at several sites. Microbiological data revealed that all three river systems showed bacteriological contamination. The PCA revealed that, especially in the dry season, mineral-related parameters and sewage-related parameters (characteristic of the first axis) accounted for most of the variation in water quality. The second axis, which explained slightly less water quality variation, was characterised by heavy metals in the dry season. By contrast, in the wet season, minerals (first axis) and sewage-related parameters (second axis) were more dominant. The PCA also demonstrated clustering of sites according to similarities in water quality in both seasons. However, only four of the 25 sites indicated clear associations between specific land uses (namely, residential and industrial) and water quality.	The study confirms the overall impact of nearby anthropogenic activity on water quality. However, with the exception of four sites, it does not demonstrate clear links between specific land uses and variations in water quality. This highlights the potential difficulty of attributing specific types of diffuse pollution to distinct land uses, especially in mixed land use catchments.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Chidamba et al. (2016)	Lower Vaal Catchment (Northwest and Northern Cape Provinces)	The aim of the study was to evaluate spatiotemporal variations in microbiological parameters in the Lower Vaal River. Monthly water samples were collected at five locations along the Lower Vaal River. ANOVA was used to compare microbiological count data obtained from water samples among the different sampling locations.	Higher bacterial counts were associated with seasonal increases in discharge rates, which the authors attributed to bacterial contamination in diffuse runoff from livestock farms during the wet season. Lower bacterial counts were typical of lower discharge rates in the dry season, with some exceptions (which the authors attributed to point-source sewage inputs, compounded by reduced in-stream dilution). The authors concluded that “significant temporal and spatial variations in microbial concentrations along the Lower Vaal River were evident, and could be linked to land use and practices over the catchment” (p. 2148).	Details of the reported correlation between microbiological contamination and land use are not given in the study. Statistical analyses of the differences in microbial contamination between sites, related to differences in land use, are not shown or explained. Nevertheless, the study once again highlights the importance of seasonality and how it may influence the relationship between land use (as a diffuse source of pollution) and water quality.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Petersen et al. (2017)	Touws and Duiwe Rivers (Western Cape Province)	The study aimed to link LULC change to water quality in the study area. Using historical data for both catchments, temporal water quality trends were linked to changes in land use. Principal Component Analysis (PCA) was used to determine if any significant links between water quality and land cover categories existed.	In each of the catchments, different classes of land cover showed either positive or negative correlations with different water quality variables. That is, different classes of land cover were associated with increases (or decreases) in the concentrations/measurements of certain water quality parameters. For example, commercial plantations were associated with increased electrical conductivity, chloride, and sulphate concentrations, while grasslands were positively correlated with sodium, silica, and alkalinity. According to the authors, "the link between land cover/use and water quality was demonstrated and when spatial heterogeneity of the catchments was altered by human or natural events, this was reflected in changes in the water quality" (p. 139).	Apart from the direction and strength of the correlations, no further quantification of the relationship between LULC and water quality variables was demonstrated in the study. Many of the links described between changes in water quality parameters and land cover attributes were speculative, though plausible. The study offers helpful, but limited insight into the relationship between water quality and land use in the two catchments.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Slaughter and Mantel (2017)	Multiple locations, including sites within the Western Cape, Eastern Cape, KwaZulu Natal, Free State, Gauteng, North West, Mpumalanga, and Limpopo Provinces	The study focused on 25 sub-catchments, grouped into four biomes (fynbos, grassland, savanna, and thicket). The Water Quality Systems Assessment Model (WQSAM) was used to model the expected in-stream nutrient concentration signatures based on flow data. Multiple regression was used to examine the links between calibrated in-stream nutrient signatures derived from WQSAM and land cover within each of the catchments. In each of the catchments the relationship was assessed between water quality and land cover across the whole catchment and within a 100 m riparian buffer zone.	Regression models indicated that non-point nutrient loads were mainly associated with agricultural and urban areas. For example, for ammonium (NH_4), the categories of cultivated, urban, forest, and natural areas were found to be influential. For phosphate (PO_4), urban areas were found to be most influential, followed by mining and irrigated cultivation. The authors noted that “for the most part, these relationships make conceptual sense, as most of these land cover categories are traditionally associated with non-point nutrient inputs” (p. 507).	The models confirm widely accepted associations between land use and nutrient inputs. The authors acknowledged that land cover fragmentation may be a factor that influences non-point nutrient inputs and so recommended that this be considered in future research.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
van der Hoven et al. (2017)	Klein Jukskei Catchment (Gauteng Province)	The study assessed the impacts of land use on microbiological and physicochemical quality of two main tributaries of the Klein Jukskei River. Water samples were collected from the tributaries' sources, and from sites upstream and downstream of different classes of land use. A one-way analysis of variance (ANOVA) was used to compare water quality variables between sites dominated by different classes of land use. Spearman's rank correlation was used to assess the relationship between the various land uses and the different water quality parameters.	Each land use class demonstrated both positive and negative correlations with various water quality parameters. The influence of season on these relationships was also evident. The study found that an informal settlement and industrial area were amongst the main contributors to the poor microbial and physicochemical quality of water in the tributaries. According to the authors, "the findings of [the study] indicate that different land uses have different impacts on the microbial and physicochemical properties of a given water catchment" (p. 13). It was concluded that "the informal settlement had the greatest negative impact on the water quality compared to the other land uses" and thus recommended that "providing informal settlements with appropriate sanitation facilities is likely to prevent pollution of the water bodies" (p. 19).	The results of the study are confirmations of already-known associations between land use and water quality. No quantifiable management targets, beyond the general recommendations given, were offered.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Asare et al. (2018)	Vryburg District (North West Province)	The study was conducted to assess impact of land use change on water quality within five ephemeral ponds in the study area. Satellite imagery from 2004 and 2013 was classified for the purposes of assessing land use change. Water quality in each of the ponds was analysed for physical, chemical, and microbiological variables. Multiple linear regression models were computed to determine relationships between land use and water quality parameters. Regression equations were produced for nitrate, conductivity, sodium, cadmium, and *E. coli*.	The land use change analysis revealed a reduction in grass cover, whereas built-up areas increased at the expense of bare land. Regression analysis demonstrated a positive relationship between bare land and *E. coli*. Grassland was positively correlated with nitrates, electrical conductivity, cadmium, and *E. coli*. It was presumed that grassland has a negative impact on water quality because it was used for grazing livestock. Grassland, however, was negatively correlated with sodium concentrations. This was presumably because increased grass cover reduced the amount of exposed rock and soil (which, when eroded, is a source of sodium).	The study demonstrates the potential of regression analysis as a tool for quantifying the relationship between water quality variables and measures of LULC.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Namugize et al. (2018)	uMngeni Catchment (KwaZulu Natal)	The study focussed on spatial and temporal trends in water quality and land use in the study area. Pearson's correlation analysis was used to analyse relationships between eight land use categories (natural, cultivated, plantations, urban/built-up, water bodies, wetlands, degraded land, and mines/quarries) and the average annual concentration of ten water quality parameters (conductivity, pH, ammonium, nitrate, soluble reactive phosphorous, total phosphorous, suspended solids, temperature, turbidity, and *E. coli*) at nine sites. Based on the correlation coefficients, the relationship between land use and water quality variables was considered as either non-existent, weak, medium, or strong.	Correlations between land use and water quality parameters varied between the nine sub-catchments investigated. However, overall, it was found that water quality was impacted by natural vegetation losses and expansions of informal settlements. The authors concluded that "the relationship between [LULC] and water quality parameters is complex and site-specific, while the correlation coefficients vary among sub-catchments" (p. 261).	The study confirms the negative impact of informal settlements on water quality, while also highlighting the site-specific nature of the relationship between water quality and LULC.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Nde and Mathuthu (2018)	Upper Crocodile River (North-West Province)	The study aimed to evaluate the concentration of potential toxic elements (PTEs) in the Upper Crocodile River catchment and investigate spatial correlations with land use in the area. Water (and sediment) samples were collected monthly between April and September 2017 in order to take seasonality into account. Each of the sampling points corresponded to a different land use (e.g., mining, agriculture, commercial, and urban). Analysis was conducted for physiochemical parameters and trace metals. Pearson's correlation analysis was used to test for significant relationships between PTEs and the different land uses in order to identify their sources.	The water quality tests indicated that most parameters were within guideline limits across all sites, except for iron (Fe), which exceeded recommended values at the sampling points representative of agricultural and commercial land use. Although not noted by the authors, Aluminium (Al) concentrations also appeared to exceeded guideline limits at most sampling points. Strong correlations were found between the water quality characteristics of urban and commercial sites, as well as between those of urban and agricultural/mining sites, leading the authors to conclude that "the sources of these metals are most likely influenced by anthropogenic activities of the same source" (p. 9). Some seasonal differences in water quality were observable, most notably in pH levels.	While the study did observe spatial correlation with regard to water quality characteristics (in that the water quality characteristics of different land use areas showed strong correlation), the study did not actually test for correlation between water quality and different land uses as independent variables. Thus, all that can be statistically concluded from the study is that the water quality at different sampling points shared similar characteristics, but not that any water quality variables were themselves correlated to land use across the samples.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Malherbe et al. (2019a)	Two regions along the southern coast of the Western Cape Province	The study assessed the individual and combined effects that (1) land use activities and (2) "landscape potential" may have had on sediment and nutrient inputs in the two study areas. Landscape potential was defined as a measure of the potential of the landscape (based on natural environmental factors such as soil type, slope, and rainfall) to influence the sediment and nutrient inputs generated by various land use activities. Different segments of the river were scored according to the potential of the land adjacent to that stretch of river to contribute to nutrient and sediment pollution. Scores for each stretch of the river were based on local land use and environmental factors (i.e., the "landscape potential").	Based on the scores calculated, the study was able to identify river reaches (segments) that could be considered as high-risk for elevated sediment and nutrient inputs based on the combined influence of local land use and landscape factors. Unsurprisingly, areas dominated by agricultural activities and informal settlements showed the highest risk of elevated sediment and nutrient inputs. However, the study demonstrated how local environmental factors can either moderate or enhance the potential of such land use activities to contribute sediments and nutrients.	The study demonstrates the potential of the methods described for performing rapid assessments that identify areas for which a relatively high risk of water pollution from the surrounding landscape exists. However, in identifying at-risk areas, the methods employed did not actually quantify the relationship between LULC and water quality based on observed data, but instead relied on assumptions about the potential impact of different land use and landscape characteristics on water quality. Furthermore, the methods used did not generate specific management targets by which the identified risk could be mitigated. The described methods may, however, serve as a first-step assessment which could trigger further investigation in any high-risk areas identified.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Malherbe et al. (2019b)	Southern coast of the Western Cape, extending from Cape Point to Struis Bay (Western Cape Province)	The objective of the study was to identify areas within the study region that showed a loss of ecosystem services (including water quality maintenance) due to land use activities. Two land use maps of the region were produced: a map reflective of current land use in the region, and one reflective of natural (reference) conditions. Each land use class was scored according to its theoretic ability to provide/maintain ecosystem services. In terms of water quality maintenance, areas of natural vegetation scored highest while irrigated cropland and informal settlements scored lowest. The scoring was based on available literature and expert knowledge. The total scores of the reference and current land use maps were compared for each ecosystem service. Additionally, across the region, the differences in ecosystem service scores between the reference and current LULC conditions were mapped for each ecosystem service. Areas for which there was a large difference in ecosystem service score were identified as having suffered a loss of ecosystem services driven by land use activities.	Based on the results of the analysis, there was across the region an overall (theoretical) reduction in the ability of the ecosystem to offer water quality maintenance services, as evidenced by the lower overall score of the map of current land use as compared to the map of reference conditions. Areas that were identified as having lost the most ecosystem service potential (in terms of water quality maintenance) were those which had been transformed from natural vegetation to agricultural land and informal settlements (which resulted in the greatest difference in ecosystem service scores between reference and current conditions).	The study, in essence, simply considered changes from reference conditions to present day LULC, and related those to probable losses in ecosystem services in the study area (based on long-established links between land use activities and ecosystem services such as water quality maintenance). The study arrived at the rather obvious conclusion that areas dominated by agricultural land and informal settlements were likely to have suffered the greatest loss in water quality maintenance services. The study affirms the role of natural vegetation in maintaining water quality.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Petersen et al. (2020)	Klein Keurbooms River and Duiwe River Catchment (Western Cape Province)	The principal aims of the study were to (1) determine the quality of runoff generated by different classes of land cover, and (2) examine the influence and effectiveness of riparian vegetation in mediating nutrient fluxes from adjacent pastures. Runoff from four study sites (each representing a different category of land cover) was analysed and compared using analysis of variance (ANOVA) and Principal Component Analysis (PCA). In-stream water quality samples were also collected, coinciding with runoff water sampling.	Water quality at three of four the study sites was within national guideline limits. Different classes of land cover generated different runoff volumes, nutrient concentrations, and associated nutrient and sediment loads. Indigenous forest generated the highest nitrogen concentrations, but also the lowest runoff volumes, and consequently had the lowest cumulative nitrogen contribution. Agriculture and alien tree land cover classes had the most significant impact on nutrient loads. The highest nutrient loads were recorded from pastures and areas of the riparian zone invaded by alien flora. The type and composition of vegetation at each site had an apparent influence on the quality of the runoff. For example, compared to a wider buffer of alien invasive vegetation, a narrower buffer of indigenous vegetation provided better protection from nutrient and sediment pollution.	The study confirms the negative impact of agriculture on water quality, and the reduced effectiveness of alien vegetation (as compared to native flora) as a buffer of sediments and nutrients. The study reinforces the need to maintain natural vegetation in riparian buffer zones in catchments dominated by agriculture.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Barnard et al. (2021)	Sabie-Sand Catchment (Mpumalanga Province)	The study aimed to determine the influence of land use and flow on phytoplankton population assemblages in the Sabie River. The influence of land use on physiochemical water quality parameters was also assessed. Water samples were collected at eight sites along the Sabie River on eight separate occasions between January and October of 2016 and 2017. Samples were subjected to physiochemical and microbiological analyses. Sub-catchments were delineated for each sampling site and the dominant land use of each sub-catchment was identified. Canonical Correlation Analysis (CCA) was used to assess whether statistically significant relationships between LULC, phytoplankton assemblages, and physiochemical water quality variables existed during low-flow (2016) and high-flow (2017) conditions.	Significant correlations were found between phytoplankton assemblages, physiochemical water quality parameters, and land use. Overall, agriculture and commercial forestry plantations were both associated with higher nitrate and phosphate concentrations, as well as nuisance cyanobacteria species. It was also found that high-flow conditions enhanced these associations.	The study confirms that agricultural activities and commercial forestry are sources of nutrients which may pollute nearby water bodies such as the Sabie River. Curiously the authors erroneously located the study region in the Limpopo Province.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Dlamini et al. (2021)	uMfolozi floodplain system (KwaZulu Natal Province)	The study was designed to investigate the impacts of cultivation on water and soil quality in the catchment. Three study sites were selected in the floodplain wetland area (two containing cultivated areas and one pristine uncultivated site). Multiple water and soil samples were collected at each of these sites during 2017 and 2018. Paired *t*-tests were performed to compare the samples collected during wet and dry seasons from each site.	When comparing cultivated and non-cultivated sites, it was found that the soil and water quality samples from cultivated sites had higher concentrations for certain water quality parameters (chloride, sodium, pH, and electrical conductivity, for example).	The study confirms that areas of agricultural land use are typical sources of ions such as chloride and sodium.
du Plessis (2021)	Multiple locations within the Upper Vaal catchment, spanning Gauteng, Mpumalanga, North West, and Free State Provinces	The study used water quality data covering a 12-year period, from June 2000 to June 2012. Land cover data for the years 1994, 2000, 2005, and 2009 were used to evaluate land cover changes over this period. Regression analysis was conducted using land cover and water quality data (mean annual concentration for each parameter) for the years 2000, 2005, and 2009. Regression equations were subsequently established for each water quality parameter using LULC as independent variables.	Significant positive and negative relationships were found between various land cover classes and selected water quality parameters (including pH, electrical conductivity, nitrate, sulphate, ammonia, phosphate, chlorophyll-α, and faecal coliforms). For example, a negative relationship was found between nitrate and several land cover classes (urban/built-up, forestry/plantations, and mining). By contrast, *E. coli* was positively correlated with the same classes of land cover. Ammonia was negatively correlated with urban/built-up and forestry/plantations. According to the authors, the regression equations could be used to predict in-stream parameter concentrations depending on the percentage of land cover in the Vaal catchment.	As with du Plessis et al. (2014, 2015), this study quantifies the regional relationship between land cover classes and water quality variables, demonstrating the use of regression analysis for this purpose.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Koekemoer et al. (2021)	Mooi River (North West Province)	The principal aim of the study was to investigate spatial variability in physiochemical water quality variables and phytoplankton density and diversity in the Mooi River. Water quality and phytoplankton assemblages at sites characterised by various land uses along several tributaries of the Mooi River were compared to water quality and phytoplankton assemblages at sites upstream and downstream of the confluence of these tributaries with the main river. Eight sites, subjected to different sources of pollution, were selected for comparison. Canonical Correspondence Analysis (CCA) was conducted to determine the relationships between the variables under investigation (to wit, water quality parameters, phytoplankton assemblages, and land uses).	In general, nutrient concentrations measured in the Mooi River (as well as in its tributaries) were high and mean values usually exceeded regional water quality targets. Noticeable patterns were observed in the spatial distribution of phytoplankton assemblages and the concentration of physiochemical water quality parameters, which related to the distribution of various land use activities. For instance, maximum densities of cyanobacteria were found in the middle reaches of the river and were usually associated with high nutrient concentrations. High nutrient concentrations downstream of the confluence of one of the tributaries were linked to the industrial area through which the tributary flowed, as well as urban and stormwater effluent that entered the river further downstream. The study concluded that “various land use activities surrounding the Mooi River’s tributaries contributed to a deterioration of water quality in the main stream of the Mooi River” (p. 1).	Despite evident spatial variation in the value of physiochemical parameters and phytoplankton populations in the Mooi River system, which could be speculatively linked to various land use activities, no correlations between water quality and land use were quantified or tested for statistically.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Mahabeer and Tekere (2021)	uMdloti River (KwaZulu Natal Province)	The study focussed on associations between water quality and existing anthropogenic activities along the uMdloti River. Fifteen sampling sites were selected along the river, covering four major land use classes (urban, peri-urban, industrial and agricultural). Water quality and sediment samples were collected over two sampling periods, representing the wet and dry seasons. For each water quality variable, a one-way ANOVA was conducted to determine if there were statistically significant differences between land uses.	Several statistically significant links between land use classes and some of the water quality variables were found (i.e., certain land use zones were associated with higher concentrations of some of the water quality variables). For example, total dissolved solid concentrations were highest in urban zones over both sampling periods. Other spatial trends in water quality were also found. For example, electrical conductivity levels were generally consistent along the river, but showed a noticeable increase towards the estuary. Total dissolved solids also displayed a general increasing trend downstream. The results also provided evidence of significant seasonal variation in the associations between land use classes and water quality parameters.	The study demonstrated that certain water quality parameters may be associated with specific land use types. The study also highlighted the significance of seasonality in influencing these relationships. However, as each sampling site was downstream of the preceding site along the same river, the observations were not independent.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Molekoa et al. (2021)	Mokopane (Limpopo Province)	The study set out to investigate spatiotemporal variation in surface water quality within the study area. Water samples collected from five sites between 2016 and 2020 were analysed for various physiochemical parameters. A time-series analysis of key surface water quality parameters was performed. The analysed water quality data were also used to calculate heavy metal pollution index (HPI) scores, heavy metal evaluation index (HEI) scores, and weighted water quality index (WQI) scores. Spatial trends in water quality were compared with LULC changes from 2015 to 2020.	Temporally, water quality was found to deteriorate between 2016 and 2019. It was also observed that the concentration of water quality parameters was higher during dry periods than during wet periods. The LULC change analysis revealed an increase of urban areas during the study period. Based on the above findings the authors concluded that land use had a significant relationship with water quality, and that built-up land had a more significant negative impact on water quality than the other land use classes.	The conclusion reached by the authors, while plausible, was not based on any statistical tests. Nevertheless, the study does demonstrate the usefulness of composite water quality and pollution indices.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Nde et al. (2021)	Upper Crocodile River Catchment (North-West Province)	The study investigated the spatial distribution of physicochemical parameters and potentially toxic elements (PTEs) within the study area. Twelve water quality samples were collected every quarter from April 2017 to July 2018. The length of the sampling regime was designed to account for the possible effects of seasonality. LULC change analysis was conducted using satellite imagery from 1999, 2009, and 2018. Four water quality sampling points were chosen along the river such that each was representative of a location under influence of a particular land use category.	The land use change analysis revealed considerable changes in land use and land cover during the two decades under study. There was, for example, a decline in built-up land and an increase in cropland. Water quality analysis showed that concentrations of Al, Mn, and Fe were above permissible guideline levels. Using Pearson's correlation analysis, it was shown that the spatial distribution of physicochemical water quality parameters and PTEs were significantly correlated to different land use types along the river. For example, concentrations of Mn were highest where agricultural and commercial land cover dominated, while Fe concentrations were highest in an area dominated by agriculture and mining.	The study confirms that different classes of LULC may be associated with different types of contamination.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Senbore and Oke (2021)	Modder River (Free State Province)	The study compared land use changes and water quality trends over a 30-year period to investigate the impact of urbanisation on water quality. LULC classification for the study area was performed using data for the years 1988, 2003, and 2018. Normalised Difference Vegetation Index (NDVI) and Normalised Difference Water Index (NDWI) scores were calculated for the same period. Historical water quality data from four monitoring points were used to calculate Water Quality Index (WQI) scores for the same period. Trends in LULC change and water quality were compared.	Land cover change analysis revealed a 22.85% increase in urban land cover from 1988–2018, which the authors described as a "rapid increase in urbanisation during the 30-year period" (p. 10). There was also a noticeable decrease in NDVI and NDWI values over the study period, indicating a reduction in forest and cropland, which corresponded with the urban sprawl that was evident in the study area. Results from the WQI analysis showed an overall decline in water quality between 1988-2018. The authors concluded that the increase in urbanisation was responsible for the corresponding decline in water quality.	While the results indicate that there may indeed be a correlation between increase urban land cover and a decrease in water quality during the period under study (as might be expected), no attempt was made to prove or quantify this relationship statistically.

Makgoale et al. (2022)	Steelpoort River, Olifants River Catchment (Mpumalanga Province)	The study aimed to assess the spatial and temporal distribution of macroinvertebrate Functional Feeding Groups (FFGs) and to determine if changes in community structure conformed to expected trends according to the River Continuum Concept (RCC). Macroinvertebrate and water quality samples were collected at six sites along the length of the river, with each site selected to represent different degrees and types of anthropogenic disturbance/land use. Analysis of variance (ANOVA) was used to compare water quality and FFG assemblages among river sites and seasons. Hierarchical Cluster Analysis (HCA) was used to group sites with similar macroinvertebrate communities. Canonical Correspondence Analysis (CCA) was used to test the influence of physiochemical water quality parameters on FFG distribution.	ANOVA showed that most water quality parameters did not differ significantly between sites, except in the case of nitrate concentrations which were significantly higher at two of the sites (representative of domestic and industrial activities, and a human settlement and grazing area, respectively). ANOVA further revealed that turbidity and temperature varied significantly between seasons across all sites. The HCA grouped sites according to similarities in macroinvertebrate community structure. This revealed spatial variation in the distribution of community structure between sites (i.e., different taxa were found to be dominant at different sites) and that the variation was related to different site characteristics. It was found, for instance, that sites with strong anthropogenic pressures had lower macroinvertebrate abundances than less impacted sites. The CCA revealed that several physiochemical water quality variables appeared to influence macroinvertebrate community structure and the authors suggested that the abundance of certain FFGs at different sites was a reflection of the better water quality at these sites. Overall, the distribution of FFGs along the river did not conform to the RRC, leading the authors to conclude that macroinvertebrate community structure in the study area was instead influenced by localised land use and water quality.	The study affirms that land use and anthropogenic disturbances influence water quality, and that this will have a subsequent impact on the health and distribution of aquatic organisms.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
Mararakanye et al. (2022)	Vaal River Catchment (North West Province)	The study aimed to assess long-term influence of LULC change on nutrient pollution over a 30-year period in the lower Vaal River catchment. Land use change was assessed and quantified using multiyear satellite imagery. Long term trends in nitrate and phosphate loads were assessed from historic water quality monitoring data. The Soil & Water Assessment Tool (SWAT) was used to model the impacts of LULC change on nutrient and phosphate loads. Input data for the SWAT model included elevation, weather, soil and land use data. The SWAT model was calibrated using observed water quality data.	LULC changes included a 262% increase in irrigated land for the period under study. At the catchment inlet, phosphate concentrations and loads increased, while nitrate concentrations and loads decreased. At the catchment outlet, only phosphate loads increased. An increase in irrigated agriculture was associated with an increase in nutrient loads over the period under investigation. SWAT model simulation suggested that irrigated land was the greatest contributor of nitrate overall. Assessment of the nutrient signatures also suggested contributions from urban areas and point-sources. A lack of weather, soil, and crop-management data was identified as a constraint which affected the performance of the model and increased uncertainty in model predictions. Based on the findings of the study, a recommendation was made to adapt crop management practices to reduce nitrate leaching.	The study confirmed agriculture as a likely source of nutrients and an expansion of agricultural land as responsible for increased nitrate and phosphate loads over time. The study confirmed the potential of models such as SWAT as a tool for explaining the links between land use and water quality at the catchment scale. However, the study also confirmed that models such as SWAT are data-intensive, and that model performance can be reduced by a lack of data.

Publication	Location	Study Objective and Outline	Results and Findings	Remarks
van Deventer et al. (2022)	Upper uMngeni Catchment (KwaZulu Natal Province)	Nine sites were chosen to be representative of different land uses within the catchment (including an undisturbed reference site). Physiochemical samples (at all nine sites) and biological samples (at six sites) were collected over a period of ten months. Water quality data was used to generate nutrient loads. Sites were also scored using the South African Scoring System (SASS5) bio-assessment protocol, which evaluates the ecological state of the system based on aquatic macroinvertebrate communities. Descriptive statistics and multivariate techniques were used to analyse the data.	Spatial and seasonal patterns in water quality and ecological condition were evident. Water quality and ecological condition were highest in areas where natural land cover and sparse settlement occurred. Noticeable declines in water quality and ecological condition were observed under commercial agriculture. The most significant declines in water quality and ecological condition occurred downstream of the settlement with elevated nutrient loads. The authors concluded that the “cumulative effects of current land use activities, urban development and agriculture… should be viewed with concern” (p. 1).	This study confirms expected associations between water quality and LULC (namely that agricultural and urban classes of land use have a negative impact on water quality, whereas the water quality of areas dominated by natural vegetation is typically higher).

Appendix 6: Details of the Sample of 58 Sub-Catchments Analysed

NCMP Site ID	Quaternary Catchment	Longitude	Latitude	Catchment Area (Ha)	MAP (mm)	Sampling Period	No. of Samples	NPI Score	Proportion of Natural Vegetation (Catchment)	Proportion of Natural Vegetation (200 m RBZ)	Mean NDVI	Proportion of Agricultural Land	Proportion of Urban Land
86712	G21F	18.616917	–33.722667	134090	569	2013/14	17	11.044	0.3250	0.5736	0.3321	0.5669	0.0411
87219	K60E	23.3675	–33.945833	75812	632	2013/14	23	0.502	0.9314	0.9298	0.1912	0.0238	0.0000
101917	G10E	19.074722	–33.313889	39714	486	2013/14	23	1.281	0.5458	0.5860	0.2381	0.3726	0.0061
101929	G10C	18.974444	–33.7075	63249	763	2013/14	23	2.404	0.6871	0.6604	0.2070	0.1716	0.0498
101937	G10J	18.759722	–33.066111	13815	420	2013/14	16	33.982	0.1298	0.3260	0.4147	0.8160	0.0288
101942	G10D	18.9225	–33.543333	4418	576	2013/14	15	13.179	0.1215	0.2887	0.4098	0.8650	0.0000
101944	G10D	18.978056	–33.479167	12236	602	2013/14	22	1.291	0.6088	0.6686	0.2718	0.3143	0.0000
101979	G22H	18.838611	–33.949444	18391	750	2013/14	19	1.663	0.5735	0.7407	0.2318	0.2935	0.0793
101986	G22J	18.841944	–34.091111	9688	808	2013/14	17	1.513	0.6623	0.6396	0.2226	0.1379	0.0989
101987	G22K	18.890833	–34.124444	2865	807	2013/14	20	1.965	0.6586	0.6050	0.2445	0.1541	0.0907
101997	G40K	19.600556	–34.405833	60306	609	2013/14	22	5.313	0.3903	0.5870	0.3283	0.5847	0.0000
101998	G40D	18.990278	–34.329722	47067	811	2013/14	23	1.165	0.7268	0.7567	0.2061	0.1761	0.0103
102002	G40E	19.215278	–34.235278	25240	781	2013/14	22	2.174	0.7107	0.7509	0.2359	0.2717	0.0036
102017	G50H	20.023611	–34.291944	38155	509	2013/14/15	21	39.742	0.1083	0.3452	0.4061	0.8887	0.0000
102019	H10D	19.30167	–33.38056	65533	433	2013/14	20	2.868	0.6650	0.6000	0.1931	0.2788	0.0112
102021	H10E	19.148333	–33.568056	8568	643	2013/14	22	0.326	0.9618	0.9672	0.1547	0.0000	0.0000
102023	H10K	19.330556	–33.756667	15210	673	2013/14	18	1.183	0.8531	0.9337	0.1561	0.0082	0.0000
102029	H10J	19.170278	–33.723333	11156	683	2013/14	23	0.668	0.8592	0.8977	0.1480	0.0029	0.0000
102043	H20G	19.503333	–33.5775	70550	402	2013/14	19	2.461	0.7350	0.6264	0.1271	0.1189	0.0027
102063	H40L	20.003333	–33.870833	119648	356	2013/14	23	11.687	0.8120	0.6814	0.1349	0.0972	0.0055
102079	H40K	19.820833	–33.992778	2509	503	2013/14	23	0.378	0.9599	0.9594	0.1736	0.0000	0.0000
102082	H40G	19.717222	–33.8675	23131	562	2013/14	19	22.157	0.8216	0.6869	0.1594	0.1170	0.0000
102083	H40H	19.795278	–33.819444	20309	459	2013/14	17	13.412	0.8785	0.6781	0.1556	0.0717	0.0000
102097	H50A	19.98	–34.040278	2547	510	2013/14	20	0.566	0.9499	0.9130	0.1813	0.0165	0.0000
102107	H60L	20.145556	–34.075556	202940	613	2013/14	22	1.600	0.5620	0.6975	0.2580	0.4073	0.0039
102121	H70E	20.533889	–34.018611	60390	377	2013/14	21	0.932	0.7990	0.7011	0.2005	0.1713	0.0045
102123	H80E	20.9925	–34.250556	77051	409	2013/14	19	4.621	0.5205	0.6260	0.2324	0.4579	0.0030

NCMP Site ID	Quaternary Catchment	Longitude	Latitude	Catchment Area (Ha)	MAP (mm)	Sampling Period	No. of Samples	NPI Score	Proportion of Natural Vegetation (Catchment)	Proportion of Natural Vegetation (200 m RBZ)	Mean NDVI	Proportion of Agricultural Land	Proportion of Urban Land
102127	H90B	21.201667	–34.006667	3377	416	2013/14	22	0.581	0.9147	0.9914	0.2179	0.0544	0.0000
102130	H90C	21.295278	–34.092222	22692	427	2013/14	20	1.919	0.7071	0.8514	0.2449	0.2536	0.0000
102132	H90B	21.166667	–34.004444	3511	418	2013/14	20	0.509	0.8370	0.9040	0.2223	0.1325	0.0000
102202	J40C	21.5875	–34.031389	9082	418	2013/14	24	0.820	0.8090	0.8532	0.2263	0.1695	0.0000
102206	K10D	22.053333	–34.031944	21630	416	2013/14	23	1.691	0.7742	0.8625	0.2323	0.2115	0.0000
102207	K10F	22.133333	–34.039722	19558	439	2013/14	22	1.369	0.8350	0.9423	0.2465	0.1486	0.0013
102217	K10B	22.010833	–34.096389	9761	429	2013/14	24	4.218	0.5831	0.6566	0.2252	0.4066	0.0000
102241	K20A	22.22222	–34.02861	12880	467	2013/14	22	1.242	0.7749	0.9691	0.2653	0.2059	0.0003
102248	K30C	22.548333	–33.970833	4621	564	2013/14	24	0.732	0.9676	0.9764	0.1902	0.0010	0.0015
102250	K30A	22.351111	–34.005833	14261	507	2013/14	23	2.759	0.5638	0.8061	0.2846	0.4052	0.0090
102251	K30B	22.4225	–33.950556	3240	530	2013/14	23	1.142	0.9169	0.8902	0.1871	0.0149	0.0295
102252	K30D	22.613333	–33.945833	7567	550	2013/14	24	0.751	0.9702	0.9870	0.1928	0.0006	0.0000
102254	K30B	22.441389	–33.972222	635	580	2013/14	20	1.436	0.5967	0.6504	0.1958	0.0000	0.3747
102275	K40D	22.8	–33.979722	11066	588	2013/14	17	1.327	0.8837	0.9621	0.2419	0.0893	0.0000
102276	K40C	22.838611	–33.881111	2177	577	2013/14	24	0.599	0.9844	0.9718	0.1955	0.0000	0.0000
102277	K40A	22.705833	–33.911667	7025	562	2013/14	23	1.031	0.9887	0.9901	0.2070	0.0000	0.0000
102293	K50A	23.031667	–33.89	13410	609	2013/14	23	0.651	0.9748	0.9870	0.2201	0.0000	0.0000
102312	K70B	23.641667	–33.954167	5684	735	2013/14	24	0.465	0.9619	0.9818	0.1990	0.0000	0.0000
102313	K80C	24.021389	–33.980556	2576	709	2013/14	25	0.474	0.9537	0.9706	0.1734	0.0039	0.0001
102316	K80E	24.439167	–34.096389	13157	734	2013/14	26	3.009	0.6225	0.8295	0.3028	0.3341	0.0128
102317	K80D	24.196389	–34.0325	11814	736	2013/14	25	1.224	0.8281	0.8912	0.2496	0.1419	0.0110
102320	K90D	24.7	–34.091944	84463	693	2013/14	25	2.605	0.8028	0.8113	0.2111	0.1355	0.0034
102353	L70G	24.618333	–33.731111	366303	454	2013/14	38	1.305	0.6547	0.5490	0.1318	0.0050	0.0014
102358	L82D	24.030556	–33.790556	162853	578	2013/14	26	0.912	0.7889	0.7473	0.1508	0.0888	0.0087
102368	M10C	25.308611	–33.797222	39398	531	2013/14	26	2.221	0.8667	0.8251	0.2277	0.0962	0.0009
102423	N40B	25.354722	–33.377778	62341	373	2013/14	15	3.127	0.7519	0.7191	0.1857	0.0030	0.0004
102427	N40E	25.659167	–33.5125	61857	468	2013/14	25	35.682	0.6399	0.6097	0.2280	0.1997	0.0022
102430	P10E	26.0775	–33.329167	144956	534	2013/14	25	11.722	0.3889	0.4023	0.1634	0.0128	0.0028
102435	P30B	26.603611	–33.554444	58450	643	2013/14	24	21.089	0.5625	0.7729	0.2060	0.1835	0.0028

NCMP Site ID	Quaternary Catchment	Longitude	Latitude	Catchment Area (Ha)	MAP (mm)	Sampling Period	No. of Samples	NPI Score	Proportion of Natural Vegetation (Catchment)	Proportion of Natural Vegetation (200 m RBZ)	Mean NDVI	Proportion of Agricultural Land	Proportion of Urban Land
102438	P40C	26.744722	–33.506389	56752	668	2013/14	24	11.385	0.6517	0.8425	0.2187	0.1740	0.0291
187987	G40M	19.4795	–34.5738	20986	571	2015/16	17	2.687	0.6916	0.8488	0.2371	0.1455	0.0000

NCMP Site ID = the unique identification number assigned to each NCMP monitoring site by the South African Department of Water and Sanitation (DWS); Quaternary Catchment = the unique identification code assigned to the quaternary catchment in which the NCMP site is located; Longitude/Latitude = the approximate coordinates of the NCMP point for which the sub-catchment was delineated, as supplied by the DWS; Catchment Area (Ha) = the size of the catchment in hectares; MAP = estimated mean annual precipitation of the sub-catchment based on historical rainfall data measured in millimetres (Fick & Hijmans, 2017); Sampling Period = the years for which NCMP water quality data were used to calculate Nemerow's Pollution Index (NPI) scores; No. of Samples = the number of individual water quality measurements, per parameter, used to compute NPI scores; NPI Score = the aggregate pollution index score calculated for the NCMP site in question based on data for the years indicated; Proportion of Natural Vegetation (Catchment) = the proportion of the total catchment area occupied by natural vegetation based on land cover data from the 2013/14 SANLC map; Proportion of Natural Vegetation (200 m RBZ) = the proportion of the 200 m riparian buffer zone occupied by natural vegetation based on land cover data from the 2013/14 SANLC map; Mean NDVI = mean Normalised Difference Vegetation Index values estimated for each sub-catchment based on 2014 Landsat 8 (OLI) surface reflectance data; Proportion of Agricultural/Urban Land = the proportion of the total catchment area occupied by agricultural/urban land based on data from the 2013/14 SANLC map.

Appendix 7: Details of the 18 Reference Sites Used to Determine Guideline Water Quality Values

NCMP Site ID	Quaternary Catchment	Location	Longitude	Latitude	Sampling Years	No. of Samples
101933	G10G	Vier en Twintig River at Drie-Das-Bosch / Groot Winterhoek Nature Reserve	19.060833	–33.133889	1990, 1991, 1992	36
194005	G10A	Robertsvlei - Berg River Dam - on Berg River U/S of Berg River Dam / Hottentots-Holland Reserve	19.072889	–33.955778	2015, 2016, 2017	27
101934	G10J	Leeu River at de Hoek Estates / Groot Winterhoek Nature Reserve	19.052222	–33.156667	1990, 1991, 1992	36
101969	G22F	Jonkershoek River at Jonkershoek/Kleinplaas	18.956389	–33.986389	1990, 1991, 1992	31
102021	H10E	Wit River at Drosterskloof	19.148333	–33.568056	1991, 1992, 1993	36
102035	H10J	Hawequas Forest Reserve on Elandsrivier	19.115	–33.734722	1996, 1997, 1998	33
102042	H20F	Rooi-Elskloof River at Roode Els Berg	19.6175	–33.461667	1991, 1992, 1993	35
102079	H40K	Houtbaais River at Schurfberg	19.820833	–33.992778	1990, 1991, 1992	35
102103	H60E	Genadendal Mission Station on Baviaansrivier	19.5575	–34.028889	1991, 1992, 1993	35
102127	H90B	At the Camp on Vetrivier	21.201667	–34.006667	2010, 2011, 2012	27
102249	K30B	Rooi River at George	22.462222	–33.933333	1990, 1991, 1992	36
102248	K30C	Kaaimans River at Upper Barbiers Kraal	22.548333	–33.970833	1990, 1991, 1992	36
102252	K30D	Touws River at Farm 162	22.613333	–33.945833	1990, 1991, 1992	36
102276	K40C	Karatara River at Karatara Forest Reserve	22.838611	–33.881111	1990, 1991, 1992	36
102312	K70B	Bloukrans River at Lottering Forest Reserve/Blaauwkrans	23.641667	–33.954167	1990, 1991, 1992	35
102313	K80C	Farm 508 Pine View on Kruis River	24.021389	–33.980556	1990, 1991, 1992	36
102314	K80C	Kwaaibrand Forest Reserve Witels on Elands River	24.050556	–33.980556	1990, 1991, 1992	35
102355	L82D	Wabooms River at Diepkloof	23.836111	–33.865833	1993, 1996, 1997	36

NCMP Site ID = the unique identification number assigned to each NCMP monitoring site by the South African Department of Water and Sanitation (DWS); Quaternary Catchment = the unique identification code assigned to the quaternary catchment in which the NCMP site is located; Location = the description provided by the DWS regarding the location of the monitoring point; Longitude/Latitude = the approximate coordinates of the NCMP point as supplied by the DWS; Sampling Years = the three years for which water quality data were used to estimate guideline values; No. of Samples = the total number of water quality measurements, per parameter, used to estimate guideline value.