Application of Remote Sensing and GIS in Monitoring Land Use and Land Cover Change in the Nandoni Dam Basin

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by

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ABSTRACT

Land use activities and land cover (LULC) changes have been widely acknowledged as the main drivers of environmental change at all spatial-temporal scales in some South African dam basins. The consequence of these land use activities causes encroachments, land cover changes, sediment deposits, deforestation, and severe flood damages, which reduces water storage capacity and economic tourism activities in dam basins. The challenges of land use activities have highlighted the need to monitor LULC changes in the Nandoni Dam basin. Remote sensing and Geographical Information Systems (GIS) methods offer the possibility of monitoring LULC changes, which could help dam basin management agencies make spatio-temporal decisions to preserve water storage capacity in dam basins. This study investigated the Nandoni Dam basin's LULC changes using Landsat TM 1997, 2005, and ETM+ 2021 images. The six LULC classes classified are water bodies, forests, floodplains, built-up land, bare land, and agricultural land. The images were successfully delineated using GIS zoning boundary data and then classified through a supervised maximum likelihood classifier. The results of the classified images showed significant changes in all classes, with built-up land being the major encroachment into the dam basin, covering 18.28% in 1997, 21.46% in 2005, and 19.12% in 2021. These findings provide considerable spatio-temporal information on factors causing LULC change patterns and improve the understanding of the amount and rate of encroachment of the dam basin. The results are recommended to the landowners, water authorities and the government for monitoring LULC change patterns in the Nandoni Dam basin.

Keywords: remote sensing, GIS, land use, land cover, Nandoni Dam basin

DECLARATION

I, Maanda Danson Lilimu, hereby declare that all work on this dissertation is my original work, except where acknowledgements are indicated by relevant references. None of this work, or any part of it, has been, is being, or is to be submitted for another degree in this or any other university. I authorize the University of Cape Town to reproduce for research either the whole or any section of the contents in any manner whatsoever.

05 September 2023

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NOTE ON REFERENCING

The style of referencing used in this dissertation complies with the Harvard-UCT (Author, Date) output style from the University of Cape Town’s Handbook on Citation (2016 edition).

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GLOSSARY OF TERMS

ALOS	Advanced Land Observing Satellite
CDNGI	Chief Directorate of National Geographic Information
DEM	Digital Elevation Model
DWA	Department of Water Affairs
DWS	Department of Water and Sanitation
ERDAS	Earth Resources Data Analysis System
ESRI	Environmental Systems Research Institute
GCP	Ground Control Point
GIS	Geographic Information Systems
ISODATA	Iterative Self-Organizing Data Analysis Technique
LULC	Land Use and Land Cover
MLC	Maximum Likelihood Classifier
RS	Remote Sensing
SPOT	Satellite Pour l'Observation de la Terre
WARMS	Water Resource Management System
WMS	Water Management System

1 CHAPTER 1: INTRODUCTION

1.1 Background

Land use activities and land cover (LULC) changes have been widely acknowledged as the main drivers of environmental change at all spatial-temporal scales in some of the South African dam basins (NWRS2, 2012). The South African dam basins in question are negatively impacted by various land use activities such as agriculture, residential, transport, commercial, and recreational activities. These activities have resulted in the encroachment into dam basins. The consequence of such encroachment has the potential to change the dam basin's natural landscape and environment due to human-environment interactions. These changes result in the malfunctioning of dam basins because of increased sediment deposits, siltation, flood damage, and deforestation (Webster et al., 2018; Franchi et al., 2019; Mariye et al., 2022).

The impact of these changes influence lack of economic development and the limitation of economic tourism activities in the dam basin. The Nandoni Dam basin is no exception in this regard. These negative impacts have demonstrated the need to monitor the Nandoni Dam basin using remote sensing and Geographical Information Systems (GIS) methods. These methods offer the possibility of monitoring changes in land use and land cover (LULC) (Islam et al., 2021), which could help water resources management agencies, government departments in charge of water resources, and water authorities, to make informed spatio-temporal decisions that could preserve the intended purposes of water conservation in the Nandoni Dam basin.

The Nandoni Dam basin is located in the north-eastern part of the Limpopo Province of South Africa. The dam basin is affected by the various LULC changes such as agriculture (grazing and pasture), residential (houses), transport (roads), commercial (accommodation, lodges and resorts), and recreational (parks and picnics). These changes are also attributed to population growth, land claims, illegal water use, and socio-economic developments encroaching into the dam basin (DWA, 2012). These challenges have negative effects on the management of the dam basin, which management is responsible for water conservation and water supply to the surrounding population (Tadese et al., 2020).

Population growth demands more land and water resources in the Nandoni Dam basin (DWA, 2014). The high demand for land and water resources in the dam basin influences the LULC changes. These LULC changes have an impact on future land use planning and water conservation (Stonestrom et al., 2009; Daba & You, 2022). The demands for land and water in the Nandoni Dam basin necessitated the need for mapping land use activities timeously to monitor LULC change patterns in the dam basin (DWA, 2014). Should these demands not be managed effectively, they can cause LULC changes that can lead to land disputes (Liaqat et al., 2021; DWS, 2021). The availability of LULC change mapping data through remote sensing time series images and the use of GIS data has the potential to map land dispute areas around the dam basin (Osborne et al., 2001; DWA, 2014; Wei et al., 2020).

LULC mapping and change monitoring are applied to manage environmental and water resources (Ghaffari et al., 2010). Developing countries, such as South Africa and Botswana, are applying remote sensing and GIS technologies for LULC change monitoring (Matlhodi et al., 2021). The application of remote sensing and GIS methods is also used for future land demand predictions and socio-economic planning (Hathout, 2002).

Most of South Africa’s dam basins need to meet the communities’ water and socio-economic demands; however, these dam basins are situated in remote and inaccessible terrain which makes it difficult to monitor land use activities and encroachments timeously. Nandoni Dam basin is, however, situated in the urban periphery with a mixture of urban townships and rural villages, but the terrain is also largely inaccessible and covers a large-scale basin area. Conventional ground surveys, field visits, mapping, and static historical records are not keeping pace with the rate of LULC encroachment dynamics, and therefore require the application of remote sensing and GIS (Osborne et al., 2001; DWA, 2014).

To resolve these LULC change challenges, periodic dam basin mapping needs to be conducted to monitor LULC change patterns (Tadese et al., 2020). This is done for the protection of water resources in the already water-scarce South Africa (DWA, 2014). Remote sensing satellite images and GIS data offer the potential for mapping and monitoring LULC changes in the Nandoni Dam basin (Liaqat et al., 2021; DWA, 2014). According to Osborne et al., (2001), the integration of image processing of remotely-sensed data and geographical information is a possible means to map problem areas emanating from LULC change dynamics in land and water resources (DWA, 2012; DWA, 2014).

1.2 Research problem statement

Nandoni Dam basin has experienced remarkable land use encroachment since its construction in 1997. Following the construction of the dam, anecdotal evidence shows that much of the basin has been encroached on, which is potentially compromising the functionality of the dam. However, there is lack of information about the causes, amount, and rate of encroachment of the basin. This study therefore seeks to leverage geospatial information to determine the drivers, extent, and rate of encroachment on the dam to enable or inform proper spatial planning and improved management of the dam basin.

Some of these land use encroachments are agriculture, residential, transport, commercial, and recreational. These encroachments have led to land cover expansion as has happened with many other dam basins in South Africa. These land use encroachments into the Nandoni Dam basin are negatively affecting the water conservation and the management of the dam basin. The increase in the demand for these land use activities is a major driver of LULC changes in the dam basin (UNEP, 2006; Luo et al., 2020). The demand for land use in the dam basin is becoming more intense, and it influences the land cover change phenomenon. As such, it needs to be monitored on a spatio-temporal basis using remote sensing and GIS data (DWA, 2014).

Land use activities have resulted in problems such as land claims, land invasions, and land grabs due to the high demand for land around the dam basin. The land use situation is getting worse as more land is needed for socio-economic development versus the land needed for water conservation and dam basin management. The land claims process requires a great deal of land rights verification and land identification activities which is a time-consuming, costly, and tedious exercise. The process to update and verify historical land ownership and servitude rights information is very lengthy and slow. Nandoni Dam basin's management, therefore, requires dynamic and modern technologies such as remote sensing and GIS to monitor such LULC change trends during the dam basin's lifetime (Osborne et al., 2001). This study attempts to solve these problem statements by investigating possible means to answer the research questions and meet the objectives regarding LULC changes in the Nandoni Dam basin, as presented in section 1.3.

1.3 Research aim and objectives

This research aims to apply remote sensing and GIS methods to monitor LULC change patterns by using remote sensing images and GIS data to quantify the spatio-temporal LULC change patterns in the Nandoni Dam basin. The objectives of this research are categorised as follows:

a) to determine LULC changes in the Nandoni Dam basin since its inception using appropriate remote sensing images and GIS data;
b) to assess the amount and rate of LULC changes in the dam basin using a suitable remote sensing classification method; and
c) to determine a suitable spatial analysis method to quantify and map the drivers (causes) of spatio-temporal LULC encroachments in the dam basin.

1.4 Research questions

Achieving the aim of this study would help in providing answers to the following research questions.

a) What are the appropriate remote sensing images that can be classified to monitor LULC change patterns in the dam basin?
b) Which remote sensing classification method is suitable to assess the amount and rate of land use and land cover change patterns in the dam basin?
c) How can the drivers (causes) of spatio-temporal encroachment into the dam basin be effectively determined and mapped?

1.5 Research rationale and relevance

Land use activities and land cover changes are becoming a threat to water conservation in the Nandoni Dam basin and similar dam basins in South Africa.

Conventional surveys, field visits and static historical records to monitor LULC change patterns are no longer effective in addressing the rate of LULC encroachment dynamics into dam basins. LULC changes, therefore, require modern technologies such as remote sensing and GIS data, which cover a larger mapping area than traditional mapping methods (Osborne et al., 2001; DWA, 2014; Parihar et al., 2022). Whereas there is a general understanding of encroachments in the Nandoni Dam basin since its inception in 1997, there are significant gaps in the data, information, and knowledge of the extent of the LULC change in the mapping of encroachments (Dean et al., 1995; Driver et al., 2005; DWA, 2014). Furthermore, the spatio-temporal extent of encroachments in dam basins has been identified as a national priority for further research (DEAT, 2004; DWA, 2012).

The rationale for LULC mapping using remote sensing images and GIS data in this study is to assist hydrologists (water conservation), surveyors (land parcels and servitudes), engineers (constructions) and water authorities to timeously monitor dam basins. The LULC mapping using remote sensing images and GIS data also seeks to assist in making spatio-temporal decisions (Luo et al., 2020), monitoring encroachments into the dam basin – thereby limiting the impacts of soil erosion (Islam et al., 2021) – dam basin deformation and floods to reduce sediment/silt deposits (Mariye et al., 2022). To meet these needs, the research is organised into various chapters as presented in the next section.

1.6 Organisation of the dissertation chapters

Chapter one begins by introducing the background, study area, and problem statements. It then highlights the opportunities and constraints of using remote sensing and GIS in LULC change monitoring in general and Nandoni Dam basin monitoring in particular. The main objectives and subsequent hypothetical questions which facilitate the task of achieving the aim of the research and an overview of the research methods are also described in chapter one.

The second chapter mainly concentrates on reviewing the application of remote sensing and GIS in LULC change monitoring in general, and water resources in particular. The literature review emphasises the use of various remote sensing satellite image sensors such as Landsat, SPOT, and Sentinel-2 among others, and their spatial, temporal and spectral characteristics, together with the different classification methods to process these images.

The third chapter describes the analytical research methods applied for remote sensing images and GIS data acquisitions, pre-processing, and LULC classification together with its application in change monitoring. The results of the relationship between LULC changes and their possible causes in the Nandoni Dam basin are analysed and discussed in the fourth chapter. The fourth chapter presents the results of the analytical research method concepts and consolidates the empirical data used to answer the research questions. To this end, summaries and conclusions with indications for future research opportunities are presented in the fifth chapter.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews the application of remote sensing (RS) and geographical information systems (GIS) for monitoring historical, current, and aftereffects of land use and land cover (LULC) change in global, regional contexts and South African dam basins in particular. This literature review first provides a broad overview of developments in the field of LULC monitoring, which frames the analytical discussion of the research. It then highlights the causes, common practices, and methods applied for monitoring LULC change using remote sensing and geographical information systems.

It further reviews constraints and opportunities for remote sensing image applications in LULC monitoring for the natural water resources in general such as watersheds, lakes, rivers, and dam basins in particular. The literature review's objectives are to provide a theoretical overview, data, information, and knowledge gaps in the application of the two sciences of remote sensing and GIS together for monitoring LULC changes in the dam basin, as reviewed in section 2.2 and subsequent sections of this chapter.

2.2 Land use and land cover changes

The term 'land use' refers to how humans are using or interacting with the land for development, conservation, residential or mixed uses. Land cover refers to the physical state of the land, for example, how much the land is covered by vegetation, forest, agricultural land, wetlands, and structures. The structures encompass buildings, pavements, dam wall embankments, and other aspects of the natural environment, together with water resources such as dam basins, river basins, watersheds, and lakes (Chen et al., 2001; Wei et al., 2020).

In the broader context of the world, authorities are facing a combination of both land use and/or land cover (LULC) changes in various land zoned for dam basins. The gap between the demand for land and water resources versus their availability and supply is widening. South African dam basins are no exception to the LULC change phenomenon, and this includes the Nandoni Dam basin in particular (DWA, 2014).

Over time, dam basin management has moved beyond mainly focusing on water conservation. The concerns now focus on the paradigm of managing land parcels around dam basins and how the LULC changes affect the dam basin lifespan. The allocation of land and water resources, whether for spatial planning purposes, water resource conservation, agriculture, or rural and urban development, has the potential to influence LULC changes in dam basins (UN, 1996; DWA, 2014).

Change in LULC affects land and water resources, and the rate at which humans react to the changes. Change in LULC has the potential to increase the severity of soil erosion and to influence environmental impacts such as climate change, resulting in severe droughts and floods (Franchi et al., 2019). These LULC impacts have high economic cost recovery because of their adverse effects on water conservation, agricultural land, infrastructure development, and water quality in dam basins (Stonestrom et al., 2009).

Land use and land cover are usually characterised by change phenomenon that necessitates the need for monitoring systems to measure the extent and magnitude of change (Green, 1992). With the integration of remote sensing and GIS, spatio-temporal maps are required to monitor the impact of change in the dam basin environment (Islam et al., 2021). However, historical cartographic maps lack the intelligence of other kinds of dam basin monitoring due to their static nature. Furthermore, they are usually outdated with limited spatio-temporal characteristics.

Several studies have been conducted to apply remote sensing and GIS methods around the world to monitor LULC changes in natural water resources. Such examples include Kenya (Mango et al., 2011); Germany (Barthel et al., 2012); Ethiopia (Legesse et al., 2003), India (Singh et al., 2021) and the Himalaya (Parihar, et al, 2022). Furthermore, various studies on the impact of land use changes on water resources have been analysed in various river basins using remote sensing images and GIS data. The study analysis provides spatio-temporal information within a very short time at less cost and effort as compared to conventional manual methods. Through these studies, remote sensing applications have proven to be a cost-effective tool for mapping these kinds of LULC changes in water resources (Jensen, 1996; Hansen et al., 1998).

Mapping LULC changes in the dam basin is essential for a wide range of applications; these include monitoring land deformation, deforestation, erosion, spatial planning, drought, and flood which all impact the management of water resources (Tadese et al., 2020).

For instance, in Ethiopia (Bishaw, 2012), LULC change mapping was successfully conducted for water catchments using Landsat TM (thematic mapper) & ETM+ (enhanced thematic mapper plus) images for the assessment of flood hazard and flood risk. India also successfully monitored LULC changes using the same TM and ETM+ images integrated with GIS data to prevent and control deforestation in the Mahananda catchment and river basin, respectively (Kiran, 2013; Chauhan &

Nayak, 2005; Jayakumar & Arockiasamy, 2003). In Vietnam, SPOT multi-spectral band satellite images were used to monitor LULC changes, and subsequently combined them with field surveys and digital topographic maps to successfully evaluate LULC changes (Giap et al., 2003).

Several studies also corroborate the fact that remote sensing has increasingly been used as the data source of information for mapping LULC of natural resources, on local, regional, and global scales (Lunetta & Lyons, 2004; Herold et al., 2003). Furthermore, according to Fan et al. (2007), satellite images enable periodically repeated analysis and monitoring of LULC changes in the rural natural water resources and urban developments. There has been a significant advancement in the development of remote sensing and GIS-based tools that offer a repetitive assessment of environmental parameters in natural water resources. The classification of Landsat’s TM and ETM+ images, the SPOT sensor’s multi-spectral band images, and Sentinel-2 images, among others, are effective examples to map and monitor the causes of LULC change. The use of these various images for mapping works much better when integrated with GIS data and additional data such as socio-economic data (Maviza & Ahmed, 2020), and population data to remotely monitor the urban expansion and cropland vanishing in and around the water resources (Langat et al., 2021).

These studies, among others, indicate that remote sensing images have the intelligence to monitor LULC changes in natural water resources. From these studies, it is evident that there is potential to analyse the impacts of LULC activities and encroachments around water resources using multi-temporal satellite images in combination with change monitoring techniques. These studies confirm that remote sensing and GIS are well regarded as a means for LULC mapping in natural environments. However, the studies fell short when it came to highlighting the monitoring of LULC changes, particularly in the dam basin environments (Foody, 2002; Parihar et al., 2022).

Whereas these studies used various remote sensing images and GIS data, the focus was generally on water resources, with limited geospatial information studies on dam basins in particular. The gap between the general water resources and the specific dam basin resource necessitates consideration of this study of LULC changes and their causes in the Nandoni Dam basin. The causes of LULC changes are reviewed in section 2.3.

2.3 Causes of land use and land cover changes

South Africa is one of the water-scarce countries in the Southern African Developing Countries (NWRS2, 2012). For example, the Nandoni Dam basin water resources development requires a large area of land for water storage in the form of a catchment, drainage area, or dam basin. Land serves as the basis for spatial planning and the management of waterworks (rehabilitation, maintenance, silt dredging, flood zone buffers) around dam basins. Land acquired for the management of the Nandoni Dam basin is affected by land claims and illegal development challenges within the dam basin. These challenges have the potential to cause LULC changes in dam basins; hence, there is a need to monitor them remotely on a regular basis.

Since the start of the development of the Nandoni Dam basin in 1997, the dam basin's land has been transformed in ownership, operation, construction, and management from the state, traditional authorities, communities, and private individuals to the water authorities. Consequently, direct and indirect LULC changes have also taken place in the dam basin since its completion in 2005 (NWRS2, 2012).

The reason for the LULC changes can be categorised into direct and indirect causes (Yu et al., 2016). The direct causes of LULC changes are the activities or actions that affect land use such as fuel-wood extraction (deforestation) and agricultural activities (subsistence farming) in dam basins. The indirect causes of LULC changes are attributed to demographic pressure, and population growth (land expansion), with a potential conflict between land needed for water conservation versus economic development in dam basins (Fan et al., 2007). In some instances, LULC changes in any dam basin are influenced by land reform, informal settlements, and accelerated urbanisation of waterfront land in various water resources (Nkwiti, 2012; Asmal, 1997).

As the dam basin ages, there is a need for spatio-temporal data acquisition to monitor the LULC changes. These include updated LULC change information to assess problem areas quickly and remotely in a proactive approach. Where there are instances of poor land usage, the LULC information is helpful in response to alleviating dam basin deformations and hydrological risks. The deformation risks are attributed to siltation (Franchi et al., 2019), and stream diversions, while hydrological risks are associated with severe flooding and erosions. All these risks, together with informal land development encroachments, have negative influences on the dam basin’s behaviour and lifespan (DWA, 2014; Desta et al., 2019). Although these risks are a result of natural phenomena, and their occurrence may not be completely stopped, their adverse effects can be mitigated by proper spatial planning and monitoring using remote sensing images and GIS data (Bishaw, 2012).

Some possible factors causing LULC changes are attributed to inappropriate land use management which becomes the dominant cause of LULC change occurrence around dam basins as illustrated in the modified Figure 2.1 (Herweg, Steiner, & Slaats, 1999).

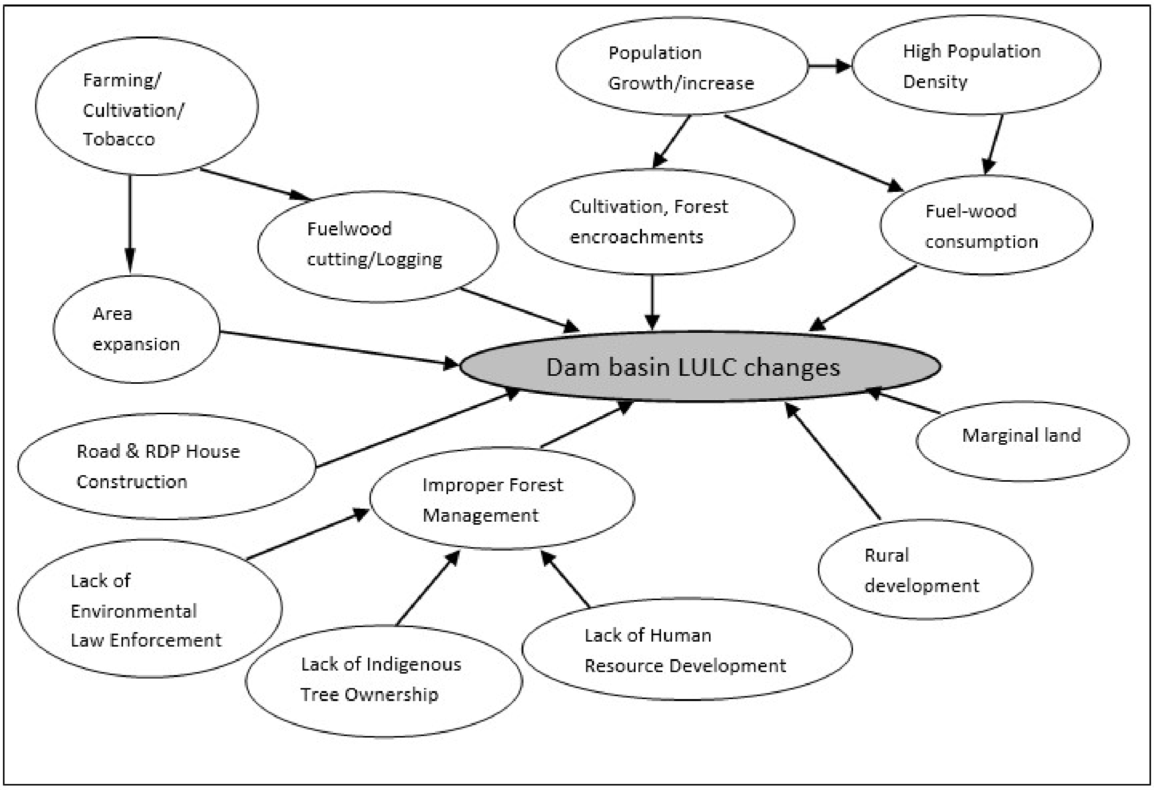

Figure 2.1 Possible factors influencing LULC changes in the dam basin

From Figure 2.1, it is evident that since population growth increases population density, more wood for fuel is harvested from the dam basin. These factors result in both LULC being negatively affected. Similarly, farming activities encroaching on the dam basin leads to the need for land use area expansion, while construction of roads and rural development programmes (RDP) have effects on LULC changes as they demand more land cover spaces and building materials that amount to built-up areas.

These causes of LULC changes are also revealed by studies done by Reis et al. (2003), which determined increasing population density due to local population growth. The narrative in Figure 2.1 is also noted by Sadoun (2009) and Liaqat et al. (2021) studies in processing and analysing Landsat satellite images from different dates using remote sensing methods through normalised difference vegetation index (NDVI). The results showed an increased distraction and desertification of cultivated and grazing lands. Although the scope of this study is not to investigate population growth statistics, remote sensing images such as Landsat, SPOT, and Sentinel-2 are applicable to map the settlement's land cover expansion (Bonansea et al., 2021), as it encroaches on the Nandoni Dam basin.

The Nandoni Dam basin has conventional monitoring processes of land use management in place, such as physical dam basin's land inspections, temporal (bi-annual) field inspections, identification and verification site inspections, and illegal water/land use inspections to determine the potential causes of LULC changes. These are less effective than remote sensing monitoring processes. The availability of LULC change monitoring processes assists in better managing water resources, evaluating risk, assessing safety, and preventing disasters emanating from these causes (DWA, 2014). These causes also apply to many other South African dam basins which are currently dependent on conventional physical field visits and traditional visual field inspections that must be reported to regulatory agencies for accurate monitoring.

The invention of remote sensing and GIS technologies and web-based platforms have made it easy to access images and spatial data at a reduced cost, economically and timeously, to monitor LULC changes for water resources (Singh et al., 2021). Remote sensing and GIS applications greatly enhance the process of data acquisition to monitor LULC changes in the status of natural resources.

2.4 Monitoring of land use and land cover changes

Remote sensing satellite images and GIS data are broadly applied in the monitoring of LULC changes since the beginning of the Landsat satellite image programme in the 1970s. The application of remote sensing was mainly in forest and agricultural areas (Campbell, 2007). However, LULC mapping and change monitoring are increasingly applied worldwide as one of the effective means to manage land and water resources such as lakes, water catchments, watersheds, river basins, and water ponds (Ghaffari et al., 2010). Many public service organisations in South Africa are involved in the application of remote sensing and GIS to monitor LULC changes (DWA, 2014). However, there are limited track records of LULC change monitoring, particularly in dam basins.

South Africa’s water authorities have also co-hosted a series of workshops and training sessions to emphasise the need to monitor water resources using remote sensing and GIS data. However, the workshops and training sessions have addressed image classifications for LULC change mapping and future predictions for water resources in general but did not fully cover the monitoring of dam basins, in particular (Moseki, 2011). Seminars were held by the Department of Water and Sanitation (DWS), in conjunction with Earth Science Research Institute (ESRI)-South Africa to promote GIS initiatives in the public sector to map water resources (Fourie, 2012). Similarly, in South Africa, the application of remote sensing image classification and GIS analysis in the water resources is not fully integrated into dam basin management, as there are limited research studies in this regard.

In South Africa, several GIS-based systems such as Water Resource Management System (WARMS) and Water Management System (WMS) were developed to manage and monitor water resources (DWA, 2014). However, these systems are not spatially based, and therefore cannot perform image classifications or GIS analysis in monitoring LULC changes to assist the engineers and hydrologists to manage dam basin behaviours.

Several studies have shown some successes, opportunities, and limitations in LULC monitoring. In India, Chowdhury et al. (2018) have successfully analysed the LULC change in Halda Watershed over the past 40-year period. The analysis used multispectral satellite data obtained from Landsat-2 MSS (multi-spectral scanner), Landsat-5 TM, and Landsat-8 OLI/TIRS (Operational Land Imager/ Thermal Infrared Sensor) together with GIS data. The study by Thakkar et al. (2017) also made use of five remote sensing images of different spatial resolutions and sensors. The datasets included two medium-resolution images (Landsat-7 ETM+ and IRS R-2 LISS III) to map LULC changes. These were complemented by two more medium-resolution images from Landsat-7 ETM and IRS R-2 LISS III for vegetation cover change detection in agricultural land. The fifth image came from a high spatial resolution Natural Color Composite (NCC) image. The NCC image was produced from the spectral merging of Cartosat and IRS P6 LISS IV images, which was used for agricultural development based on visual image interpretation for post-classification analysis. These studies demonstrated the application of various image sensors to map water resources and are relevant to the investigations of the Nandoni Dam basin as one of the water resources.

In recent years, the focus of LULC changes in water resources has been to determine the relationship between humans and their environment. Nowadays, the focus is also directed on change detection and taking actions to protect the land and water resources from the adverse effects of human activities. Remote sensing images and GIS data have therefore become an attractive research topic for LULC change monitoring in dam basins (Luo et al., 2020; DWA, 2012). From these reviews, it is evident that a combination of various image sensors, with different spatial resolutions and temporal characteristics, are applied to monitor LULC changes such as vegetation, forestry, agricultural land, and watersheds. However, their application scale has not adequately addressed the monitoring programmes or systems in dam basins, hence this study is necessary to bridge such gaps.

The advantage of remote sensing images is that they require minimal field work, if any, compared to traditional field visits and conventional surveys. Traditional surveys require actual presence in the field, while remote sensing images can be acquired and processed using spatial information without going to the field. The greatest advantage is that, instead of a few scattered survey points, the result comes in a dense array of geocoded image pixels of various spatio-temporal and spectral characteristics that yield a detailed LULC map of the surface. When the remote sensing images are classified, the pixels produce LULC mapping data of the surface for managing water resources with information that is compatible with various GIS data and systems (Holcomb, 2011). The remote sensing data (images) are further reviewed in detail in the following section.

2.5 Remote sensing data in monitoring LULC changes

The remote sensing data acquisition started with the Landsat programme in July 1972, as reviewed in the previous section 2.4. The Landsat programme is the longest-running enterprise for the acquisition of satellite images of Earth (Roy et al., 2014; Maviza & Ahmed, 2020). The Landsat satellites provide the longest track record of earth observation stretching over 40 years, from Landsat 1 to 8 (Loveland & Dwyer, 2012). Landsat images have the potential advantage to cover most of the dam basins established around the 1970s to date, including the Nandoni Dam basin.

This literature review considers the three remote sensing satellite sensors, viz: Landsat, SPOT, and Sentinel-2 to conduct this investigation. The Landsat programme provides the longest image acquisition data coverage in the Nandoni Dam basin. SPOT image brings in the series of satellite constellations 1 to 8, with the first series launched in February 1986 and the current satellite being constellation 8 at the moment. Lastly, a review of the Sentinel-2 satellite constellation of the European Space Agency (ESA) which was launched in June 2015.

Landsat and SPOT satellite orbits are 16 and 5 days respectively, while Sentinel-2 orbits are designed to ensure a revisiting time of about 5 days at the equator. Considering both satellites, the revisiting orbit time is deemed as the appropriate period for a LULC study. Sentinel-2's Multi-Spectral-Instrument (MSI) has a very wide field of view of about 290 km swathe width, while Landsat's OLI trails behind at 185 km, (Roy et al., 2014; Loveland & Dwyer, 2012; SANSA, 2006; Drusch et al., 2012). The SPOT image sensor covers the smallest 60 km swathe width. All coverages are potentially large enough for most of the dam basin coverage area including the Nandoni Dam basin, except for the Sentinel-2, which was launched in 2015 after the Nandoni Dam basin was completed.

Landsat, SPOT, and Sentinel-2 images have multi-spectral resolution capabilities to conduct time series mapping. SPOT image resolutions are divided into different categories based on spatial resolution such as coarse multi-spectral (10 m), medium (5 m) and fine panchromatic (1,5 m), (SANSA, 2006). Landsat image series carries Multi-spectral Scanner (MSS), Thematic Mapper (TM) instruments, and an Enhanced Thematic Mapper Plus (ETM+) scanner (Maviza & Ahmed, 2020).

Furthermore, Landsat's OLI provides high-quality multi-spectral images at a resolution of 30 metres (and 15 m for panchromatic) (Roy et al., 2014; Loveland & Dwyer, 2012). The Sentinel-2 sensor is equipped with identical MSI capable of acquiring data in 13 bands at different spatial resolutions (between 10 m and 60 m) (Mandanici & Bitelli, 2016). The latest Landsat-8 is equipped with two instruments, which are the OLI for optical bands and the TIRS for thermal bands. Sentinel-2 satellite images have four visible and near-infrared bands at 10 m pixel size, which roughly correspond to the equivalent Landsat's Thematic Mapper (TM) bands, and six near-infrared bands with short wave infrared bands at 20 m pixel size (Roy et al., 2014).

While Sentinel-2 is ESA's medium spatial resolution (10 – 60 m) and super-spectral instrument aimed at ensuring data continuity for global land surface mapping for Landsat and SPOT images, the Sentinel-2's MSI instrument has a set of bands with very similar spectral windows to the main bands of the Landsat TM family of instruments but falls short of the image temporal coverage obtained by Landsat 1 to 5, which makes it disadvantageous for mapping past LULC changes in the Nandoni Dam basin.

The study by Clark (2017) also indicates that the repeatability of image acquisitions from satellite sensors is important for LULC classification, irrespective of sensor spectral resolution. It is evident that in most cases the three sensors (Landsat, SPOT, and Sentinel-2) can be combined as input data; however, some inconsistent issues such as spatial, spectral, or temporal characteristics are likely to arise when classifying different images for different periods and purposes.

Although the triangulation of the three image sensors is desirable, Landsat and SPOT are both advantageous in spatio-temporal and spectral resolution characteristics, among others (Langat et al., 2021). Some drawbacks are that SPOT data acquisition is costly, while the Sentinel-2 falls short of the temporal coverage before June 2015 versus this study period required for the Nandoni Dam basin. Whereas the remote sensing images can be used independently, the integration of GIS data helps to improve the image analysis and in the delineation of areas of interest, rather than using the whole image as reviewed in section 2.6.

2.6 GIS application in monitoring LULC change

GIS with the integration of remote sensing applications helps in the delineation of an area of interest (AOI) that poses potential LULC change. In this regard, the application of GIS data is useful in delineating dam basin zones using spatial data for monitoring purposes (Joshi & Gairola, 2004). The application of GIS spatial data facilitates the ability to integrate geographic data with other various spatial data to and from systems such as computer-aided draughting (CAD), Global Positioning Systems (GPS), and data mining systems for further LULC map's spatial analysis on water resources such as dam basins (Weng, 2002; IEEE, 1990).

The following studies indicate that remote sensing and GIS data interoperability in monitoring LULC is being applied worldwide and is also applicable to this study. In China, Weng (2002), and in Gaborone, Daba & You (2022), investigated LULC change dynamics by integrating Landsat TM remote sensing images with GIS spatial data using stochastic and Markov modelling methods. In Turkey, Reis et al. (2003) recommended that settlement areas that have experienced rapidly changing characteristics are better analysed using satellite images and GIS data. The satellite images are classified much easier and faster when combined with GIS data rather than the conventional surveying methods, and would be useful, especially for dam basin administrators who need automated details for monitoring (Tadese et al., 2020). The results further indicated that there has been notable and uneven urban growth and a tremendous loss in cropland for the study period. These studies demonstrated that the integration of remote sensing images and GIS data is an effective approach for analysing the direction, rate, and spatio-temporal patterns of LULC change for water resources.

Several information systems are also being used to integrate remote sensing images with geographical information. Integrated Land and Water Information System (ILWIS), a GIS component of the system, was also applied successfully for the integrated analysis of classification results and other geographic data in Indonesia (Yijun & Hussin, 2003), while Chowdhury et al. (2018) also analysed LULC using pixel-by-pixel basis classification and cross-tabulation analysis through GIS systems and Semi-Automatic Classification Plugin (SCP).

The ILWIS application of GIS systems was mainly used in the delineation of the area of interest process. It was then also applied in the clipping of the images and re-projecting them into Universal Transverse Mercator (UTM) and Gauss Conform projections, respectively. The application of ILWIS's GIS component also aided the coordinate system conversions (CSIR, 2010).

The production of LULC changes with the aid of GIS datasets has a long history which goes hand in hand with the evolution of superimposing map/image layers one over the other (Johnson et al., 1996; Alberti et al., 2004; Gong & Howarth, 1990). The study by Thakkar et al. (2017) supports this, where they used GIS to digitise topographic maps to obtain the area of interest (AOI) using overlayed vector data. The study successfully delineated and classified Landsat-5 TM images and 7 ETM+ images to superimpose them over aerial photographs and GIS spatial datasets for further LULC change analysis.

Whereas remote sensing serves as the primary resource data, GIS becomes handy for cartographic map production, AOI, and flood boundary delineation. In this study, the delineation of AOI is required for processing decision-making information in managing dam basins (Demers, 2005; Luo et al., 2020). The GIS system is a commonly used standard software worldwide and is known for its excellent capability in map creation for study areas. GIS is required in this study to integrate classified images and process geographic data for cartographic maps to perform spatial analysis. Remote sensing software, such as ERDAS IMAGINE and eCognition, integrates seamlessly with GIS systems, such as ArcGIS, IDRISI, and QGIS (Daba & You, 2022). The spatial data processed in these systems, in addition to the feature collection and vector editing tools, gives better spatial visualisation when integrated with remote sensing data.

Furthermore, remote sensing images and GIS spatial data are widely applied in identifying, analysing and monitoring LULC change (Jensen & Cowen, 1999; Hathout, 2002; Parihar et al., 2022). In Vietnam, Giap et al. (2003) conducted a study on the application of remote sensing and GIS by integrating socio-economic and environmental data into the GIS database, detecting land use change, and identifying and estimating potential areas for aquaculture development in watershed ponds. While, in Ethiopia, Bishaw (2012) conducted the application of GIS and remote sensing techniques for flood hazard and risk assessment, and Desta et al. (2019) investigated runoff response to LULC change in the catchment, respectively. In Turkey, Reis et al. (2003) and in the Himalayas, Parihar et al. (2022), LULC changes were investigated using Landsat images and GIS data according to their topographic structure (slope and altitude). Similarly, Kindu et al. (2015) and Rozenstein & Karneili (2011) also indicate that GIS data is better applied in preparing LULC maps of an area, as it helps in the demarcation of the study area, extraction of the study area, and spatio-temporal data analysis, all of which are applicable in the Nandoni Dam basin study area.

In these reviews, it is evident that GIS integrates seamlessly with multi-spectral band images such as Landsat, SPOT, and Sentinel-2 images, among others. It is also evident that remote sensing image analysis integrated with GIS data improves the classification process and aids LULC change verification of watershed ponds for aquaculture development. Moreover, flood hazard and risk assessment confirmed that it is possible to manage flood hazard causative factors to alleviate or minimise flood risk using remote sensing and GIS methodologies, such as Multi-Criteria Evaluation (MCE-GIS) techniques. The MCE-GIS technique is also known as Weighted Overlay in the GIS environment and it is used for delineating areas that are prone to flood hazards and flood risks such as dam basins (Bishaw, 2012; Desta et al., 2019).

The availability of LULC changes mapping data through remote sensing time series images and the use of GIS to spatially delineate affected areas is critical to identify affected zones. The delineated areas are useful in cases where there is a need to avert potential land disputes around water resources (DWA, 2014). The need for delineation is also supported by Fan et al. (2007) and Liaqat et al. (2021) studies, which applied additional data such as vector administrative boundary and county-level socio-economic data generated by GIS software based on topographical maps to obtain subset images of each AOI in the county.

Contrary to historic applications of remote sensing independently of GIS, nowadays, the two sciences (remote sensing and GIS) are commonly applied together in the management of land and water resources planning. Remote sensing techniques based on multi-temporal and multi-spectral satellite-sensor data combined with geographical data demonstrate the potential means to detect, map and monitor natural landscape changes (Coppin et al., 2004), at various spatial locations and temporal periods (Lambin, 1997). However, to meet the spatial and temporal characteristics of the remote sensing images, the images have to be subjected to geometric corrections, of which the topic is covered in section 2.7.

2.7 Geometric corrections

This study makes use of remote sensing images that are not originally geometrically located in the required AOI positions. Therefore, there is a need to geometrically correct the images to the correct spatio-temporal and spectral characteristics to the required standard. Geometric corrections are an essential pre-processing technique to correct the inaccuracies between the location coordinates of the picture elements in the image data and the actual location coordinates on the ground (Santosh & Renuka, 2011). The corrections of the satellite images are therefore necessary to geometrically correct images with reference to the already rectified master image.

The corrections are done by making use of ground control points (GCP) (Jensen, 1996). These GCPs are quantified by selecting pairs of suitable fixed points on remote sensing images in an appropriate geometric model. The typical model should consist of a set of well-distributed GCPs that are taken on the crossroad networks, drainage junctions, and isolated features like check dams, to perform polynomial orders (first, second, third, etc.) or low-, medium-, and high-frequency distortions (Chen et al., 2001), using the nearest neighbourhood resampling algorithms (Thakkar et al., 2017; Friedmann et al., 1983; Baboo & Devi, 2011).

Before interpretation, remote sensing images are subjected to enhancement methods such as linear contrast stretching and histogram equalisation to help identify ground control points (GCP). This is done through the application of RMSE (Root Mean Squared Error) to assess the quality of geometric corrections. These enhancements are usually in the form of image georeferencing, registration, and/or ortho-rectification using topographic maps and DEM data applicable (Desta et al., 2019).

These geometric corrections are also supported by studies done by Fan et al. (2007) and Maviza & Ahmed (2020), which corrected two Landsat images (TM and ETM+) by georeferencing them using a map-to-map method. The images were also geometrically corrected by re-sampling them using the nearest neighbour algorithm with a first-order polynomial. GCPs were further used for correcting the images through a registration method with an RMSE of 0.49 pixels after verification calculation. Studies by Desta et al., (2019) and Parihar et al. (2022) emphasise the collection of ground truth points during field reconnaissance using GPS. The emphasis is that these points are useful for georeferencing in a supervised classification and accuracy assessment.

Topographic maps, which are scanned and digitised on-screen using GIS methods to obtain the delineation of settlement areas in a vector form, are also applicable in georeferencing data into different projections and coordinate systems. This is supported by Thakur et al. (2008); Giap et al. (2003) and Maviza & Ahmed (2020) studies, which geometrically corrected Landsat-5 and 7 ETM+ images through georeferencing using topographic maps. The images were also georeferenced to the UTM map projection system on WGS 84 coordinate system using both ERDAS and ENVI remote sensing image processing software.

The main problem encountered during the georeferencing was using the data from different coordinate systems. The problem resulted in scale and swing rotations and structural stretching of raster images and vector datasets. However, these problems were overcome by adding more GCPs to obtain accurate georeferenced images.

These studies indicate that remote sensing images, whether Landsat, SPOT, or Sentinel-2 among others, have a global scale of georeference. To achieve the desired localised AOI position, the images need to be geometrically corrected through one or more of the geometric correction techniques; for example, georeferencing, registration, or ortho-rectification. However, of the three techniques, georeferencing appears to be the most recommended (Singh et al., 2021). Once the images are geometrically corrected, they are ready for further processes such as image classification.

2.8 Image classification methods

Following the image geometric corrections, the objective of image classification in this study is to systematically categorise pixels in digital remote sensing images into different themes to form LULC classes. Image classification, as defined by Jensen (1986), is the process of arranging image pixels into various information classes. This definition is also consistent with Jensen (1996), which substantiates that a basic assumption in digital change detection is that a pixel will have different brightness values in two different time frames for LULC change. While according to Muttitanon and Tripathi (2005), the understanding is similar in that it aims to investigate LULC changes on a digital image to obtain feature changes of interest between two or more different time frames. These definitions concur with Lillesand and Kiefer (2004), in that image classification is a process of categorising all pixels in an image or raw remotely sensed satellite data to obtain a set of labels or LULC themes over a given period.

There are various methods of image classification, such as traditional pixel-based, object-oriented, artificial intelligence, and data mining classification as utilised by various image analysts for different purposes. These image classifications are commonly categorised under supervised or unsupervised remote sensing image classification methods (Keuchel et al., 2003). The image classifications can be performed using standard image classification software, such as ERDAS IMAGINE and eCognition which are the products of Hexagon Geospatial Systems and Definies, respectively. Nowadays, most GIS systems such as ArcGIS are also capable of performing basic image supervised and unsupervised classifications (Yijun & Hussin, 2003; Daba & You, 2022).

Supervised image classification is a method in which the analyst defines small areas on the image called training sites; these become representative of each desired LULC class (Keuchel et al., 2003). Conversely, unsupervised classification is based on the identification of natural groups within multi-spectral classes (Tou & Gonzalez, 1974; Jensen, 2005; Jensen, 1986; Jensen, 1996).

Several studies have been conducted globally using various classifications of LULC change using remote sensing and GIS data. For example, in Ethiopia, Desta et al. (2019); in the Himalayas, Parihar et al. (2022), and in India, Singh et al. (2021), both supervised and unsupervised, were applied to classify Landsat TM, ETM+, and OLI/TIRS images. These images were integrated with DEM (digital elevation model) data to analyse the historical land cover changes that have taken place in the catchment and their effect on the run-off effects (causes) in the catchment. In the United State of America (USA), Alberti et al. (2004) successfully applied supervised and unsupervised classification of Landsat TM and ETM+ images to interpret and assess land cover changes at several scales (landscape and sub-basins). In Egypt, Chowdhury et al. (2018) also used the maximum likelihood classifier (MLC) algorithm of supervised image classification together with additional GIS data and ground truth data as reference points (collected using GPS) to obtain optimum accuracy assessment of the classification results. While Fan et al. (2007) and Liaqat et al. (2021) also applied supervised MLC techniques using remote sensing's ENVI software, where training polygons were digitised on-screen based on terrain knowledge acquired during fieldwork and distributed throughout the study areas. Similarly, in Turkey, Reis et al. (2003), and in Gaborone, Matlhodi et al. (2021), investigated LULC changes using Landsat images and GIS data through MLC's supervised classification technique.

Although the above various image classifications have different characteristics, they also have distinct advantages and disadvantages, from one application to the other, but with common LULC classification (change) objectives. Supervised classification's advantage is that the analyst trains the algorithm to recognise spectral values or signatures associated with well-known training sites. The software then uses these signatures to classify the remaining pixels. The delineation of training areas is most effective when an image analyst knows the study area and has experience with the spectral properties of the land cover classes. However, the training of spectral feature classes' role is disadvantageous if it is biased toward the analyst (Soofi & Phillips, 2005; Lillesand & Kiefer, 2004; Keuchel et al., 2003).

The advantage of unsupervised classification, on the other hand, is that there is no need for extensive prior knowledge of the study area as is required in supervised classification. Unsupervised classification poses a minimum opportunity for human errors as the process is semi-automated, and unique classes are recognised as distinct units; furthermore, no training time is required (Skidmore, 1989).

According to Skidmore (1989), the significant disadvantage of unsupervised classification is that it poses difficulty in matching the identified spectral classes to the desired information class. There is a possibility that unknown spectral classes do not match with the desired classes at the end of the classification processes. Once more, the derived clusters are likely unidentifiable at the end of the classification process, which results in a fruitless exercise. Unsupervised classifications make use of post-cluster identification which is also a time-consuming and tedious exercise as compared to supervised classification (Rozenstein & Karneili, 2011).

The drawbacks of unsupervised classifications are that they are prone to mis-classification and mismatching of classes, respectively. Image mis-classification uncertainties are also challenging to manage at the end of classification (Shukla et al., 2018). However, Yijun and Hussin (2003) says that these uncertainties are likely eradicated by adding more training samples (which is also time-consuming), while Gebremicael et al. (2017) concur that additional geographical (GIS) data assist with the improvements of the classification accuracy but are tedious and time-consuming.

The application of both supervised and unsupervised classification produces more tangible LULC information than when using either of them separately. Moreover, adding additional data such as population and statistical data using GIS techniques has the potential to improve the LULC mapping accuracy by up to 10% (Soofi & Phillips, 2005).

Whereas the unsupervised-based classification method has the potential to acquire more information than supervised classification, it is prone to mis-classification. Supervised pixel-based image classification is superior in all urban-rural-natural environmental areas and considered to be the most common image classification method with reliable results in all the terrain (Yijun & Hussin, 2003). The various classification techniques are further reviewed in detail in section 2.9.

2.9 Classification techniques

The previous section 2.8 reviewed the image classification methods, namely, supervised, and unsupervised methods among others. This section 2.9 further reviews various supervised and unsupervised techniques (classifiers) applied by these methods.

Supervised classification methods make use of classifiers such as Parallelepiped, Minimum Distance To Mean, and Maximum Likelihood Classifier (MLC). While unsupervised classification uses classification techniques such as migrating means clustering classification (MMC), Hybrid Classification, K-Means, Iterative Self-Organizing Data Analysis Technique (ISODATA), and Expectation Maximization (EM) classifications (Jensen, 1996; Jensen, 2005; Tou & Gonzalez, 1974).

Supervised MLC techniques are commonly applied in change detection analysis performed using systems such as ERDAS Imagine (Mariye et al., 2022) and eCognition. The application of MLC prepares LULC maps from multi-spectral remotely-sensed data such as TM and ETM+ to improve classification for LULC mapping. Unsupervised classification technique such as MMC is used to cluster pixels in a dataset into classes based on statistics. This is applied to calculate class means that are evenly distributed in the data space and then iteratively cluster the remaining pixels using minimum distance techniques (Kiran, 2013).

The supervised classification's MLC technique further clusters pixels in a dataset into classes corresponding to the user-defined area of interest (AOIs) or training classes which are selected as representative areas of the output mapping. The training sites are selected based on the ground-truth coordinates which are collected during field reconnaissance using the global positioning system (GPS). However, in the absence of field GPS coordinates, a typical model should consist of a set of well-distributed GCPs that are taken on the crossroad networks, drainage junctions, and isolated features like check dams of the images to perform polynomial orders (Desta et al., 2019; Gebremicael et al., 2017; Shukla et al., 2018).

Furthermore, this study at the Nandoni Dam basin considers various image classification techniques such as Maximum Likelihood Classifier (MLC), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Cellular Automated Markov (CA-Markov), Multi-Criteria Evaluation (MCE-GIS) techniques and RUSLE models.

Various classification techniques have been applied in various investigations worldwide. In India, Thakkar et al. (2017), the impact assessment of LULC change was conducted on watershed and reservoir management dynamics using remote sensing and GIS. The assessment was successfully achieved with the application of NDVI and NDWI indexes during the supervised classification stage. The two indexes were also applied during post supervised classification stage to improve the classification accuracy (Alberti et al., 2004).

The NDVI index used a combination of five (5) multi-sensory remote sensing data within different study periods. The spatio-temporal and spectral characteristics from five different images were then used to calculate the NDVI (Langat et al., 2021), and subsequently, the NDVI differencing to detect the change of vegetation cover in agricultural land. The NDVI index required the datasets to be registered, inter-calibrated, and corrected for atmosphere and topography to ensure the accuracy of the land cover change assessment.

Other studies in countries such as Morocco and Ethiopia applied Cellular Automated Markov (CA-Markov) model and MCE-GIS techniques. In Morocco, Jazouli et al. (2019), and Gaborone, Matlhodi et al. (2021), classified multi-date satellite images of Sentinel-2, Landsat OLI-8, and ETM+ using CA-Markov model to forecast the LULC map and their change detections. While the Ethiopian study developed flood causative factors using remote sensing and GIS's MCE-GIS technique to obtain flood hazard and flood risk mapping (Bishaw, 2012).

The classification of remote sensing images in combination with geographic information using CA-Markov techniques results demonstrated that it (CA-Markov) is a suitable method for forecasting LULC change, while the RUSLE technique is suitable for accurately measuring the quantity of soil losses in the future (Mariye et al., 2022). These studies indicate that there is also a potential to integrate remote sensing and GIS with a CA-Markov model for a rapid assessment of the future LULC change simulation in a watershed (Maviza & Ahmed, 2020).

In summary, CA-Markov is a suitable model for forecasting future LULC change, while the MCE-GIS technique is commonly applied to obtain flood hazard and flood risk mapping. The indexes such as NDVI and NDWI are best suited for vegetation and water indexing respectively (Singh et al., 2021). The MLC model provides generic but focused methods to map problems associated with environmental changes and human activities regardless of the specific nature of LULC to be mapped and therefore becomes a classifier of interest in the Nandoni Dam basin study.

While the application of supervised and unsupervised classification together is capable of producing more classifications than the supervised or unsupervised classification alone, the application of both methods does not significantly improve the classification accuracy (Rozenstein & Karneili, 2011).

The success of the Nandoni Dam basin’s LULC change monitoring investigation depends on the quality (resolution) and quantity (repeatability) of satellite remote sensing information available (Huisman & de By, 2009) for dam basin management. Remote sensing data integrity, quality, and quantity are as accurate or valid as the data it contains. The concept of garbage-in garbage-out (GIGO) is more applicable in this regard as the validity of final LULC maps is as good as the appropriate classification method applied, the quality of the remote sensing images, the GIS data used, and the set of LULC classes applied. The LULC classes are further discussed in section 2.10, regarding the type of classes to be classified and the most suitable classification scheme to be applied.

2.10 Land use and land cover classes

The Nandoni Dam basin study subscribes to the international standard for mapping LULC classification such as the Food and Agricultural Organization of the United Nations (FAO, 2010), and United State Geological Surveys (USGS, commonly known as the Anderson Classification Scheme). The Anderson scheme consists of primary classes called vegetated and non-vegetated areas (Anderson et al., 1976). These classes are applicable to map the first levels regarded as the main classes of mapping LULC (CSIR, 2010). South Africa's land cover classification scheme (SALCCS) also conforms to this set of international hierarchical classifiers (CSIR, 2010; Di Gregorio & Jansen, 2005).

These classes are also supported by the Bishaw (2012) investigation that classified LULC changes using classes such as shrublands, grasslands, and open woodlands. A similar class approach is supported by Giap et al. (2003), in a study that investigated major LULC changes in the natural forests, paddy fields, and planted vegetation (including planted forests, tea plants, and shrubs). While the Kiran (2013) study area included five (5) dominant LULC classes such as mixed forest, built-up land, open forest, dense forest, and rivers.

Other studies used seven (7) types of LULC classes which included urban, forest, cropland, orchard, water, dike-pond, and developing land (Fan et al., 2007). Elsewhere Desta et al. (2019) used six (6) LULC classes for classification in a formatted FAO classification scheme viz: built-up area, cultivated land, planted forest land, grassland, bushland, and water body. In a study by Chowdhury et al. (2018), the watershed was classified into five (5) major LULC classes viz; agriculture, bare soil, settlements, vegetation, and water body. While Yijun and Hussin (2003) classified eight (8) classes (dense forest, moderately dense forest, sparse forest, heavily logged area, less heavily logged area, old conversion area, new conversion area, cloud and shadow).

The Nandoni Dam basin's environmental attributes classes are informed by the LULC classes derived from the potential causes of land-based activities in the dam basin (Tadese et al., 2020), such as a change in hydrology, floodplains occurrence, soil erosion, forestry/logging, dam basin deformation, stream flow diversion, human settlements, and encroachments. An overview of the existing LULC in the Nandoni Dam basin is characterised by visual LULC such as towns, roads, settlements, agriculture, water bodies (rivers and dams), and forests. The set of LULC classifiers is tailored to the major LULC classes and hierarchically arranged according to their mappability and therefore grouped into potential classes. After the classes are identified and classified, they are subjected to accuracy assessments to validate their relevance to the Nandoni Dam basin study area as described further in the next section.

2.11 Accuracy assessments

This study conducts an accuracy assessment to evaluate the performance of classifiers reviewed from the previous section (2.9 and 2.10) to have a valid dam basin LULC change map. The accuracy assessment allows the analyst to evaluate the utility of a thematic map against the validity and reliability of the intended dam basin LULC change map (Tadese et al., 2020). The accuracy assessment involves different spatio-temporal remote sensing images and GIS datasets of the dam basin that are compared to one another within various classification techniques (Islam et al., 2021).

The inaccuracies in spectral classification are then measured from a set of reference pixels in and around the dam basin. Using reference pixels, the most commonly used method for accuracy assessment is derived from a confusion or error matrix (also called contingency table) and Kappa statistics (Congalton & Green, 1999).

Several studies recommend the application of the accuracy assessment in the form of an error matrix for descriptive and analytical statistical analysis (Fan et al., 2007; Stehman, 1999; Chowdhury et al., 2018; Thakur et al., 2008). In these recommendations, random sampling for accuracy assessment was also used to compare the results of change detection together with the ground truth which was obtained from aerial photos and field visits. Amongst these methods, the Kappa coefficient was one of the most recommended measures in addressing the difference between the actual agreement and change agreement, which had many attractive features as an index of classification accuracy (Islam et al., 2021).

In the accuracy assessment processes, geometric registration accuracy is also applied between two or more images in terms of Root Mean Square Error (RMSE) (Thakur et al., 2008). Several authors recommend a maximum tolerance of RMSE value of fewer than 0.5 pixels (Gautam & Narayn, 1983). However, Townshend et al. (1992) identified acceptable RMSE values ranging from 0.2 pixels to 0.1 pixels depending upon the type of change being investigated. Although sub-pixel alignment is desirable in the Nandoni Dam basin investigations, a tolerance of between 0.5 to 2.0 pixels for RMSE and overall accuracy of 80% or more for KIA is within an accepted norm in this type of LULC change investigation.

In these reviews, an accuracy assessment of the resultant classified images is carried out to determine the quality of information derived from the data using a random sampling method using ground truth points. The ground truth data points are also randomly selected to produce an error matrix to assess errors in the final classification. In addition, Kappa statistics along with the total accuracy of the classified images are also applied to measure the extent of classification accuracy. The resulting co-registered images show successful registration accuracy in terms of Root Mean Square Error (RMSE) (Tadese et al., 2020).

In summary, this chapter on literature review discussed different LULC change studies using remote sensing and GIS data in monitoring natural environments in general, and water resources such as river basins, watersheds, and lakes (Chen et al., 2001; Wei et al., 2020). The review also discussed the potential direct causes such as deforestation and agricultural activities, together with indirect causes, that are attributed to demographic pressure, population growth (settlement and land expansion), and land development encroachments in the water resources such as dam basins (Yu et al., 2016; Langat et al., 2021; Fan et al., 2007).

Remote sensing images and GIS data for LULC change monitoring since the beginning of the Nandoni Dam basin development in 1997 were also discussed in section 2.4. The reviews revealed that, although raw remote sensing image data (Landsat, SPOT, and Sentinel-2) are readily available with spatio-temporal coverage of the study area for some of the three study periods (1997, 2005, and 2021), there were limited applications of knowledge, less production of value-added spatio-temporal data, characterised by GIS spatially enabled systems shortages, and capacity gaps to cope with conventional monitoring methods. Furthermore, the review indicates that there were limited track records of LULC change monitoring using remote sensing and GIS, particularly in South African dam basins.

Amongst the three image sensors reviewed (Landsat, SPOT, and Sentine-2), the Landsat fulfilled all the spatio-temporal and spectral characteristics required to meet the aim and objectives to answer the research questions for this study. However, SPOT fell short on its accessibility and strict user-pay policies, while Sentinel-2 was limited on temporal coverage characteristics.

Due to these shortcomings, the review recommends that the raw image datasets be processed through geometric and radiometric corrections in preparation for image classifications. The literature review recommends the application of supervised pixel-based classification using a modified Anderson Classification Scheme with a significant number of classes. The classification has to be subjected to accuracy assessment such as confusion matrix techniques. The analytical research methods emanating from these reviews are presented in detail in chapter 3.

3 CHAPTER 3: ANALYTICAL RESEARCH METHODS

3.1 Introduction

The analytical research methods described in this chapter are informed by the literature review in chapter 2. The previous chapter discussed the application of remote sensing (RS) and geographical information systems (GIS) for monitoring historical, current, and aftereffects of land use and land cover (LULC) change in global, regional and water resources in particular. The literature review provided a broad overview of developments in the field of LULC change monitoring, which framed the analytical research methods discussed in this chapter, to achieve the aim and objectives of this study. The analytical research method begins by defining the study area and then outlines the research design methods to be applied. The study area is described in the next section 3.2, indicating the spatio-temporal characteristics, selection criteria among other dams, and topographical features of the Nandoni Dam basin.

3.2 Study area descriptions

The study area covers the Nandoni Dam basin, which is located in the north-eastern part of the Limpopo Province of South Africa as shown in Figure 3.1. The approximate geographical coordinates of the study area were defined by 30º 28' 20” and 30º 36' 25” eastern longitudes 22º 57' 41” and 23º 04' 11” southern latitudes.

Nandoni Dam basin is located along the Luvuvhu River, which flows into the Limpopo River. Approximately a third of the land area of the study area falls within the rural areas of Mutoti, Budeli, Mulenzhe, and Dididi villages. The remaining area comprises Thohoyandou town’s urban periphery. Luvuvhu River forms the main inter-basin water transfer in the catchment area. The river has hydrological importance regarding the monitoring of LULC changes for the various land and water-based activities in the catchment management area (DWA, 2014). The Nandoni Dam basin study area is shown in Figure 3.1.

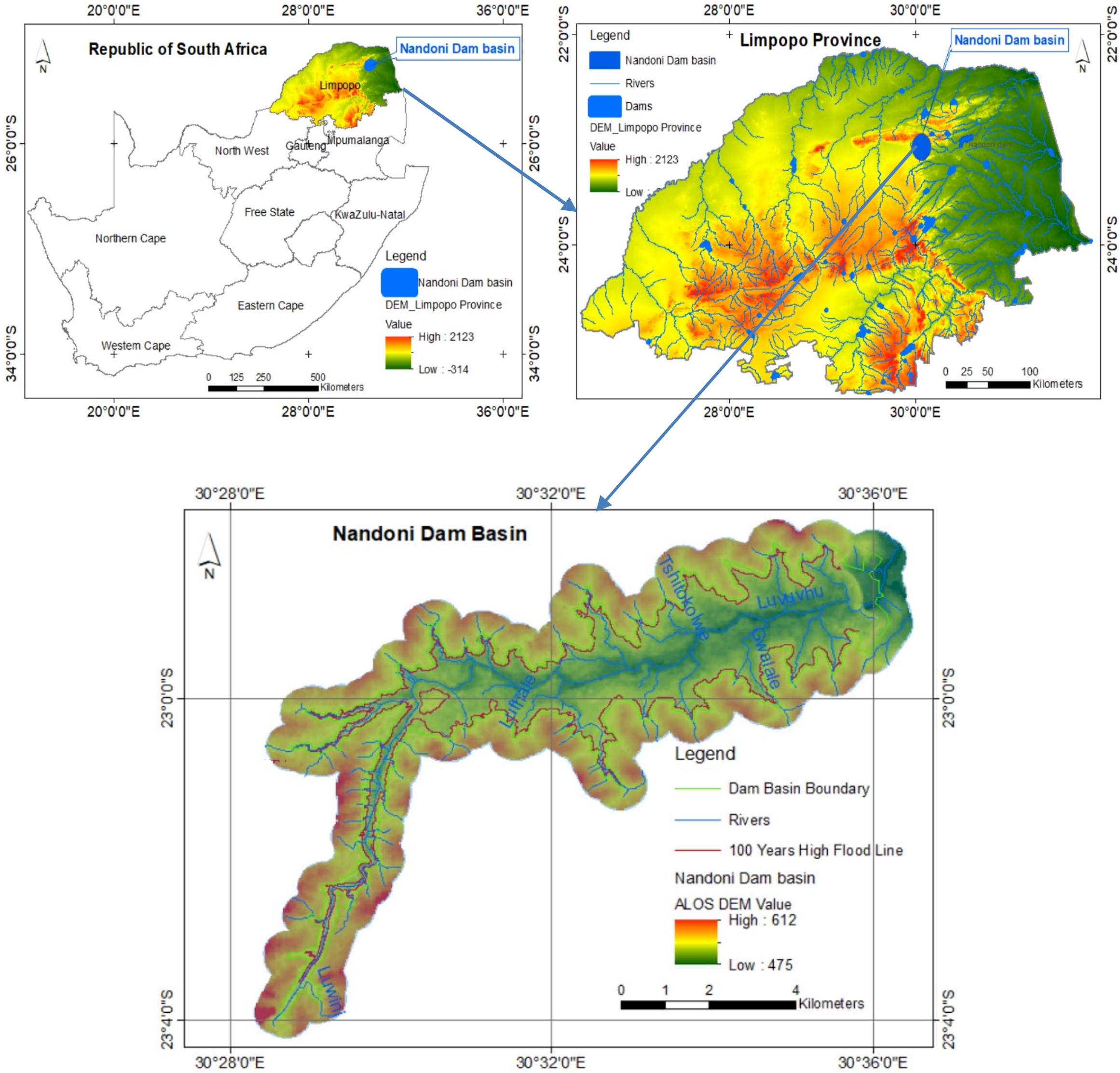

Figure 3.1 Study area - Nandoni Dam basin

Nandoni Dam basin is the largest storage dam basin in the Luvuvhu River catchment. It covers a surface area of approximately 1570 hectares (ha), which stretches approximately 2215 metres (m) horizontally across the dam wall, which is 43 metres high. Nandoni Dam basin spatially covers the largest dam basin catchment area of 1380 kilometres square. It has the highest full water capacity, of 164 million cubic metres, among other dam basins in the area such as the Vondo, Phiphidi, Tshakhuma, Dzindi, Dzingahe, and Damani Dam basins. The Nandoni Dam basin supplies water for various land uses to towns such as Thohoyandou, Makhado, Sinthumule-Kutama, Giyani, Matoks, Middle Letaba, and surrounding villages. The dam basin attracts tourism, fishing activities, and accommodation such as lodges, and resorts in and around the dam basin (DWA, 2012).

The selection of the Nandoni Dam basin as the study area was based on the issues highlighted in section 1.2 under the research problem statement and the potential dynamic LULC change activities in both rural areas and the urban periphery. The dam basin had general land and water activity encroachment characteristics that were common to more than 300 other South African dam basins. The case study area is demarcated by a dam basin boundary buffer line, followed by flood and watermark (shoreline) zones (DWA, 2014).

Nandoni Dam basin is a newly developed dam basin compared to other South African dam basins (NWRS2, 2012; DWA, 2012). Historically, homesteads were evenly distributed along the Luvuvhu River basin. Each family in the area owned its subsistence farming fields and fruit trees. The establishment of the Nandoni Dam basin in 1997 caused the relocation of homesteads from the Luvuvhu River basin to make way for the dam basin.

Due to the relocation of homesteads, there are land disputes that still exist around the Nandoni Dam basin’s impounded land. Land claims are between DWS and the various chieftaincies around the dam basin, such as Chief Ramovha of the Mulenzhe villages and Chief Mphaphuli of the Mphaphuli villages (DWS, 2021). The relocation of homesteads, and impoundment of arable land due to the dam basin, necessitated the mapping of LULC changes to monitor the LULC change effects on the topographical, climatological, and vegetation cover of the Nandoni Dam basin. The topographical features of the study area, which also influence the climatic, hydrological, and vegetation cover, are further described in detail in the following section 3.2.1.

3.2.1 Topography of the study area

The Nandoni Dam basin's topography is characterised by a flat area with low-lying floodplains of the Luvuvhu River flowing in an eastwards direction towards the Limpopo River on the Zimbabwean border. According to the Advanced Land Observing Satellite (ALOS) digital elevation model and the field land survey coordinates, the average elevation ranges from 612 m.a.s.l. (metres above sea level) upstream to 475 m.a.s.l. downstream in the east. The elevation change in topography, as described below, gives rise to varied climatic conditions, vegetation cover, and hydrological characteristics which influences the LULC changes in the study area (DWA, 2012).

The climatic conditions of the Nandoni Dam basin are largely influenced by the topography of the area which ranges in high rainfall and humid areas from the northwest town of Thohoyandou (DWA, 2012). The climate is generally subtropical, although mostly semi-arid to arid at times. Rainfall ranges from 300 mm to 1000 mm per year, with an average of about 800 mm per annum. The peak rainfall period is experienced during summer (December to February) when the average rainfall comprises typically 50 – 60 % of the MAP (mean annual precipitation). The urban area's average daily temperature is approximately 31 Degrees Celsius (ºC), whereas the winter average temperature was estimated at approximately 15 ºC. In the central basin, these temperatures were approximately 2ºC lower (DWA, 2012).

There is diverse vegetation cover in the Nandoni Dam basin characterised by grassland, sparse bushveld shrubs, and trees covering most of the terrain with isolated baobab trees. The dam basin is also characterised by increasing river abstractions from run-off river flow, which causes changes in the river flow as it is the mainstream river in the dam basin (DWA, 2012).

The hydrological, topographical, climatic and vegetation characteristics of the Nandoni Dam basin are important as they have the potential influence on the environmental and geohydrological LULC change phenomenon of spatial and temporal data to be mapped and monitored through this research. To monitor the LULC change phenomenon, this study makes use of research design methods as further presented in section 3.3.

3.3 Research design

The analytical research design method adopted in this study is illustrated in Figure 3.2. The flowchart begins with spatial data collection of remote sensing images, GIS data, and ancillary data. It then illustrates the analytical image pre-processing in the form of geometric and radiometric corrections. The integration of GIS data was then applied in the delineation of the Nandoni Dam basin study area to produce LULC base maps. Subsequently, the image classification and accuracy assessments were carried out towards achieving the classified LULC maps and change analysis as illustrated by the analytical method of image processing flowchart diagram in Figure 3.2.

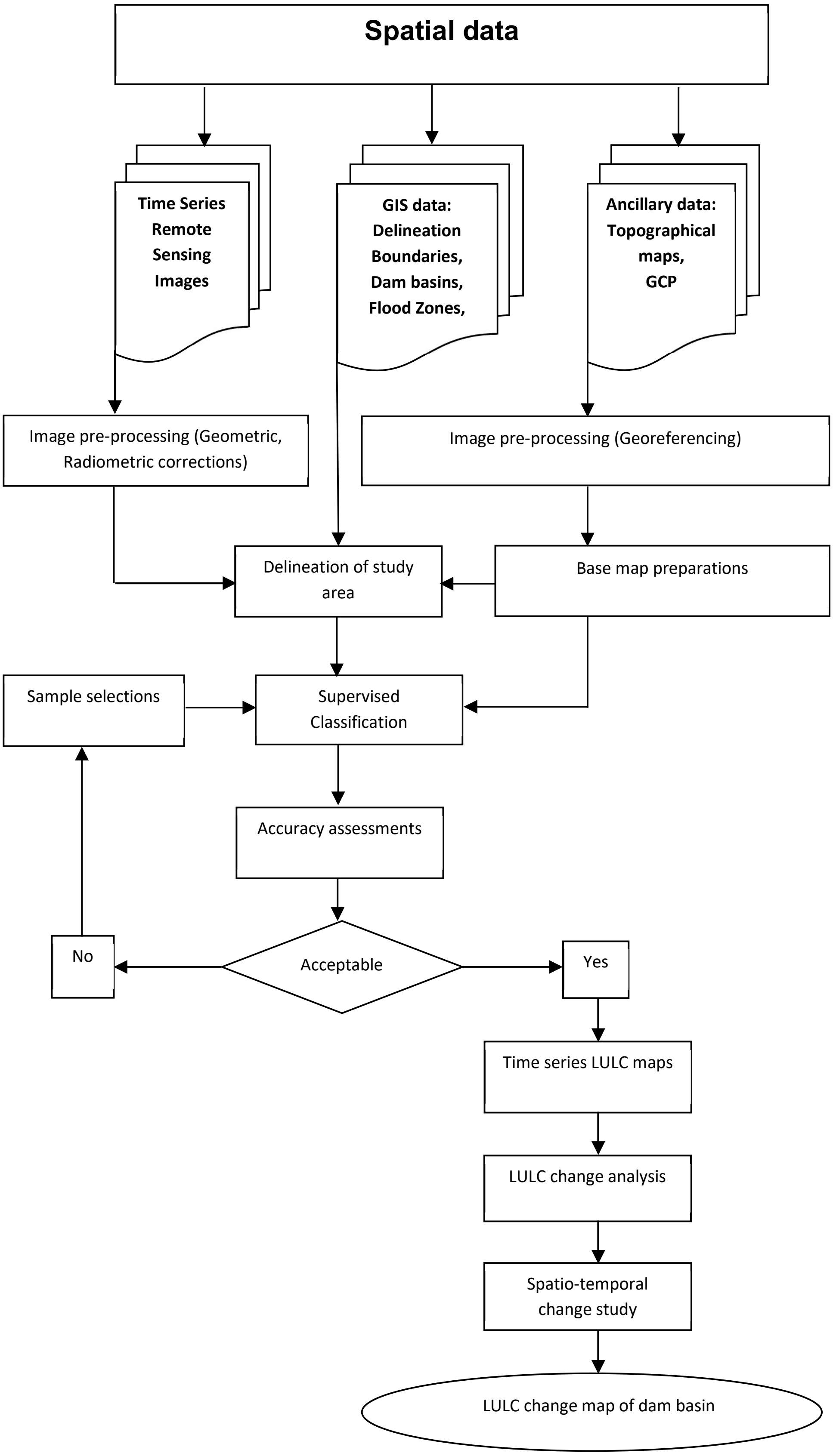

Figure 3.2 Analytical method of image processing

3.4 Spatial data acquisition

The spatial data collected for this study, as illustrated in Figure 3.2, includes remote sensing images for classification purposes, GIS data for delineating dam basin zones and areas of interest, and topographical maps for georeferencing. The remote sensing images collected for this study cover the period before, during, and after the dam basin development. Satellite images utilised in this study to classify the LULC changes in the Nandoni Dam basin include Landsat 5 TM 1997 and 2005, and Landsat 7 ETM+ 2021. The remote sensing images used in this study were freely acquired from the United States Geological Survey (USGS) earth explore websites (https://earthexplorer.usgs.gov/).

The acquisition time of the satellite images was in September of the selected years. September is considered to be in the spring and rainy season in the Nandoni Dam basin area, as such, images that are free from cloud cover were selected. Selecting images from the same period of the selected years helped to reduce the risks of vegetation, phenomenal, and sun-angle seasonal variations rather than the LULC changes themselves (Congalton & Green, 1999). Additional criteria used for the selection of the images include image quality, and availability of scenes (Path/Row) within the desired period, with less or no cloud cover.

The characteristics of remote sensing images considered in the analytical method of image pre-processing and classification of LULC maps are described in Table 3.1 according to their satellite image provider, date, spatial resolution, sensor, path, and row.

Table 3.1 Table of remote sensing images

No.	Image	Date	Resolution (m)	Sensor	Path	Row
(a).	Landsat 5	1997	30 × 30	TM	169	076
(b).	Landsat 5	2005	30 × 30	TM	169	076
(c).	Landsat 7	2021	30 × 30	ETM+	169	076

The downloaded images as listed in Table 3.1 are presented in Figure 3.3 (a), Figure 3.3 (b), and Figure 3.3 (c), respectively. Although the Landsat 7 ETM+ image had some cloud cover, the actual area of interest (AOI) of the image as delineated using GIS spatial data, was free from cloud cover.

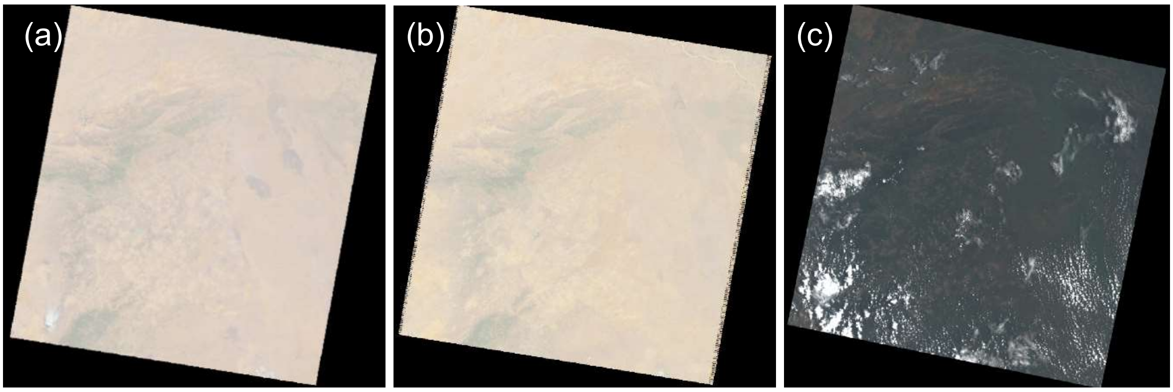

Figure 3.3 Remote sensing images; (a) Landsat 5 image (1997); (b) Landsat 5 image (2005); (c) Landsat ETM+ image (2021)

The GIS spatial data acquired and used to define the AOI on these images are described hereunder, while the three images are further pre-processed in section 3.5.

The Nandoni Dam basin GIS spatial (property) boundaries were obtained from the Surveyor-General's office of South Africa, while Nandoni Dam basin flood and water mark (shoreline) zoning data were obtained from DWS as the land and dam basin custodian (DWA, 2013). The dam basin boundaries were obtained in the form of GIS shape files (feature class), computer-aided design files (CAD), and hardcopy map format. The dam basin boundaries played an important role in the delineation of buffer zones, in the Nandoni Dam basin. The GIS spatial data was used in the delineation of flood zones, and dam basin spatial boundaries, and to produce AOI and cartographic LULC maps from the remote sensing images (Liaqat et al., 2021). The remote sensing image pre-processing and delineation of AOI using GIS spatial data are discussed further in the following section 3.5 and sub-section 3.5.3, respectively.

3.5 Remote sensing image pre-processing

The remote sensing image pre-processing methods used in this study followed a sequential analytical process of geometric and radiometric correction models in one or more images as shown in Figure 3.2 of the analytical method of image processing flow diagram (Jensen, 1996; Coppin et al., 2004; Baboo & Devi, 2011). The pre-processing of satellite images was essential for the accurate classification of LULC change.

For remote sensing image pre-processing, layer stacking was conducted using ERDAS Imagine software to convert the bands into a single layer. The bands of remote sensing images were merged using the layer stack commands in preparation for geometric and radiometric corrections (Liaqat et al., 2021). The objective of geometric corrections during image pre-processing was that all images were located in the same coordinate system with common spatial characteristics. Radiometric corrections, on the other hand, were performed to ensure accurate spectral LULC reflectance values (Green et al., 2000). Geometric and radiometric corrections, together with GIS data integration into LULC change analysis are further described in detail in sections 3.5.1, 3.5.2, and 3.5.3 respectively.

3.5.1 Geometric corrections

To use remote sensing images for LULC change monitoring, the images need to be corrected to common spatial, temporal, and spectral characteristics. In this investigation of the Nandoni Dam basin, geometric corrections were applied to eliminate the inaccuracies and distortions between the picture elements in the image data and the actual location on the ground. The geometric corrections were applied through georeferencing.

The georeferencing was performed using topographical maps as a reference. The topographical maps sheets applied for georeferencing were 2230CD, 2230DC, 2330AB, and 2330BA, with a scale of 1: 50 000, and were obtained from the CDNGI (Chief Directorate of National Geographic Information). Landsat images were then georeferenced using topographical maps into the Hartebeesthoek 94 datum and projected to the Transverse Mercator coordinate system on central meridian or longitudinal section 31 (Jensen, 1996; Coppin et al., 2004; Jensen, 2005; Baboo & Devi, 2011).

The geometric corrections were processed to enable accurate measurements to be done on the LULC maps for distance, polygon area, location, and direction (bearing) information (Jensen, 1996). The other corrections that were applied were the radiometric corrections, which are discussed in the next section.

3.5.2 Radiometric corrections

Radiometric corrections applied in this study required contrast stretching that was computed by applying radiometric adjustment operations from the original image so that it was assigned to the new image and to obtain accurate pixel reflectance values. This computation was applied by loading breakpoints from the original image into the subset images. The advantage of the radiometric adjustment, amongst others, was that the original image and its image spectral signatures were not altered (stretched), but the visual quality of the image was altered (Baboo & Devi, 2011).

Radiometric corrections were also carried out to remove atmospheric errors and adjust contrast stretching to make the original image and the subset images comparable to one another. Each remote sensing satellite image was imported and checked for radiometric characteristics. This process was essential for the visual interpretation of the image data (raster) and the GIS data (vector) to determine training areas together with class characteristics (Jensen, 1996).

Radiometric corrections, also known as intensity interpolation, computed the intensity values or digital numbers (DNs) of the remote sensing image to obtain accurate pixel values. In other words, the radiometric operation extracted the brightness/grey value from the original (distorted) input image and its relocation to the appropriate location in the rectified output image (Jensen, 2005).

After both geometric and radiometric corrections pre-processing were applied, the Nandoni Dam basin study area was then delineated through sub-setting or clipping of the stacked images using GIS’s dam basin boundary data. The GIS layer of the dam basin boundary was integrated into remote sensing data using ArcGIS and ERDAS Imagine software as described below.

3.5.3 GIS data integration in LULC change analysis

Globally, GIS is known for its capabilities in the delineation of study areas and cartographically producing geographical LULC change maps. The GIS capabilities include the ability to integrate GIS data with various spatial-based systems such as ERDAS Imagine (Weng, 2002; IEEE, 1990). This statement is also supported by Demers (2005) and Singh et al. (2021) studies in that, remote sensing serves as the resource data, while GIS is commonly applied in data collection, database storage/management, cartographic mapping, analysis, and mapping of the LULC change classes.

The role of GIS data in this study was to delineate locality maps, dam basin boundaries, and flood zones to formulate the area of interest (AOI), which were pre-processed using ArcGIS software (Johnson et al., 1996). The dam basin boundary spatial data were projected into the Hartebeesthoek 94 datum and the Transverse Mercator coordinate system on the central meridian or longitudinal section 31 so that it can be aligned with various zoning boundaries in the dam basin.

Nandoni Dam basin zoning includes land outside the dam basin’s watermark, which also influences the LULC change situation on the dam basin. The land outside the dam basin’s watermark was defined by buffer layers from the full supply zone (watermark/ shoreline), followed by the high flood zone area, and delineated by the purchase line or the dam basin boundary. The buffer zones are critical to delineate areas not authorised for building structures, restrict unauthorised developments, and delineate government waterworks zones within the dam basin. GIS data showed the capability of delineating dam boundary zones which were useful for sub-setting remote sensing images to focus on the specific AOI during geometric corrections and image classification processes (Singh et al., 2021).

In summary, to integrate different images under the same geometric concept, each raw image was separately stacked and converted into an ortho-image so that it was georeferenced and radiometrically adjusted for integration with GIS vector data (Marakas, 2003; Jensen, 2005). Therefore, all the images were pre-processed through geometric and radiometric corrections. These corrections prepared the images to be ready for delineation using GIS data for integration into LULC change maps for monitoring the Nandoni Dam basin. These corrections allowed seamless integration of remote sensing and GIS data to classify LULC change correctly in the Nandoni Dam basin study area. The LULC change classification is further described in the following section under LULC classification according to the Anderson Classification Scheme using the pixel-based supervised classification methods.

3.6 Land use and land cover classification

This study applied an international standard mapping for LULC classification emanated from the Food and Agricultural Organization of the United Nations (FAO, 2010), and the United State Geological Surveys (USGS), commonly known as the Anderson Classification Scheme, as discussed further in the next section.

3.6.1 Anderson Classification Scheme

The six classes investigated in this study were adopted from a modified version of the Anderson scheme with the interpolation of the SALCCS (CSIR, 2010). The Anderson scheme comprised eight (8) classes, namely, built-up land, bare land, agricultural fields, floodplains, forest, water bodies, tundra, and rangeland. Although this study concentrates on the water bodies (dam basin), the sea/ocean and snow/ice land cover classes do not form the scope of the investigation. This study area is located in the inland area with rare or no snow/ice mappability. The wetland and tundra classes were combined with water bodies and forestry classes respectively, while the rangeland and grassland were covered by agricultural land. This combination reduced the number of classes from eight (8) to six (6) in this study.

The environmental attributes that informed the LULC classes were derived from the potential causes (Tadese et al., 2020), of land-based activities in the Nandoni Dam basin such as a change in hydrology, floodplains occurrence, soil erosion, forestry/logging, and dam basin deformation, stream flow diversion, human settlements, and encroachments. The set of LULC classifiers was tailored to the major LULC and hierarchically arranged according to their mappability and therefore grouped into the following six (6) classes viz: a) water bodies, b) forests, c) floodplains, d) built-up land, e) bare land, and f) agricultural land.

These classes were defined using the delineation of this study area's AOI, and training of sample areas from a combination of base LULC maps, using potential LULC change satellite images (Parihar et al., 2022). GIS spatial data in the form of property boundaries, high flood zones, and dam basin boundary zones were used as buffer areas of interest in preparation for pixel-based image classifications as described hereunder.

3.6.2 Pixel-based image classification

The objective of pixel-based image classification in this study was to automatically categorise all pixels in a digital remote sensing image into LULC classes or themes, as previously discussed in section 2.8 of the literature review chapter. The classifications allowed for the visual interpretation of observed data, and then to automatically classify the features through quantitative supervised pixel-based image classification to assign each pixel to a particular spectral class (Johnson et al., 1996). Whereas other classification techniques such as the object-oriented have the potential to increase the acquisition of more information about the object in urban structured scenes, supervised pixel-based image classification is superior in rural-urban-natural areas such as dam basin environments (Yijun & Hussin, 2003; Xiaodong et al., 2009). The supervised classification and the algorithm used in this study are further discussed below.

3.6.3 Supervised classification

Among the two well-established classification methods (supervised and unsupervised), the supervised classification method is the most essential scientific method used for extracting quantitative information from remote sensing images (Tou & Gonzalez, 1974; Richards, 1993; Keuchel et al., 2003; Jensen, 2005; Desta et al., 2019), and therefore selected as the most applicable method to be used in the Nandoni Dam basin study area.

Whereas unsupervised based classification methods have the potential to acquire more information than supervised classification, it is semi-automated which divorces the analyst from the process and is prone to mis-classification. However, the supervised pixel-based image classification technique is more accurate than other existing image classification methods (Keuchel et al., 2003; Yijun & Hussin, 2003). Supervised classification is the most commonly used pixel-based method, which takes into account the spectral information of LULC classes (Lillesand & Kiefer, 2004). The maximum likelihood algorithm was used for the supervised classification of the images. The mathematical equation of normal distribution that the likelihood (***Lk***) was defined as the posterior probability of pixel belonging to class (***k***) was given as follows:

Equation 3.1 Mathematical equation of Maximum likelihood classifier

$$\mathbf{L_k(X)} = \frac{1}{(2\pi)^{\frac{n}{2}}|\sum_k|^{\frac{1}{2}}} \, exp\left\{-\frac{1}{2}\,(X-\mu_k)\sum_k^{-1}(X-\mu_k)^t\right\}$$

Where,

$\mathbf{L_k(X)}$ = **L**ikelihood of **X** belonging to class **k**

n = number of bands

X = image data of **n** bands

$\mathbf{\mu_k}$ = mean vector of class **k**

$\mathbf{\sum_k}$ = variance-covariance matrix of class **k**

$|\mathbf{\sum_k}|$ = determinant of $\mathbf{\sum_k}$

The supervised classification was further validated through accuracy assessments using a confusion matrix to evaluate the performance of the maximum likelihood classifier, as discussed in the next section.

3.7 Accuracy assessment

Accuracy assessment was used to evaluate the performance of the maximum likelihood classifier regarding Landsat images of the three study periods of 1997, 2005, and 2021. It evaluated the utility of a thematic map against the validity and reliability of the intended LULC change. The accuracy assessment involved different spatio-temporal remote sensing images and spatial datasets that were compared to one another within the maximum likelihood classifier (MLC) of the supervised classification methods (Congalton & Green, 1999; Langat et al., 2021). The inaccuracies in spectral classification were measured from a set of reference pixels. Using the reference pixels, the most widely used method for accuracy assessment was derived from a confusion or error matrix (also called contingency table) (Stehman, 1999).

3.7.1 Confusion matrix

The confusion matrix method is widely considered to be effective in preparing reliable LULC change, irrespective of the spatial, spectral, and radiometric resolution of the remote sensing image differences as discussed in section 2.8 of the literature reviews. The confusion matrix method involves the tabulation of an error matrix to statistically include or exclude non-existent ground features for each class. Furthermore, quantitative statistical measures of overall accuracy known as the Kappa coefficient which indicates the percentage of overall accuracy classification assessment and the Kappa (k) value for the three study periods were then generated (Congalton & Green, 1999).

The error matrices were generated in the form of cross-tabulations of the mapped class versus the reference class (Kuchay & Ramachandra, 2016). The cross-tabulations assisted in the descriptive and analytical statistical analysis. Random sampling for accuracy assessment was also used to compare the results of change detection and the ground truth, which was obtained from topographical maps and field inspection.

The error matrix compared the relationship between known reference data (ground truth) and the corresponding results of automated classification. The Kappa coefficient, which was the common measurement used to demonstrate the effectiveness of the classifications, and the most popular measure in addressing the difference between the actual and change phenomenon, was applied (Chowdhury et al., 2018). The Kappa (κ) statistics were therefore computed to determine the classification accuracy. According to CSIR, (2010) the accuracy of classified images was measured at 80% or more for valid and reliable results using the Kappa Index of Agreement (KIA) classification (Anderson et al., 1976; Lillesand & Kiefer, 2004; Fan et al., 2007; Kuchay & Ramachandra, 2016).

Geometric registration accuracy was also assessed between remote sensing images in terms of Root Mean Square Error (RMSE) (Thakur et al., 2008). Several authors recommended a maximum tolerance of RMSE value of less than 0.5 pixels (Gautam & Narayn, 1983). However, Townshend et al. (1992) identified acceptable RMSE values ranging from 0.2 pixels to 0.1 pixels depending upon the type of change being investigated. Although sub-pixel alignment was desired, a tolerance of between 0.5 to 2.0 pixels was within a generally accepted norm in this type of LULC change investigation as supported by the literature review in chapter 2.

In summary, several pre-, and post-image processing techniques were applied in a series of analytical operations. These include but are not limited to geometric corrections (through georeferencing process), radiometric corrections, the integration of GIS spatial boundary data, and MLC's supervised image classification according to LULC's various classes. The LULC classes were adopted from a modified version of the Anderson scheme with the interpolation of the SALCCS comprising six classes, namely, water bodies, forests, floodplains, built-up land, bare land, and agricultural land. The classification result was validated by error matrices in the form of cross-tabulations accuracy assessment to derive valid LULC classes. The methods and techniques discussed in this chapter are, therefore, applied in the analysis stage as discussed in chapter 4 to achieve the aim, and the objectives to answer the research questions of this study.

4 CHAPTER 4: RESULT AND DISCUSSION

4.1 Introduction

This chapter presents the results of an investigation of the spatio-temporal patterns emanating from chapter 3 to monitor LULC changes in the Nandoni Dam basin. The LULC changes were investigated using quantitative statistical information classified from Landsat TM 1997, 2005, and ETM+ 2021 remote sensing images. The images were pre-processed, sub-set using GIS spatial boundary data, and then classified through a supervised maximum likelihood classifier using ERDAS Imagine software, as outlined in the previous chapter.

The objective of this study was to monitor LULC change patterns using Landsat TM 1997, 2005, and ETM+ 2021 for the three study periods as discussed in the main body of this thesis. As mentioned earlier in section 3.4, the research period to monitor the LULC changes covered the period before the dam basin construction in 1997, during the completion of the dam basin development and beginning of water impoundment in 2005, and after the dam basin was impounded with full water capacity in 2021.

Furthermore, the objective of this section formed the basis of all the analyses carried out in this chapter. The three objectives of this study were to determine LULC changes in the Nandoni Dam basin since its inception using appropriate remote sensing images and GIS data; to assess the amount and rate of LULC changes in the dam basin using a suitable remote sensing classification method, and to determine a suitable spatial analysis method to quantify and map the drivers (causes) of spatio-temporal LULC encroachments in the dam basin.

To achieve these objectives, the remote sensing images were classified, and the results were presented in the form of classified maps, statistical charts, and tables. Table 4.1 represents the results of LULC change analysis for the three study periods 1997, 2005, and 2021 respectively as classified in the previous chapter. The LULC changes were tabled according to the class, the area measured hectares (ha), and the overall percentage (%) of land usage and land covered. The table of LULC change analysis was further presented in a histogram bar chart in Figure 4.4. To validate the remote sensing classifications, an accuracy assessment was carried out with results presented in section 4.4, while the causes of LULC changes are outlined in section 4.5. The rate of change and the impacts of encroachments into the dam basin emanating from LULC changes as classified and presented in Table 4.1 were analysed further in section 4.6 of this chapter.

4.2 Classification of LULC change patterns

This section presents the results of the classification of LULC patterns from the six (6) classes, namely, water bodies, forests, floodplains, built-up land, bare land, and agricultural land as pre-processed in previous section 3.5 and further analysed in this chapter in section 4.3. Before the classification process for the six LULC classes commenced, the supervised MLC's image classification method took the following summarized analytical procedure:

- Firstly, the geometrically and radiometrically corrected image was displayed on ERDAS software, and the visible channel, near-infrared channel, and other channels were also associated with the respective six LULC classes. Available features were determined as a set of classes into which the image was segmented.

- Secondly, representative training samples for each of the desired classes were chosen from the colour composite image to form training data.
- Thirdly, the training samples were used to estimate the mean vectors and covariance matrixes for the MLC classifier and to determine the properties of the multivariate normal models.
- Fourthly, the trained classifiers were used to classify every pixel in the image into one of the desired classes.
- Lastly, the decision rule for the supervised maximum likelihood algorithm was applied. As a result, a colour-coded classified image was produced, where classes that did not meet the above decision rule were classified as unknown classes. The number of pixels and area for each class were estimated and shown as statistics for each class and tabled for further validation through accuracy assessments.

The results of this remote sensing image classification are figuratively presented in Figure 4.1, Figure 4.2, and Figure 4.3. The LULC change map represented in Figure 4.1 shows the classification before the Nandoni Dam basin was constructed in 1997. The image represents stream flows before dam basin impoundment during that period. Figure 4.2 represents the Nandoni Dam basin's LULC change map soon after the construction was completed and started with water impoundment in 2005. Subsequently, Figure 4.3 represents the LULC change map after the dam basin was impounded with full water capacity in 2021. The results of the classified images are discussed in sub-section 4.3.1.

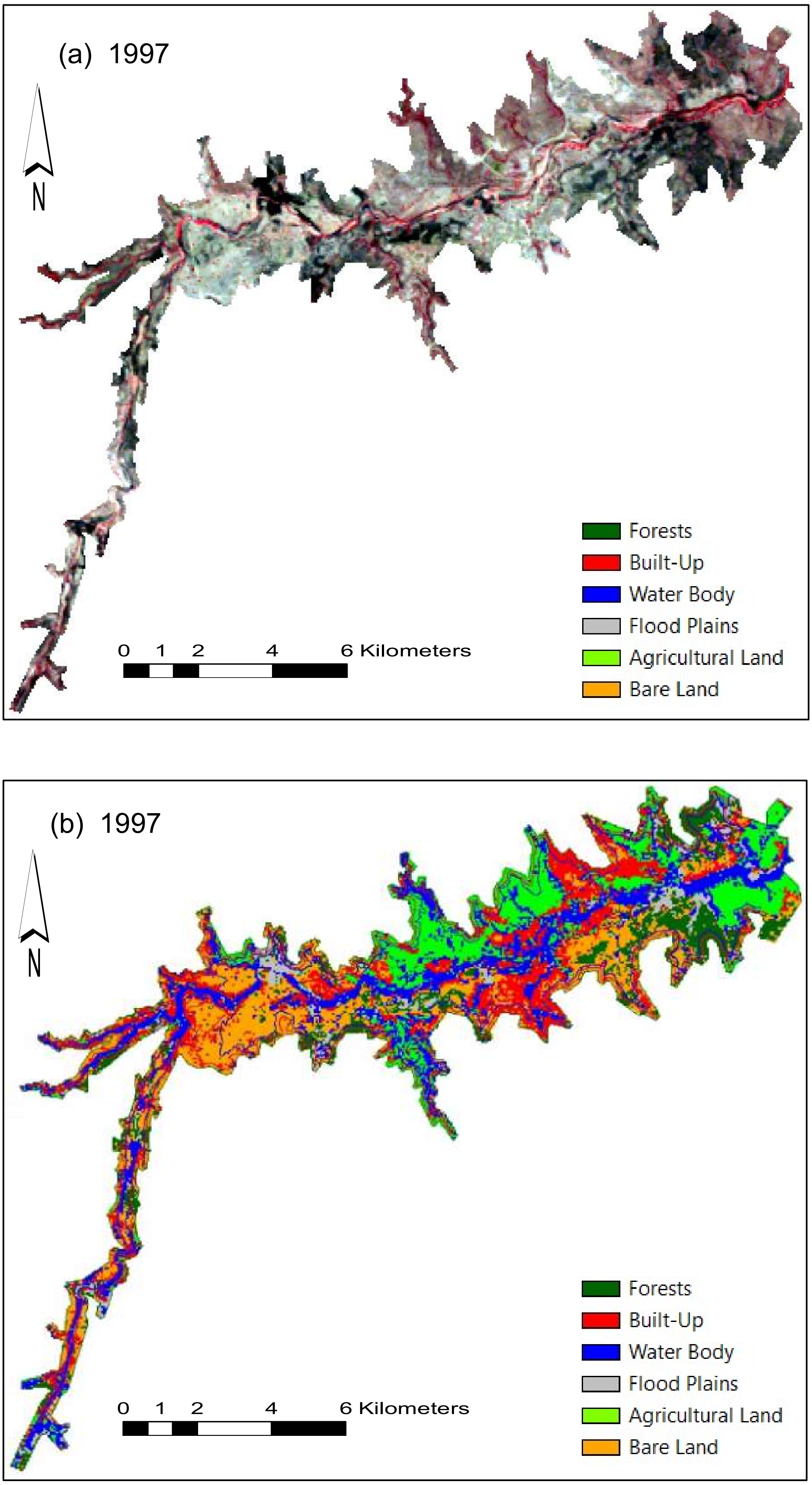

Figure 4.1 LULC change classification (1997); (a) Landsat TM 1997 before classification; (b) Landsat TM 1997 after classification

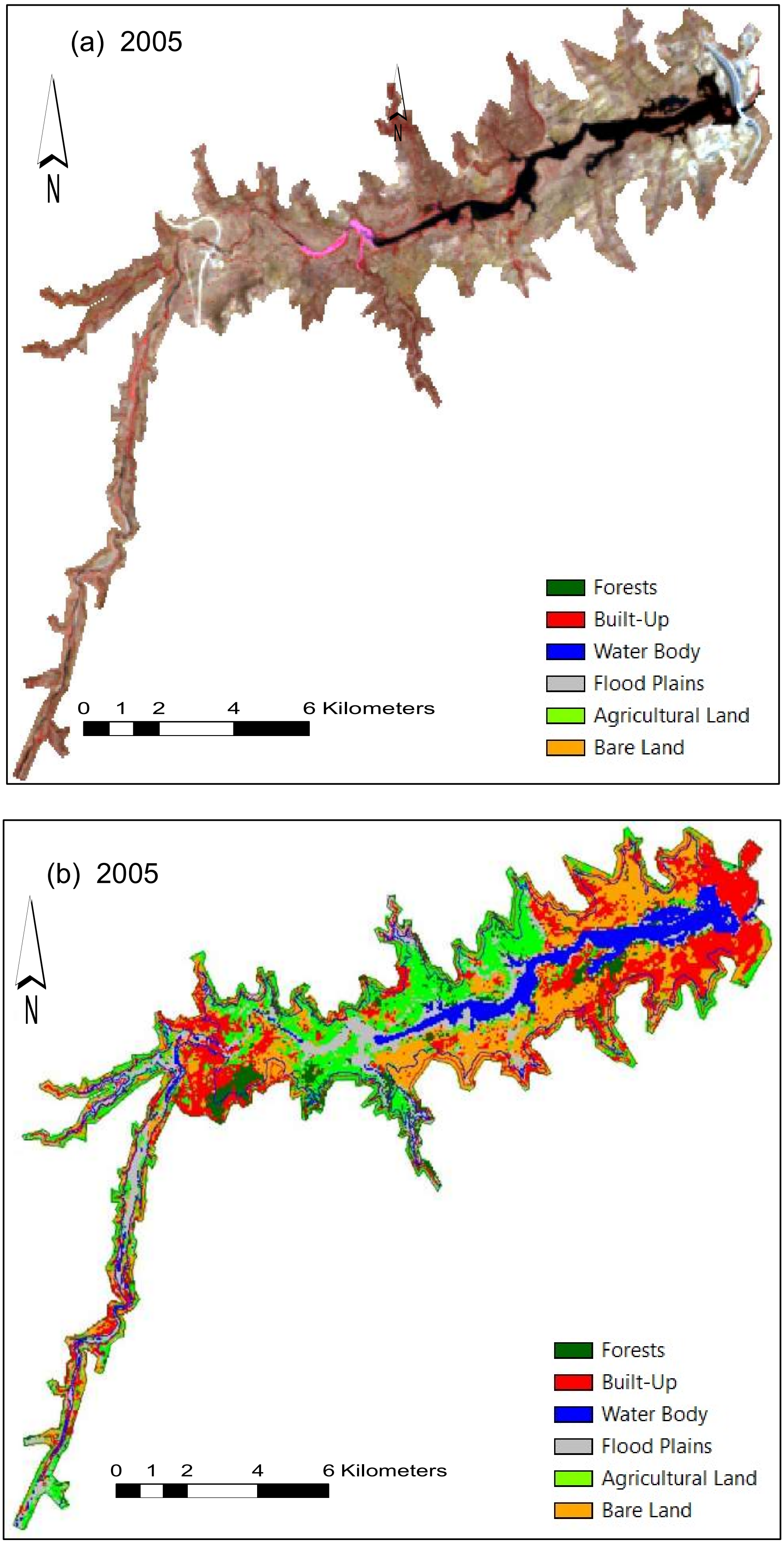

Figure 4.2 LULC change classification (2005); (a) Landsat TM 2005 before classification; (b) Landsat TM 2005 after classification

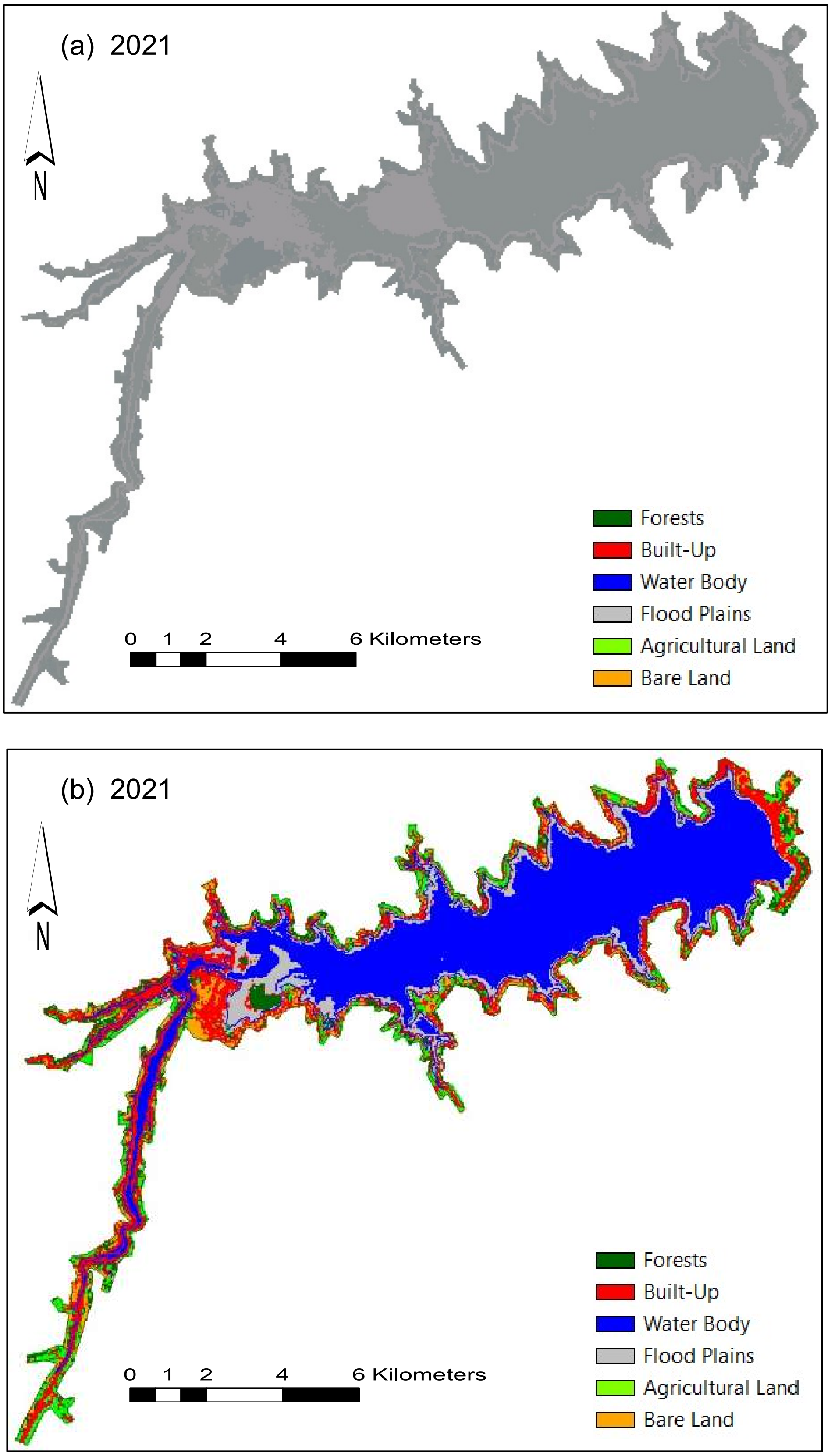

Figure 4.3 LULC change classification (2021); (a) Landsat ETM+ 2021 before classification; (b) Landsat ETM+ 2021 after classification

4.3 Land use and land cover change analysis

As discussed in section 4.2, following the application of the decision rule for the supervised maximum likelihood algorithm, a colour-coded classified image was produced through segmentation, wherein the number of pixels and areas for each class were estimated for each study period. The results are shown as statistics for each class in Table 4.1 in terms of hectares (ha) and percentages (%) of land usage and land coverage in the dam basin for the three study periods 1997, 2005, and 2021. The LULC change classification results presented in Table 4.1 are also shown on the histogram bar chart in Figure 4.4.

Table 4.1 LULC change classification (1997-2021)

Year	**1997**		**2005**		**2021**	
Classes /Area/Percentage	**ha**	**%**	**ha**	**%**	**ha**	**%**
Water Body	578.97	21.95%	219.78	8.33%	1 203.30	45.61%
Forests	334.98	12.70%	173.61	6.58%	195.93	7.43%
Floodplains	144.09	5.46%	366.12	13.88%	314.55	11.92%
Built-Up	482.31	18.28%	566.01	21.46%	504.45	19.12%
Bare Land	592.47	22.46%	667.17	25.29%	172.26	6.53%
Agricultural Land	505.35	19.16%	645.48	24.47%	247.68	9.39%
Total Area	2 638.17 (ha)					

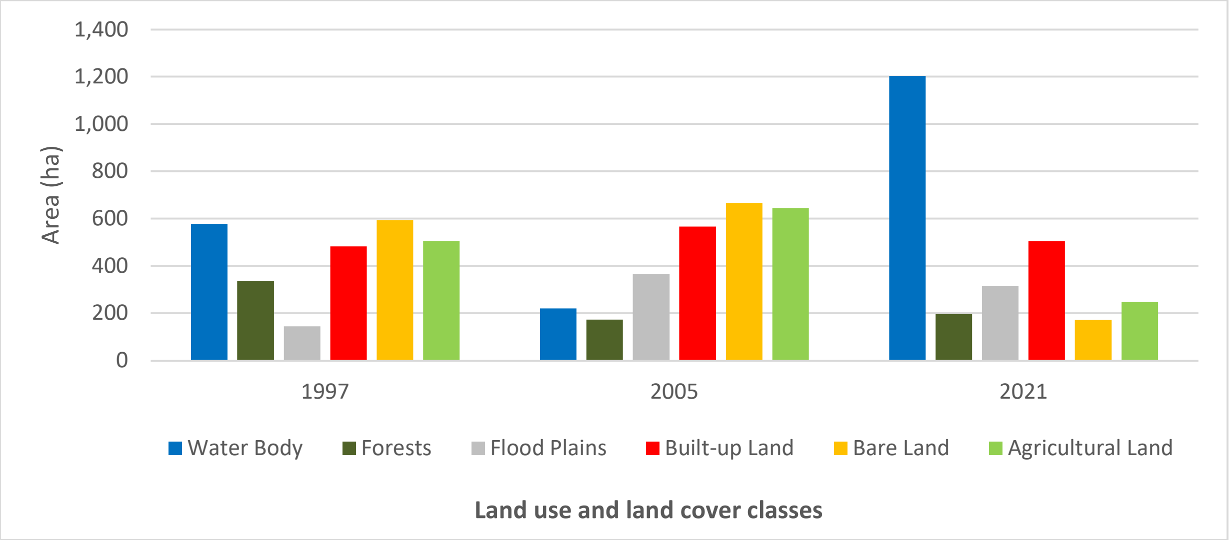

Figure 4.4 LULC change classification 1997 - 2021

The results shown in Table 4.1 and Figure 4.4 of the histogram bar chart are further discussed in the next sub-section, 4.3.1.

4.3.1 Discussion of the land use and land cover change analysis

The above classified Landsat TM and ETM+ images indicated that there was a significant change in all classes during the periods 1997, 2005, and 2021 as shown in Table 4.1, Figure 4.1, Figure 4.2, and Figure 4.3, respectively. The major changes were the water bodies that changed from 21.95% before the dam basin, to 8.33% during construction in 2005, and then drastically increased to 45.61% after the dam basin completion in 2021. The catchment of the water bodies covers 1 203.30 ha amounting to almost half (45.61%) of the total dam basin catchment area (2 638 ha). The field investigation confirmed that the huge change in the water bodies was due to water scattered all over in 1997, which was reduced due to open channels during construction in 2005 and the damming up of water after the construction of the dam wall in 2021. These changes are supported by the photographs in Figure 4.5.

The LULC classification in Table 4.1 and Figure 4.4 (bar chart) showed a decrease in forest cover from 12.70% in 1997 to 6.58% in 2005 and a similar trend of 7.43% in 2021. The floodplains had more than doubled their existence in the dam basin from 5.46% in 1997 to 13.88% and 11.92% in 2005 and 2021, respectively. The doubling in the size of floodplains’ land cover was because of the damming up of water upstream during heavy rains and also over spilling of water downstream due to flood occurrence observed during the field investigation. These changes are also supported by the photographs in Figure 4.5.

These observations were also validated through the DWS's flood gauging station number A9R004 in the dam basin, which recorded evidence of dam wall overflow reading measured at 1 311 cubic metres per second (m³/s) which amount to flooding during the year 2021, as shown in Figure 4.5.

Figure 4.5 LULC change dynamics in the dam basin; (a) picture of LULC during construction in 1997; (b) picture of LULC after construction in 2005; (c) picture of LULC at full water capacity in 2021

Figure 4.5 illustrates the reflection of LULC changes observed during field investigations as represented through photographs of the parts of the Nandoni Dam basin versus the statistical image classification information in Table 4.1. Table 4.1 indicates that agricultural land use/cover fluctuated from 19.16% in 1997, to 24.47%

in 2005, and decreased to 9.39% in 2021. The agricultural land use/cover trend showed that it was mainly covering the middle-upper basin and the north-eastern part of the dam basin in 1997, then changed to the middle-upper and middle-lower stream of the dam basin and started to cover up along the dam basin boundary in 2005. Agricultural land further changed its land cover in the form of a lining shape around the dam basin boundary in 2021. During the field investigation, it was observed that the fluctuations were caused by the reduction of the original agricultural land for subsistence farming, which was now submerged under water, the clearing of dam basin debris, grading of access roads, construction of dam walls, and treatment waterworks constructions, as shown by the photographs in Figure 4.5. The verification and field inspection described in this paragraph was further evaluated for their validity and relevance in terms of accuracy assessment in the next section 4.5.

4.4 Land use and land cover change accuracy assessments

To validate the correctness of the LULC change analysis, an accuracy assessment was conducted using topographic maps and unclassified Landsat TM and ETM+ images (Singh et al., 2021). The accuracy assessment results obtained ranged between 80% to 90% for overall accuracy statistics as shown in Table 4.2. Visual inspection of the original Landsat data listed in chapter 3 under Table 3.1 (Table of remote sensing images) validated a quantitative level of consistency and similarity in the dam basin.

LULC cross-reference indicated that there was good consistency on or above 80% across all classes (Parihar et al., 2022), especially the water body and the built-up land, due to their change in density. The good and consistent performance of the accuracy assessment classifier was presented according to the year investigated, overall accuracy percentage (%), and the Kappa values (k) in Table 4.2.

Table 4.2 Classification accuracy assessment and Kappa statistics

Year	**Overall Accuracy (%)**	**Kappa Value (k)**
1997	90.00	0.87
2005	80.00	0.74
2021	90.00	0.86

The area used for accuracy assessment was the sub-set classified AOI image verified using the stacked Landsat 5 TM and Landsat 7 ETM+ images (Singh et al., 2021). Accuracy assessment was performed using ten (10) randomly selected ground truth points for each of the six classes (60 randomly selected ground truth points in total) with a colour scheme as a reference to the master or original image, independent from training areas (Islam et al., 2021). All the classified images showed a good overall accuracy of 80.00 % to 90.00%. These good assessments gave further confidence in the quality of the derived multi-temporal classification that all six classes had performed well with a very good overall accuracy (Congalton & Green, 1999). The assessment indicated that all the classes were accurately classified to determine the causes associated with the LULC changes as described in the next section.

4.5 Causes of land use and land cover changes

The causes of LULC changes and their impacts were variable from before, during, and after dam basin development for each class (Tadese et al., 2020). Although the analytical research methods of this study did not make use of interviews to collect data, the LULC dynamic classification results in section 4.2 and analysis in section

4.3 correlated with the views of local communities, the walk-about observations during field investigation, and when analysing the classified remote sensing images.

The views of DWS water authorities, local households, and the land disputes meetings conducted by Public Protector, Black Dot Valuers, Office of Valuer-General land valuations reports (DWS, 2021), and field observations as represented by the photographs in Figure 4.5 confirmed that both natural processes and man-made activities have caused LULC changes in the dam basin. The remote sensing image classification results of this study, supported by a series of these views, showed that various causes were related to natural and man-made processes as driving causes of LULC changes in the Nandoni Dam basin.

The water body was the main land cover change caused by 1 203.30 ha (45.61%) coverage in 2021. This was due to the dam basin being fully impounded with water as the main purpose of the dam basin. Built-up land was the second largest land cover change in the Nandoni Dam basin (after the water body) with a land coverage of 504.45 ha (19.12%). According to the field investigation observations and as shown in the photographs in Figure 4.6, these LULC changes were mainly driven by built-up land developments in and around the dam basin which resulted in the demand for land (lodges), and water (for recreational facilities).

Floodplains came third with a land coverage of 314.55 ha (11.92%). Agricultural land and forest followed with 247.68 ha (9.39%) and 195.93 ha (7.43%), respectively. Lastly, bare land coverage was measured at 172.26 ha (6.53%) coverage and classified as the least of the LULC change causes.

The causes of these changes varied from one class to the other, and from one study period to the next (Tadese et al., 2020). According to the data presented in Figure 4.5 (a), read in conjunction with Table 4.1 and Figure 4.4, there was a significant forest cover of 334.98 ha in 1997, compared to Figure 4.5 (b) which shows as less than 173.61 ha in 2005. This then increased to 195.93 ha in 2021 as seen in Figure 4.5 (c). The field investigation observations and consultation with the DWS authorities (DWS, 2021), at the dam basin, showed that forest was cleared to make way for the dam basin, access roads, dam wall, the water treatment works and some forests were submerged under water during 2005, before it naturally emerges again above water in 2021, as shown by the photographs in Figure 4.5.

Figure 4.4, Figure 4.5, and Table 4.1 data indicate that built-up land showed evidence of a 482.31 ha spatial change cover pattern from the centre of the dam basin in 1997, which reshaped to 566.01 ha built-up land cover towards the eastern part in 2005 and then decreased to 504.45 ha that covers along the dam basin boundary in 2021. The field observations, Public Protector, Black Dot, and Office of Valuer-General land valuations reports (DWS, 2021) confirmed that the built-up land in the centre of the dam basin was occupied by the settlements before impoundment, and the eastern part of the built-up land was observed as a dam wall, water treatment plant, and operational offices construction (Figure 4.5), while the changes along the dam basin boundary were caused by the access road and the buildings for accommodation camps such as lodges (see Figure 4.6).

The classification showed that although the built-up land and agricultural land had remained noticeable within the dam basin between 2005 and 2021, their presence in the dam basin was regarded as an encroachment that put land and water resources at risk as they tend to increase the severity of floods and consequently sediment deposits into the dam basin. The LULC changes were caused by land encroachments and unlawful water use (lodges and various accommodation) respectively as neither was legally demarcated/allocated the land or licensed for water use (NWA, 1998). According to field investigations, there was evidence of deforestation which was characterised by forest clearance as shown by the photographs in Figure 4.5. This forest clearance had the potential to influence soil erosion and consequently sediment deposit which in turn causes siltation and reduction of water capacity in the dam basin (Mariye et al., 2022).

Built-up land and agricultural land change trends showed as being lower in 1997 with 482.31 ha and 505.35 ha respectively, but after completion in 2005, these increased, covering even bigger areas of 566.01 ha and 645.48 ha, hence the encroachments around the basin as per the classified images. Although built-up decreased slightly from 566.01 ha to 504.45 ha in 2021, agricultural land decreased by almost half from 645.48 ha to 247.68 ha in 2021. Built-up land and agricultural land are considered one of the main encroachments into the Nandoni Dam basin. According to the dam basin's boundary zones, it was evident that built-up land and agricultural land activities encroachments were the major threat to the dam basin's management because they influence siltation through flooding (floodplains) and result in sediment deposits.

According to field investigations, agricultural land encroachments into the dam basin were caused by agricultural activities in search of water bodies, bare land, floodplains, and forest areas that were relatively rich, fertile, and moist soils around the dam basin. However, built-up land encroachments were mainly caused by socio-economic activities such as fishing camps, boat slipways, lodges, and guest houses being built around the dam basin’s waterfront as shown by the annotated photographs in Figure 4.6.

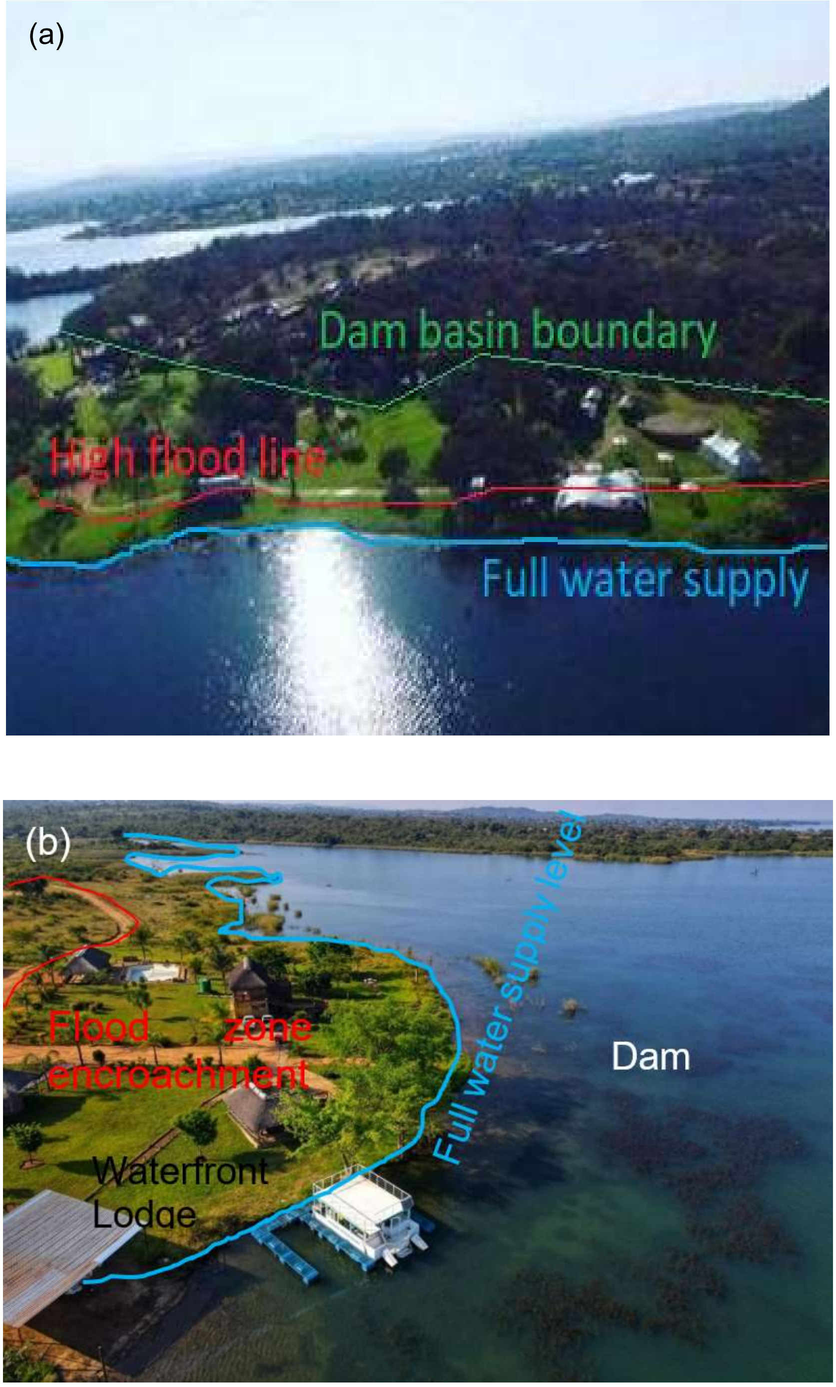

Figure 4.6 LULC change dynamics after dam basin development; (a) picture of dam basin encroachment; (b) lodge encroachments into a flood zone

The rate of built-up land encroachments into the dam's basin full water supply line (shoreline) was increased for the three-study period as discussed in the next section.

4.6 Rate of land use and land cover change

The LULC statistics were calculated and summarised to monitor the rate of changes that occurred between 1997 and 2005 (8 years) and 2005 to 2021 (16 years) as shown in Table 4.3. A percentage rate of change was a useful indicator to show the increase or decrease of LULC in the dam basin between these study periods 1997 – 2005 – 2021 amounting to 24 years. The rate of change was calculated using the formula: rate of change = (PresentYearValue - PastYearValue)/PastYearValue * 100. For example, the rate of change in water bodies in hectare percentage for the 1997 to 2005 period was calculated as follows: (219.78 - 578.97)/578.97*100 = -62.04%. The rate of LULC change in the Nandoni Dam basin is shown in Table 4.3 and bar chart Figure 4.7, respectively.

Table 4.3 Rate of change in LULC classification (1997-2021)

	Rate of change (%)	
Classes	**1997 – 2005 (8 years)**	**2005 – 2021 (16 years)**
Water Body	-62.04%	447.50%
Forests	-48.17%	12.86%
Floodplains	154.09%	-14.09%
Built-up Land	17.35%	-10.88%
Bare Land	12.61%	-74.18%
Agricultural Land	27.73%	-61.63%

From the data represented in Table 4.3, it can be deduced that water bodies decreased drastically by -62.04% within eight (8) years between 1997 – 2005 but increased to 447.50% in the next sixteen (16) years between the 2005 – 2021 study period. Forests also followed a similar trend with a decrease of -48.17% in the 1997

– 2005 period and increased to 12.86% during 2005 – 2021. Floodplains, built-up land, bare land, and agricultural land all showed an increase for the period 1997 – 2005, and interestingly, they all showed a decline in the period 2005 – 2021.

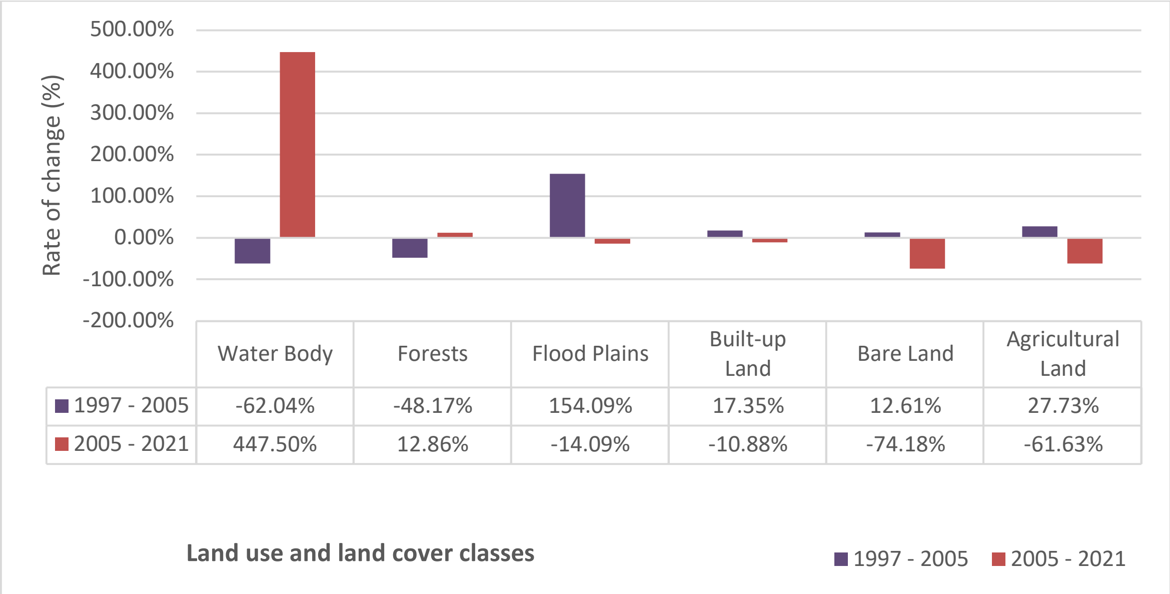

Figure 4.7 Rate of change in LULC classification (1997–2021)

The rate of LULC change presented in Figure 4.7 (bar chart) was supported by field investigations and consultation with DWS water authorities in the Nandoni Dam basin (DWS, 2021), which indicated that the increase in the rate of floodplains, built-up land, bare land, and agricultural land during 1997 – 2005 was mainly due to the conversion of forest cover into agricultural land for subsistence farming. The increase in the rate of change was also attributed to safeguard plots to be evaluated for expropriation with compensation, including illegal sand mining for bricklaying and construction of the dam, and buildings (houses, buildings, and roads) respectively as validated by the Public Protector, Black Dot and Office of Valuer-General land valuation reports (DWS, 2021). However, during the 2005 – 2021 period, an agricultural land decrease of -61.63% was mostly lost due to water impoundment covering 447.50% in the Nandoni Dam basin. The large percentage of water impoundment had caused a significant amount of LULC change impacts and attracted encroachments into the dam basin. These impacts are further discussed in the following section 4.7.

4.7 Impacts of LULC change encroachments into the dam basin

Land use and land cover changes have a significant effect on water conservation, supply capacity, and demand from the dam basin. The information obtained from LULC change classification can help policymakers and spatial managers to better understand the impacts and rate of encroachment patterns into the dam basin. The rate of LULC changes from the classified Landsat TM and ETM+ image in section 4.6 showed that there was LULC change observed at a variety of spatial and temporal scales before, during, and after dam basin water impoundments.

The LULC changes were caused by both humans and nature, resulting in various kinds of land use activities to secure socio-economic needs that caused encroachments into the Nandoni Dam basin as shown in Table 4.1, Figure 4.2, and Figure 4.3. According to the data represented in Table 4.1, Figure 4.2, and Figure 4.3, although water bodies had increased very high from 219.78 ha in 2005 up to 1 203.30 ha in 2021, they were the main reason for dam basin development and therefore confirm that the LULC monitoring using remote sensing images was effective (Islam et al., 2021). Forest change was fairly stable at 173.61 ha and 195.93 ha between 2005 – 2021, while bare land reduced by -74.18% from 667.17 ha to 172.26 ha for the same period. Bare land had relatively less impact on encroachment, as such areas were usually regarded as land reserved for dam basin management. However, dense forests in the dam basin demand too much water which negatively impacts on the dam basin’s water conservation capacity (Tadese et al., 2020).

From the LULC change classifications shown in Figures 4.1 to Figure 4.3, it was evident that the 2021 built-up land around the dam basin and agricultural land in the periphery were the dominant encroachments in the Nandoni Dam basin with approximately 504.45 ha and 247.68 ha, respectively.

Nandoni Dam basin encroachment resulted in several hydrological and economic impacts. Hydrological impacts of the LULC changes in the dam basin were that clearance of forest in favour of access roads, dam wall, and treatment work, influence increased sediment deposit which negatively reduces the dam basin water capacity. Likewise, economic encroachment affects restrictions in the dam basin resulting in the reduction of socio-economic activities such as tourism, fishing, boat camps, and recreational activities such as picnics.

In summary, this chapter analysed and presented the results of the LULC change classification and accuracy assessments to validate the relevance of the image classifications. It further analysed and described the causes of encroachments, the rate of LULC change, and subsequently the impacts of LULC change and encroachments into the dam basin. The results and analysis findings are further summarised in the conclusion chapter 5.

5 CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

The results of this study as presented in the previous chapter demonstrate the ability of remote sensing images and GIS data in monitoring LULC changes in the Nandoni Dam basin. This chapter presents the conclusions, recommendations, and possible future research study opportunities relating to monitoring dam basins remotely.

5.2 Conclusions

The Nandoni Dam basin study presented various LULC change patterns and encroachment trends with characteristics that were common to other dam basins, mostly in South Africa. This study shows that land cover changes due to land use encroachment activities are becoming a threat to water conservation in the Nandoni Dam basin and similar dam basins in South Africa. It is, therefore, important to devise procedures to remotely monitor these changes so that the threats can be mitigated. Whereas there is a general understanding of encroachments in the Nandoni Dam basin since its inception in 1997, there are significant gaps in the data, information, and knowledge of the extent of the LULC change and the mapping of such encroachments (Dean et al., 1995; Driver et al., 2005; DWA, 2014; Daba & You (2022). Furthermore, the spatio-temporal extent of encroachments in dam basins has been identified as a national priority for further research (DEAT, 2004; DWA, 2012), hence the need for the rationale behind and relevance of this study.

This research aimed to apply remote sensing and GIS methods to monitor LULC change patterns by using remote sensing images and GIS data to quantify the spatio-temporal LULC change patterns in the Nandoni Dam basin. This was achieved by pursuing the objectives of this research as set out in chapter 1.

In achieving the aim of this study, the first objective met was to determine LULC changes in the Nandoni Dam basin since its inception using appropriate remote sensing images and GIS data. This study considered various remote sensing image sensors to cover the twenty-four (24) year time span of this study (1997 – 2021). However, the final results of this study indicate that the appropriate images were the Landsat 5 TM images for the years 1997 and 2005, and Landsat 7 ETM+ images for the year 2021 with a spatial resolution of 30 m.

The images from sensors such as SPOT and Sentinel-2 were also considered but found to be less useful in this investigation for various spatio-temporal limitations. Limitations are attributed to Sentinel-2's unavailability for the period 2021, and its limited image coverage gaps for the period before the establishment of the Nandoni Dam basin in 1997 and completion in 2005, as it was launched in 2015 (Mandanici & Bitelli, 2016). While Landsat and Sentinel-2 images present user-friendly policies and were available for free if not limited costs (Singh et al., 2021), SPOT image availability was guided by strict user-pay policies which were costly to derive value-added products.

The second objective of this study was to assess the amount and rate of LULC changes in the dam basin using a suitable remote sensing classification method. In achieving this objective, various classification methods were also presented in the literature review in chapter 2, and further streamlined in the analytical methods of image processing in chapter 3. Supervised maximum likelihood classifier was preferred over any of the unsupervised classification techniques due to several advantages (Jensen, 2005; Desta et al., 2019).

The advantage of supervised image classification was that the image analyst trains the software to recognise spectral values or signatures associated with the training sites (Kucukmehmetoglu & Geymen, 2007; Coskun et al., 2008). Whereas unsupervised classifications pose a minimum opportunity for human errors as their processes were semi-automated and unique classes were recognised as distinct units and no training process was required (Skidmore, 1989; Shukla & Gedam, 2018); what’s more, they lacked guidance and direction from the analyst, which divorced the analyst from being able to be involved in a step-by-step process. The unsupervised classifications’ further drawback characteristics were that they were prone to mis-classification (Skidmore, 1989; Soofi & Phillips, 2005; Shukla & Gedam, 2018). Although mis-classifications may be reduced by adding training samples at later stages (Yijun & Hussin, 2003) and using additional geographical (GIS) data to improve the classification accuracy (Gebremicael et al., 2017), these additional countermeasures were deemed to be time-consuming, tedious exercises and did not guarantee the optimum valid classification accuracy (Singh et al., 2021).

Compared to other classifiers, MLC was the most commonly used and preferred method, for its simplicity yet statistically effective classifiers, which did not require the user to set any free or unknown parameters (Langat et al., 2021). It was capable of achieving valid separation of classes, while other methods were characterised by semi-automated iteration which was prone to mis-classifications (Keuchel et al., 2003; Soofi & Phillips, 2005).

The third and final objective addressed by this research was to determine a suitable spatial analysis method to quantify and map the drivers (causes) of spatio-temporal LULC encroachments in the dam basin. The quantification of LULC change data of the Nandoni Dam basin was an important milestone for the water authorities. It has been widely acknowledged that LULC changes are an important driver of environmental change at all spatial-temporal scales in some of the South African dam basins (NWRS2, 2012). However, spatio-temporal LULC change datasets for dam basins are limited as they are mostly done on conventional field survey methods. Often, conventional LULC change monitoring studies tend to describe its existence without specifying the “what, how much, and where” questions of LULC change that have occurred.

The analytical methods and procedures adopted in the research design (section 3.3) of this study proved that remote sensing and GIS offer efficient, safe and expeditious means of monitoring LULC patterns in dam basin areas, thus providing timeous and strategic information into the dam basin decision-making process. The results from this study successfully answered the research questions, quantified as to what LULC classes have changed, and determined when and where the changes occurred spatio-temporally, as measured by the percentage rate of change in land coverage, and provided evidence of why encroachments occurred in the dam basin. These answers made it easy to draw up recommendations for this study, as presented in the next section.

5.3 Recommendations

The remote sensing technique with the integration of GIS data is a recommended time- and cost-effective way to monitor LULC changes in the Nandoni Dam basin. It is a very convenient and recommended approach to analyse the LULC change patterns of dam basins in particular. The application of remote sensing and GIS techniques is a semi-automated process, starting from the classification of image pixels to estimate LULC change areas. On the other hand, conventional survey methods, field visits, and static historical records to monitor LULC change patterns are time-consuming, and expensive because they require extensive survey data collection which is no longer compatible with the rate of encroachment dynamics into dam basins. This study concludes that LULC changes, therefore, require modern technologies such as remote sensing and GIS data which cover a large mapping area more effectively than traditional mapping methods (Osborne et al., 2001; DWA, 2014).

Before this investigation, limited information was available concerning the LULC change patterns on a dam basin scale in the Republic of South Africa (RSA). The study improved the understanding of factors causing LULC changes and encroachments in the Nandoni Dam basin, which is important in preserving the intended purpose of the dam basin’s water conservation. This study recommends the use of a supervised pixel-based (maximum likelihood) classifier when classifying images to assist the water resources management agencies, government departments in charge of water resources, and water authorities to make informed spatio-temporal decisions to preserve the intended purposes of water conservation in dam basins (Matlhodi et al., 2021).

More importantly, the results provide considerable information on the potential LULC change patterns. They also provide a point of departure for future dam basin monitoring efforts, insight into data collection, and for spatial planning. Water scientists, engineers, and the government can use these results to promote monitoring systems for dam basins. Furthermore, this study recommends remote dam basin monitoring methods which present the water authorities with an opportunity to prevent LULC change impacts such as floods, deforestation, and to plan remedial actions for the LULC change phenomenon.

The results of using remote sensing images and GIS data in this study are recommended to assist hydrologists (water conservation), surveyors (land parcels and servitudes), engineers (constructions), and water bodies to timeously monitor dam basins. The LULC change monitoring using remote sensing images and GIS data also emphasised the ability to make spatio-temporal decisions and monitor encroachments into the dam basin, thereby limiting the impacts of soil erosion (Islam et al., 2021), dam basin deformation and floods to reduce sediment/silt deposits.

The analytical research method and the results of this study which used Landsat TM and ETM+ images integrated with GIS spatial zoning data are recommended to monitor LULC changes in the Nandoni Dam basin and other various dam basins in South Africa in the future. The recommended future research opportunities into various other dam basins in RSA are presented in section 5.4.

5.4 Future research opportunities

There is a need to continuously monitor dam basins for LULC as these changes affect the whole geo-hydrological ecosystem and consequently, the environmental changes follow suit in various dam basins. Nandoni Dam basin monitoring presented holistic LULC change phenomenon before its development in 1997, during the dam basin development in 2005, and after the dam basin development with full water capacity in 2021. This study presented that the conventional methods of monitoring the Nandoni Dam basin's LULC changes need to be improved and integrated with the use of remote sensing and GIS methods.

While remote sensing and GIS methods presented a platform for spatio-temporal LULC change monitoring for 24 years (1997 – 2021), the results of this study further present opportunities for near-to-real-time research. These further research opportunities have the potential to assess LULC changes using a combination of historical remote sensing images and near-to-real-time systems such as drones or unmanned vehicle systems (UVS). The objective is to assess LULC change monitoring on a near-to-real-time basis as the changes happen dynamically on an ongoing basis. An analysis of the LULC change phenomenon and its impacts on the other dam basins would shed light on the need for future prediction on spatial planning in dam basins in South Africa.

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