Sustainable management of water resources through Real Time Control with University of Cape Town dam as a case study

Prepared by:

Malesela Michael Mogano, BSc. Civil Eng

Supervised by:

Dr. John Okedi, Pr. Eng, PhD

Dissertation submitted in fulfilment of the requirements for the degree of Master of Science in Civil Engineering

Department of Civil Engineering
University of Cape Town, Private Bag Rondebosch, 7700
South Africa

Plagiarism declaration

1. I know that plagiarism is wrong. Plagiarism is to use another's work and to pretend that it is one's own.
2. I have used the Harvard Convention for citation and referencing. Each significant contribution to and quotation in this report form the work or works of other people has been attributed and has been cited and referenced.
3. This dissertation is my own work
4. I have not allowed and will not allow anyone to copy my work with the intention of passing it as his or her own work.

Student Number	MGNMAL003
Name and Surname	Malesela Michael Mogano
Date	15 June 2023
Signature	Signed by candidate

Abstract

There is a growing interest in South Africa to supplement water demands by harvesting stormwater as concerns over the security of the country's water supply increase. Studies have demonstrated the potential for stormwater harvesting (SWH) to simultaneously provide water to meet non-potable water demand and mitigate flooding by minimising stormwater flows to downstream locations of urban catchments. To determine pathways to enhance these benefits, application of Real-Time Control (RTC) system to operate a dam outlet could potentially be used to store stormwater.

To investigate the economic viability of harvesting stormwater through RTC from an existing dam, a case study was performed on a representative urban catchment – the UCT watershed, located in Cape Town, South Africa. RTC procedures were applied to the UCT dam operations to initiate pre-storm releases in real time based on rainfall forecast. Four different stormwater harvesting configurations that modelled non-potable water demands were developed. A catchment stormwater model and a Life Cycle Cost Analysis (LCCA) were used to model the four configurations.

The study identified benefit in application of RTC linked to increase in harvested stormwater and reduction of water loss through overflow. Continuous simulation was employed at the UCT dam to determine the prospects of enhancing SWH to deliver non-potable water for irrigation of sports fields. The study compared performance of Static control approaches to SWH with application of RTC. The dynamic management of the UCT dam with RTC approaches increased yield and volumetric reliability whilst maintaining the required level of service of a stormwater harvesting system. Static control approaches result in water savings of approximately 9% in comparison to RTC. In addition, Static configurations harvested stormwater at a relatively low unit cost in comparison to RTC configurations. Hence, RTC approaches increase yield and volumetric reliability with relatively low-cost implications. In addition, RTC approaches has the potential meet about 6.4% to 10.9% of the residences potable water demand respectively whilst satisfying irrigation demands if stormwater could be fully treated. It was found that SWH with RTC required special design as it provides an active operation which, across varying climatic conditions optimizes the performance of the system.

It was concluded that the SWH system with RTC technology exhibits great potential; the ability of an RTC system to provide centralised control and failure detection, which can be readily adapted to variation of climate and local conditions over both the short and long term provides a system that is more stable and reliable.

Table of Contents

List of tables

List of figures

Acknowledgements

I thank God for granting me the grace and strength to complete this MSc research programme at the University of Cape Town. My grace is sufficient for you, for my power is made perfect in weakness (2 Corinthians 12:9). I truly appreciate my family; especially my parents, Mr and Mrs Mogano, siblings Mpho and Thomas who provided a social support structure that enabled me to complete the MSc programme.

I wish to extend my sincere gratitude to my supervisor and mentor Dr John Okedi for his availability, direction and advice throughout the course of this research, he supported me both academically and emotionally and helped me improve my report writing skills. His guidance and mentorship have made me an improved person academically and professionally. Department of Water and Sanitation (DWS) funds made this MSc programme possible. I also appreciate the colleagues and friends associated with the Urban Water Management research group that supported me in the MSc programme including Professor Neil Armitage, Dr Kirsty Carden, Miriam Arinatiwe, Anabel Matalanga, Motlatsi Monyake and Roberto De Oliveira. Special thanks to my friends including Sanele Baloyi, Sam Makhoane and Hlasoa Mahlelebe.

Lastly, I appreciate the South African Weather Service (SAWS) and City of Cape Town (CCT) for proviting data that was used for this research. My gratitude to the community of PySWMM for assisting me in completing this MSc programme. Special thanks to UCT and SAWS staff members including Thomas Slingsby, Lionel Smit, Nthabiseng Letsatsi and Robin-Lee Batties. I thank you all.

Acronyms and abbreviations

AGCMs	Atmosphere-only General Circulation Models
API	Application Programming Interface
BDC	Beaverdam Creek
BMPs	Best Management Practices
BOM	Bureau of Meteorology
CCT	City of Cape Town
CMAC	Continuous Monitoring and Adaptive Control
CoCT	City of Cape Town
CPI	Consumer Price Index
CSAG	Climate System Analysis Group
CSIR	Council for Scientific and Industrial Research
CSO	Combined Sewer Overflow
DDS	Decision Support System
DEAP	Distributed Evolutionary Algorithms for Python
DEM	Digital Elevation Model
DEWA	Division of Early Warning and Assessment
DEWNR	Department of Environment, Water and National Resources
DORA	Dynamic Overflow Risk Assessment
EA	Evolutionary Algorithms
EAC	Equivalent Annualised Cost
EC	Environment Canada
ECC	European Control Conference
EPA	Environmental Protection Agency’s
GCMs	General Circulation Models
GEP	Global Ensemble Product
GFS	Global Forecast System
GIS	Geographic Information System
IoT	Internet of Things
LCCA	Life Cycle Cost Analysis
LID	Low Impact Development

LPV	Little Princess Vlei
LQR	Linear Quadratic Regulators
MPC	Model Predictive Control
MUSIC	Model of Urban Stormwater Improvement Conceptualization
NCDENR	North Carolina Department of Environment and Natural Resources
NCEP	National Centre for Environmental Prediction
NSE	Nash-Sutcliffe efficiency
NWP	Numerical Weather Prediction
NWS	National Weather Service
OWA	Open Water Analytics
PBIAS	Per cent Bias
PID	Proportional-Integral-Derivative
PLC	Programmable Logic Controller
QPF	Quantitative Precipitation Forecasting
RBC	Rule-Based Control
RTC	Real-Time Control
RWH	Rainwater Harvesting
SAWS	South African Weather Service
SC1	STATIC CONTROL 1
SC2	STATIC CONTROL 2
SCADA	Supervisory Control and Data Acquisition
SCM	SAWS Coupled Model
SCOOP	Scalable Concurrent Operations in Python
SS	Suspended Solids
SST	Sea Surface Temperatures
SWH	Stormwater Harvesting
TSS	Total Suspended Solids
UDS	Urban Drainage System
UNEP	United Nations Environment Programme
WDA	Water Demand Alternatives
WPCP	Water Pollution Control Plant
WSUD	Water Sensitive Urban Design

WWTP	Wastewater Treatment Plant
ZAR	South African Rands

1 Introduction

1.1 Background

The role of stormwater management becomes crucial to the sustainability of urban environments as development continues to increase (Schmitt et al., 2020). Urbanization is known for restricting infiltration, thus altering flow regimes of ground and surface waters resulting in ‘flash’ flows and larger runoff volumes characterized by higher velocities and increased peak discharges (Dietz & Clausen, 2008; McGrane, 2016). Hydrologic changes result in degradation of surface waters downstream of areas due to loss of biodiversity and aquatic habitat, increased sediment loading and erosion (Jackson & Booth, 1997; Vietz et al., 2015).

Integration of existing stormwater infrastructure with Real-Time Control (RTC) is a promising, low-cost adaption for adjusting or improving functionality to a changing hydrologic environment (Kerkez et al., 2016). RTC allows for adaptive stormwater management through combination of the technology of the Internet of Things (IoT) with science of urban hydrology (Schmitt et al., 2020). An RTC system uses conditions and actuators (pumps, motorized valves, etc.); and employing internet-connected (flow meters, precipitation gauges, depth sensors, etc) for response to stimuli through manipulation of the outlet discharge in ‘real-time’ or almost instantaneously. The term Continuous Monitoring and Adaptive Control (CMAC) may be considered equivalent to RTC found in previous studies (Lefkowitz et al., 2016; Roman et al., 2017; Wright & Marchese, 2018).

RTC has been used to mitigate harmful combined sewer overflow (CSO) events in combined sewer systems (Schmitt et al., 2020). RTC implemented in South Bend, in a Midwestern city took advantage of existing capacity, resulting in a cost approximately $150 million less than a traditional infrastructure upgrade and reduced CSO volumes by as much as 50% (Montestruque & Lemmon, 2015). Similar results have been accomplished for other case studies in Spain, Denmark, Germany, Canada and United States (Nielsen et al., 2010; Ocampo-Martinez et al., 2013; Seggelke et al., 2013; Stinson et al., 2000). The application of RTC is a relatively new area for separation of storm sewers, with differences in objectives to those of combined sewer system (Schmitt et al., 2020). Marsalek (2005) showed the potential of RTC to persevere the hydraulic mitigation time whilst maximizing detention time because RTC allows adoption of flexible operating strategies that are appropriate to the conditions that prevail over the catchment and inside the pond at a given instant. For dry ponds, this basically implies maximizing water retention time by adapting the outlet opening percentage, while still being able to completely open it for severe storms (Gaborit et al., 2016).

While stormwater infrastructure is largely static, the ability of dynamic weirs, gates and valves to more closely achieve desired hydraulic conditions have long been recognized. The use of manually adjustable valves can be applied for dredging purposes, emergency facility drawdown, or other maintenance activities and is common practice in the design and maintenance of extended detention ponds (Nashville & Davidson County, 2009; ODOT, 2014; US EPA, 2009). It is feasible to add automatic controls to previously manually or passive controlled stormwater facilities due to recent advancements and reduced cost of internet connected sensors and actuators (Bartos et al., 2017; Kerkez et al., 2016). A heuristic or rule-based control algorithm is commonly applied as an automation of RTC (Gaborit et al., 2013; Goodman & Quigley, 2015; Jacopin et al., 2001; Middleton & Barrett 2008). Here, control rules are manually programmed typically in the style of an 'if-then-else' logic structure before the RTC system is online (Schmitt et al., 2020). Design and implementation of Rule-based control (RBC) typically require expert knowledge of the urban drainage system (Vitasovic, 2006).

Gravitational settling in dry detention facilities provides water quality benefits, however, are short in nature; during the next large event, sediments will likely be re-suspended without regular dredging (Schmitt et al., 2020). The studies by Papa et al. (1999) and Vallet (2011) showed the potential of settling to improve water quality through removal of suspended solids with associated pollutants. Maximizing the retention time of water inside the pond maximizes settling (or sedimentation) (Gaborit et al., 2016). Hence, during the day; this could, for instance, allow UV disinfection (Vergeynst et al., 2012). However, increased probability of outflows following large storm events would result in an attempt to reduce the structure's maximum outflow to increase the detention time (Guo, 2002; Marcoon & Guo, 2004). This is not desirable since smoothing the flow pattern of the larger storms is an objective of the basin (Shammaa et al., 2002). The RTC of detention basins can limit the intensity and duration of flows that are erosive from high frequency storm events (typically smaller the 2-year storm) that cause streambank instability to best improve water quality (Jackson & Booth, 1997; Palhegyi, 2010; Tillinghast et al., 2011; Vietz et al., 2015).

Thus far, the use of optimization-based control approaches such as model predictive control and linear-quadratic regulators is a shift that RTC practitioners and researchers have turned towards for prevention of downstream capacity exceedance by urban drainage systems (García et al., 2015; Marinaki & Papageorgiou, 2003; Wong & Kerkez, 2018). However, operations personnel cannot easily understand and adjust these systems which are computationally intensive and make decisions in a 'black box' (Vitasovic, 2006). The implementation of translucent, rule-based or optimization-based control could mitigate the novelty of RTC technology for stormwater management applications that may be a hinderance to its adoption (Schmitt et al., 2020).

1.2 Problem statement

Conventional management of urban stormwater *i.e.*, promptly collect and convey runoff to downstream locations usually leads to loss of a valuable water resource especially from a water scarce and drought affected area like South Africa. Dynamic management of stormwater with RTC *i.e.,* continuous control of flow rates and storage volumes would provide capacity for SWH, additional peak flow attenuation to mitigate flood risk and water quality improvement from extended detention.

1.3 Research question

Can SWH from the UCT dam located at the University of Cape Town be enhanced by linking the outlet to rainfall prediction such that the dam is emptied ahead of major storm events and optimise use of available storage.

1.4 Research objectives

1. Identify and review the different rainfall forecasting systems that are currently available, and which are most appropriate for South Africa
2. Assess the reliability of these rainfall forecasting systems with respect to various rainfall intervals at a specific location; and
3. Assess the likely impact of the forecast on an RTC system for stormwater harvesting.
4. Provide guidance on dynamic management of storage with RTC to enhance SWH

This thesis consists of six chapters. Chapter 1 (this one) provides an introduction including a background, problem statement, research question and objectives. Chapter 2 is a review of the available literature relating to water scarcity in South Africa, real-time control systems; methods to model, analyse and improve a stormwater harvesting system. Chapter 3 includes an overview, study area, available data, economic analysis, methods used in modelling SWH. Chapter 4 presents the results of this research by analysing the performance measures of stormwater harvesting configurations; the chapter also discusses the impact of RTC technology and cost. Chapter 5 concludes the dissertation, providing a concise summary of its findings. Chapter 6 offers a list of recommendations for future research. A reference list and appendices are provided at the end of this thesis.

2 Literature Review

2.1 Overview

This chapter presents various approaches and examples in literature that were used to develop the concept for the study on enhanced stormwater harvesting (SWH) at the University of Cape Town (UCT) dam through application of Real-Time Control (RTC). Section 2.2 discusses water scarcity. Section 2.3 features conventional management of water resources. Section 2.4 contains dynamic management of water resources. Section 2.4 highlights approaches to storage sizing. Section 2.6 focuses on rainfall forecasts that are applicable to South Africa. Section 2.7 presents models for rainfall-runoff such as PCSWMM, MUSIC, WEAP, PySWMM and Csoft. Section 2.8 explains SWH performance indicators, Section 2.9 highlights the control of urban drainage system in general such as passive control and RTC, operational goals for RTC and impediments to the application of RTC. Section 2.10 discusses RTC strategy by focussing on the general strategy, radar-based flow forecast, expected cost, optimization routine and connection to local control units. Section 2.11 contains level of control of RTC ranging from local to regional to global. Section 2.12 focuses on Rule-based RTC such as the heuristic control logic. Section 2.13 highlights the Optimization-based RTC such as linear-quadratic regulator, evolutionary strategies, model predictive control (MPC) and population dynamic-based control. Section 2.14 discusses the principles of MPC such as the receding horizon principle and optimization. Section 2.15 presents the procedure for assessing RTC for a given system by considering three main steps. Section 2.16 features urban drainage systems with Rule-based RTC technology implemented in South Africa, Canada and Iran. Section 2.17 presents urban drainage system with Optimization-based RTC technology while section 2.18 focusses on summary findings in the literature review.

2.2 Water Scarcity

Conserve Energy Future (2018) defines water crises as the lack of sufficient unpolluted water resources within a region to meet water consumption demands which has become an indisputable reality for some cities around the world. This is due to increased water demand for consumption and occurrence of drought alongside growth of urban populations. Water crises was also intensified by other factors *inter alia* lack of maintenance of infrastructure changing climate and water supply (Swyngedouw et al., 2002; Bakker, 2013a, b). Water crises in many countries around the world has led to the use of non-conventional water sources such as stormwater to meet non-potable water demands including *inter alia* garden irrigation, toilet flushing *etc* (Mitchell, *et al*., 2008). Water crises is evident in countries such as the United State of America, Australia, Brazil and South Africa.

2.3 Dynamic management of water resources without RTC

Water crises in the state of Florida, USA which occurred in November 2005 due to severe drought led to the construction of stormwater harvesting facilities to augment water supplies (Philp *et al*., 2008). The tropical climate of the south of Florida has 70% rainfall which occurs from May to September, which gives a lot of potential for storage of stormwater (O'Malley, 2007). This means that, Stormwater could be potentially harvested during wet season in most regions in south Florida and utilized for irrigation and other uses during the dry period (Shukla & Jaber, 2006). Many areas of the State of Florida use nearly 50% of potable water delivered to residential units for irrigation of lawns (Winielista, 2006), which means that stormwater storage facilities could supplement potable water used for irrigation with non-potable water (Philp et al., 2008). The Australian cities such as Brisbane, Melbourne and Perth experienced the so-called 'millennium drought' (1996-2010) which led to reduction of water supply levels to meet water demand for different regions due to variations in conditions aggravated by climate change (Fitzgerald, Stanford & Khan, 2014; Lindsay & Supski, 2017). The Brazilian city of Sao Paulo in the Southeast region experienced water crises in 2014 to 2015 which was driven by political intransigence and drought which resulted in reduced water supply (Millington, 2018). Water crises in South Africa is exacerbated in that, unpolluted water resources are distributed unevenly and disproportionally available relative to demand (UNDP et al., 2000; Blignaut & Heerden, 2009; UNEP, 2010; Carden, 2013).

Underutilised water resource such as stormwater could potentially be used as source on non-potable water to meet water consumption demands in urban areas. Stormwater is increasingly being utilized by cities around the world as an alternative water supply. Stormwater harvesting (SWH) is the collection, storage, and use of runoff from urban surfaces such as roads and drains that would otherwise drain to a water body (DECNSW, 2006; O'Connor *et al*., 2007; NRMMC *et al*., 2009a; Akram *et al*., 2014). International experience has shown that SWH is more economical than rainwater harvesting (RWH) on a broader scale (*e.g.,* Marsden Jacobs Associates, 2006). Villarreal and Dixon (2005) has shown a 10-year study that reduces runoff volumes by 58% through combined rainwater/stormwater harvesting system and annual water savings of approximately 2.43 ML.

Challenges with respect to resource shortages, environmental degradation and water management are evident in a developing country such as South Africa (RSA) (Kok & Collinson, 2006; Turton, 2008; DEA, 2010; UNEP, 2010; RSA, 2011a, 2011b; Fisher-Jeffes *et al*., 2012; DWA, 2013). Fisher-Jeffes (2015) found that although there was significant climate variation across South Africa, SWH had the potential to reduce the total residential potable water demand of the Liesbeeck River Catchment in Cape Town by more than 20% only if stormwater was stored for non-potable demands such as toilet flushing and irrigation which can result in a significant saving for the City of Cape Town.

2.4 Dynamic management of water resources with RTC

Water resources, agriculture, and the economy in Southern Africa is often extensively impacted by periods of low rainfall and prolonged droughts. The region is vulnerable to extreme climate events due to the variability of rainfall (Shongwe et al., 2009). The most severe impacts of climate on the natural environment and human society over Southern Africa are due to extreme climate events such as floods and drought, among others (Phakula et al., 2018). The severe droughts of 2003/2004, 2002/2003 and 1991/1992 in South Africa (Cook et al., 2004), and the water crises in Cape Town in 2018.

In various studies, it was determined that performance of SWH systems can be improved through the application of RTC, a technique that offers the opportunity to actively manage runoff volume and peak flows to mitigate flood risk. RTC is generally defined as using collected data and monitoring the function of a system for optimal performance by controlling certain aspects of the system (Schutze *et al*., 2004). Rohrer & Armitage (2017) showed that the volumetric yield of stormwater ponds can be improved using RTC without significantly impairing the flood mitigation provided by the system at a comparable cost to what the local residents were already paying for potable water. This finding suggests that a cost-effective way of stormwater harvesting can be achieved.

Extensive investigations around the RSA for implementation of alternative water resources including, *inter alia*, desalination facilities, exploiting aquifers, raising dam walls and new dams have been considered. However, only Rohrer & Armitage (2017) and Okedi (2019) have considered the application of Real Time Control (RTC) to enhance stormwater harvesting as a viable resource in the context of South Africa.

2.5 Approaches to storage sizing

Two approaches that are considered when sizing storages are viz. over-year storages that go through the full-empty-refill-spill cycle over a long period, and within-year storages that go through this cycle several times a year (Mitchell, *et al*., 2008). Locations where high levels of supply security is required, and streamflow is highly variable such as for large urban water supply dams is considered to be over-year storages. Over-year storages buffer against inter-annual runoff variability. In comparison, within-year storages are required when there is low variability of urban runoff or limitation of storage capacity due to space constraints. Storage capacity requirements of urban stormwater storages that are within-year nature has the potential of being influenced due to within-year inflow variability and inter-annual inflow volume. Sequential methods such as behaviour analysis/operational study incorporate temporal pattern of inflows (supply) and outflows (demand and losses) that best analyse within-year storages (MacMahon & Adeloye, 2005).

2.6 Climate Forecasts applicable to South Africa

Production of temperature and rainfall forecasts in real time at different timescales, including seasonal timescale are currently being applied at different institutions in South Africa, including the South African Weather Service (SAWS). However, SAWS produced seasonal forecasts that did not provide information with specific needs to users. In addition, there has been an increasing demand from agriculture and other user communities (*e.g.* hydrologists) for forecasts of the weather statistics within a season (intra-seasonal statistics) for assistance in decision making (Tadross et al., 2005; Hudson et al., 2011).

The process of predicting future conditions is defined as forecasting. Information of atmospheric variables (such as rainfall) expected over the next 3-5 days, often on a sub-hourly or hourly basis are provided by weather forecasts. However, it is not possible to predict individual day's conditions in detail beyond that due to the nature of the climate system (Iseh & Woma, 2013). Forecasts of the expected climate conditions for the next three to six months and more are defined as seasonal climate forecasts, are typically expressed not through weather conditions on individual days but as seasonal or monthly means of weather variables. As such, seasonal climate forecasts occupy an intermediate zone between, and are different than, climate projections and weather forecasting (Doblas-Reyes et al., 2013).

Climate predictability is the extent in which, if optimum procedures are used, an informative prediction is possible. Weather and seasonal forecast differ in terms of sources of predictability. The current state of the atmosphere (i.e., initial atmospheric conditions) determines the weather forecast predictability. The influence of these current state of the atmosphere does not vary long due to the extreme sensitivity to initial conditions (i.e., chaotic nature) of the climate system. However, when the influence of the initial atmospheric conditions still manifests, the weather forecast is only used for several days ahead. As seasonal climate forecast spans well beyond the time of persistence of the intimal atmospheric conditions (Brayshaw, 2018; Krishnamurthy, 2019), it can be concluded that which is applicable for weather forecast may or not be applicable for seasonal climate forecast. Instead, persistence of boundary conditions influences seasonal forecast. The slowly varying boundary conditions such as sea ice, soil moisture and sea surface temperatures (SST) are the common sources of inter-annual and seasonal timescales influence seasonal forecast (Li & Ding, 2015).

Uncertainty is lack of disagreement or information about what is known that results to a state of incomplete knowledge. DeChant & Moradkhani (2014) defines uncertainty as an inevitable yet unfortunate part of any forecasting system. Initial condition and model uncertainty can be attributed as the two main causes of uncertainties within the context of seasonal climate forecasting. Werndl (2017) regards model uncertainty as being more important than initial condition uncertainty. To account for the initial condition uncertainty, seasonal climate forecasts are based on an ensemble of model simulations (Figure 2-1) and their probabilistic nature (Klopper & Landman, 2003). When viewing model uncertainty, a multi-model ensemble is used to capture model uncertainty.

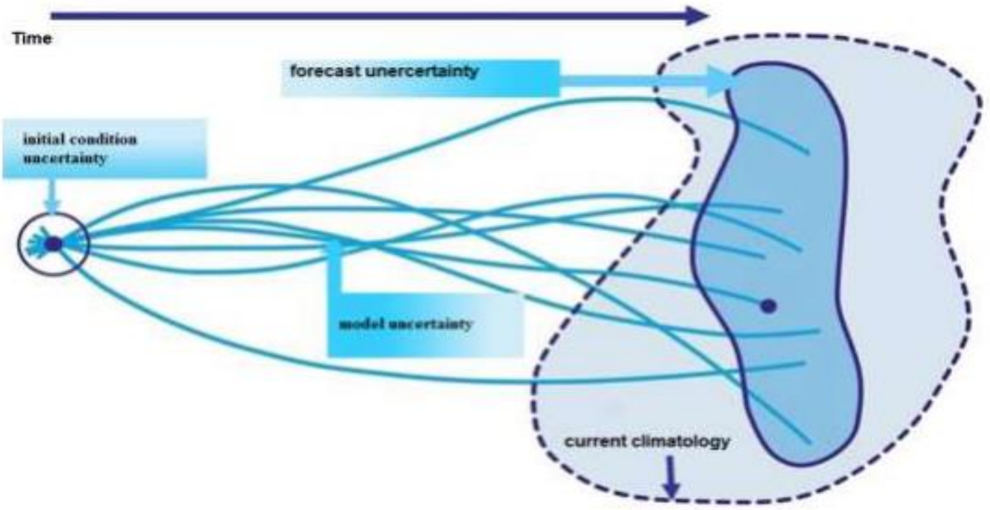


Figure 2-1: Schematic of a probabilistic forecast using initial condition uncertainties
(Slingo & Palmer, 2011)

Apart from model uncertainty quantification, multi-model ensemble forecast provide a better forecast through reduction of forecast errors (Tebaldi & Knutti, 2007). The intra-seasonal forecasts are needed mainly due to the fact that; without medium-term information, seasonal climate forecasts (statistical and dynamical) have limited benefits (Landman & Tennant, 2000). Moreover, intra-seasonal forecasts may cover the timescale of about 10 – 60 days (*i.e.*, bridging the gap between weather and seasonal forecasting) (Hudson et al., 2011). Intra-seasonal forecasts are of great importance for the agricultural and economic sector at large although they are regarded as the most difficult to predict (Phakula et al., 2018). Accurate prediction of weather statistics within a season may supplement existing seasonal forecast produced in real time although the chaotic nature of the atmosphere makes it difficult for prediction of about 2 weeks to 2 months (Luo & Wood, 2006).

Quantitative precipitation forecasting (QPF) or rainfall forecasting can be obtained through both short-term forecast (nowcasting), usually for a few hours and long-term forecast (up to 7 days) (He *et al.*, 2013). The real-time control of urban drainage systems can be improved through the use of QPFs to prevent critical situations such as flooding, sewer overflow and overflow of dams/ponds by extending forecast lead times. The most driving force for a hydrological system is the utilization of QPF within a flood forecasting system, as the capability of any flood forecasting system is ultimately determined by forecasted precipitation.

Traditionally, QPFs can be achieved by solving equations of a Numerical Weather Prediction (NWP) or through extrapolation of future distribution from a sequence of radar images (i.e., radar-based rainfall forecasting). High-resolution spatially distributed data are provided by weather radars. Hence, urban hydrological applications which require data with high temporal and spatial resolution are suitable for radar-based rainfall estimates. Radar can capture very well the initial precipitation as provided by the radar rainfall estimates since they based on the assimilation of the initial precipitation state; which makes radar-based rainfall nowcast to have a better skill for short lead time forecasting according to various studies (Smith & Austin, 2000; Lin et al., 2005). However, increasing lead times rapidly decreases the accuracy of radar-based rainfall nowcast, as radar nowcasting techniques do not model processes such as decay and growth of precipitation (Golding, 1998). At longer lead times, NWP produces higher accuracy of QPFs, which solves the physics and dynamics of the atmosphere (He et al., 2013). Qualitative-quantitative rainfall forecasting tools at 72, 48 and 24 h can be validated by viewing by various NWP model studies (Chuang & Sousounis, 2000; Palmer et al., 2000; Untch et al., 2006). Lin et al. (2005) proposes that, after a threshold time (*e.g.* 6 h for a continental case), the weather model has an approximately constant skill that will excel the radar nowcasting. This time threshold can be reduced to less than 3 h for a local area with much smaller domain size (Xuan et al., 2004). Radar nowcast performs best for very short lead time of precipitation (0-3 h), whereas forecasts based on numerical models is better for longer lead times as they could provide signal of heavy rainfalls (He et al., 2013).

Forecast verification is the assessment of the degree of similarity between that forecast and the observed conditions to determine the quality of a forecast (Mandal et al., 2007). Verification of forecast is mostly performed if the results between the observations and the forecasts provide a strong relationship and an accurate indication of how bad or good subsequent forecast will be (Mason, 2008).

The U.S National Weather Service (NWS) runs a Global Forecast System (GFS) which is a global numerical weather prediction system containing a global variational analysis and computer model. The GFS produces forecast up to 16 days in advance and is run four times a day. The FV3 model with a resolution of approximately 13 km is used by the forecast component. The model is divided into 127 layers in the vertical. Forecast output every hour for the first 120 hours, then 3 hours for days 5 to 16 can be produced by the GFS. The model is regularly adjusted, and constantly evolving for performance improvement and accuracy of forecasts. A base horizontal resolution of 28 km is associated with the model; and between grid points for forecasts between one week to two weeks, horizontal resolution drops to 70 km.

In a study by Okedi (2019), rainfall forecast data was obtained from the GFS model managed by the National Centre for Environmental Prediction (NCEP) which was used for simulation of RTC for SWH in the Zeekoe Catchment of Cape Town, South Africa. The results of the study showed that a capacity of 1 Mm^3 (about 5.5% of the mean annual stormwater volume) can be provided through the application of RTC on the stormwater ponds in the Zeekoe Catchment. It was also concluded that the capacity (1 Mm^3) was inadequate as the supplied stormwater from the storage with a spill (water lost as overflow) of 35 – 51%, would only meet 44 – 60% of the demands.

The application of seasonal forecasts in South Africa have evolved from a simple statistical model to forecasts based on statistical downscaling and the Atmosphere-only general circulation models (AGCMs), fully coupled general circulation models (GCMs) and integrated within multi-model (Landman, 2014). The SAWS Coupled Model (SCM), which is the first of its kind in both South Africa and the region; is a fully interactive coupled modelling system that is currently operated by SAWS which is the country’s official meteorological service (SAWS, 2018). A multi-tiered forecast system consisting of a dynamic modelling process, combined with a consensus discussion and a statistical approach is used each month by the SAWS scientists to produce a 3-month temperature and rainfall outlook (Landman et al., 2001; Johnston et al., 2004).

Until a few years ago, two additional institutions, apart from SAWS, produced and generated numerical seasonal climate forecasts which were then made available every month online. These were at the Climate System Analysis Group (CSAG) of University of Cape Town and at the Council for Scientific and Industrial Research (CSIR). The CSIR initiative has been merged with that of SAWS due to a number of human resources and institutional reasons, whilst the CSAG's forecast has since been discontinued in 2016 due to ethical concerns around the consequences of its poor skill and concerns around the poor quality of forecast for water management, agricultural and other contexts in decision making.

In a study by Fisher-Jeffes (2015), six (three private citizens, two SAWS and one DWS) ten-year daily rainfall data were used for SWH modelling. The results of the study showed that potable water demand in the Liesbeek River Catchment, Cape Town, South Africa can be reduced by up to 20% through SWH. In addition, Rohrer & Armitage (2017) have shown that the volumetric yield of stormwater ponds can be improved using RTC without significantly impairing the flood mitigation provided by the system at a comparable cost to what the local residents were already paying for potable water. This finding suggests that a cost-effective way of stormwater harvesting can be achieved.

South Africa is becoming more established in terms of the use of seasonal climate forecast for climate information. These seasonal climate forecasts have potential uses in the water management sector (Klopper et al., 2006; Winsemius et al., 2014) and in the agricultural sector (crop type, irrigation and planning planting dates). For instance, Kgakati & Rautenbach (2014) focused at dissemination of early warnings to reduce risks faced by farmers by examining the use of seasonal climate forecast information in the agricultural sector in South Africa. The study assessed the channels through which information of seasonal climate forecast is disseminated to the end-users. The results showed that through improved structures and channels that are timely and reliable, seasonal climate forecast information can serve as an early warning which can helpful for farmers. However, due to lack of forecast skill, communication and inability to see the relevance of seasonal climate forecast for specific farming reasons; the integration of seasonal climate forecast information by smallholder farmers into their farm planning has been poor (Chisadza et al., 2020).

Amongst other studies in South Africa on seasonal climate forecasts, is the use of seasonal climate forecasts as an early warning system for malaria in the health sector (Kim et al., 2019). The study assessed a malaria early warning system in conjunction with an effective malaria prediction model by using high-quality climate forecasts and well organised malaria surveillance. Weekly time series data including precipitation, temperature and malaria cases from 1998-2015 in Vhembe, Limpopo, South Africa was used to develop the weather-based malaria prediction model. In addition, weather-based malaria was also applied to seasonal climate forecast. The results showed that the weather-based malaria prediction model developed could be applicable in practice together with existing malaria surveillance data and skilful seasonal climate forecasts.

2.7 Models for rainfall-runoff

2.7.1 SWMM and PCSWMM application

Storm Water Management Model (SWMM) was developed by the United States Environmental Protection Agency (US EPA) in 1971 and has been widely accepted as the tool of choice to model the hydrological processes in a catchment (Akhter & Hewa, 2016). SWMM has been upgraded over the years and widely used across the globe to model continuous quantity and quality aspects in rural and urban catchments or dynamic rainfall runoff for a single event (James *et al.,* 2010). SWMM is used to plan, design, analyse and simulate processes related to sanitary sewers, combined sewers, storm water quality and other drainage systems in urban areas, and rural catchments (Rossman, 2010). SWMM is a catchment scale model and edits input data of a given study area through the provision of an integrated environment which results in various formats that can be viewed (Sun *et al.*, 2014). The use of SWMM is evident in several studies (Lee, 2008; Sun *et al*, 2014; Wella-Hewage, 2013; Abdul-Aziz & AI-Amin, 2015; Yu *et al.,* 2014).

SWMM has a wide range of applications and numerous advantages but limited in capacity to account for any spatial interference (Akhter & Hewa, 2016). Hence, PCSWMM which is a commercially available advanced model was developed in 1984 with a Geographic Information System (GIS) linkage to comprehensively provide a range of applications (CHI, 2015). PCSWMM is comprised of GIS and US EPA SWMM which provided a complete and scalable package for 1D and 2D analysis of rainfall runoff processes. PCSWMM has real-time control analysis, comprehensive river modelling, time series management, native GIS support, Digital Elevation Model (DEM) support, automated reporting and Google Earth visualization for water quality, hydraulic and hydrology modelling (Akhter & Hewa, 2016).

PCSWMM has also been used widely across the globe, for example in Mponga catchment located south of the Australian capital, Adelaide. The Mponga catchment covers an area of 122 km^2 and drains into a flow gauge station which is managed by the Department of Environment, Water and National Resources (DEWNR) (Akhter & Hewa, 2016). The sedimentary aquifers in the Mponga catchment consists of Permian sands, Quaternary sediments and Tertiary limestone (Barnett & Rix, 2006). The soil type that are dominant in the catchment sand and loamy sand. The major land use in the Mponga catchment is used for broad scale cattle and sheep grazing. It was reported that 75% of the catchment was used for livestock (cattle and sheep grazing) in 2002 but this reduced to 69% in 2014 due to increase in residential use from 4% to 24% during the same period (Wella-Hewage, 2013). The 69% of the catchment land use which accounts for grazing includes silage, modified pasture and cropping. The 24% of the catchment was used for commercial and residential activities. Groundwater was pumped for irrigation purposes in the catchment during the summer season (Barnett & Rix, 2006).

The study utilized PCSWMM which conceptualized the rainfall runoff process using water flow and material between its environmental sectors. All the process was assigned into four compartments namely: land surface compartment, atmospheric compartment, ground water compartment and transport compartment. Evaporation and rainfall data were required for the atmospheric compartment. The study utilized evaporation data for one station and rainfall data for five selected stations were obtained from Bureau of Meteorology (BOM) (BOM, 2015). The Thiessen Polygon method was used to compute the catchment weighted average rainfall for the Mponga catchment (Akhter & Hewa, 2016). The Thiessen polygon method states that the mean rainfall calculation is computed by accounting for the area of influence of every observation point when the observation points within the area are not evenly distributed (Nganro *et al.*, 2020). It is assumed that the rain on an area within the watershed is the same as that at a nearest station so that the area is represented by the recorded rain at that station (Triatmodjo, 2013; Yekti & Permana, 2007; Kawet & Halim, 2013).

2.7.2 Music application

MUSIC is a stormwater model with a unified approach to simulate both water quality and hydrology of a watershed. It is comprised of a range of stormwater control measures (SCMs) such as bioretention basins, sediment basins, vegetated swales, ponds and constructed wetlands (Wong *et al.,* 2006). The simulated watershed in MUSIC is represented as a series of source, receiving nodes, junction, receiving nodes and treatment connected by drainage links (Gagrani *et al.,* 2013).

Chiew *et al.* (1996) developed the SimHyd model which was used to run the rainfall-runoff algorithm of MUSIC for a study. In SimHyd model, initial abstraction must first be met for rainfall on impervious areas to generate runoff (Gagrani *et al.,* 2013). Runoff occurs when rainfall exceeds the infiltration capacity of the Land. Pervious area runoff was modelled as the infiltration exceeds runoff. Evapotranspiration was subtracted from the soil moisture store depending on the areal potential evapotranspiration rate and the amount of water in the soil store. The linear recession of the groundwater storage was modelled based on the base flow. Soil type and characteristics were used to compute the pervious area model such as groundwater depth, infiltration capacity coefficient and exponent, field capacity, soil storage, recharge and discharge rates using MUSIC based on methods described in Macleod (2008). The study used 6-min interval rainfall and runoff data compiled for the duration from May 2007 to June 2009 (Gagrani *et al.*, 2013). Four U.S Geological Survey (USGS) rain gauges stations were used to compute the average precipitation of the sub-catchment using the Thiessen method.

The Music model was used on the Beaverdam Creek (BDC) watershed located in the southwest Mecklenburg County, North Carolina. The watershed has a total drainage area of 11.8 km^2 and lies in the humid subtropical climate zone in the Koppen climatic classification (Gagrani *et al.*, 2013). it drains into a water supply reservoir (Lake Wylie) which was classified as a eutrophic lake due to excessive nutrient loading from agricultural and urban land uses in its watershed (NCDENR, 2003; Buetow, 2008). The study focused on a 1.92 km^2 sub watershed which was characterized by steep-walled valleys produced by incised stream channels with broad floodplains toward the outlet of the watershed (Gagrani *et al.*, 2013). The watershed was underlain with norite gabbronorite, horneblende gabbro and gabbro granodiorite rocks of plagioclase, quartz minerals, olivine and biotite (Goldsmith *et al.*, 1988). The lithology of the watershed comprised of acidic to strongly acidic soils including the Cecil sandy clay loam and Mecklenburg fine sandy loam (USDA-NRCS, 2010). It was reported that since 2003, the land use for the sub watershed was defined as 21% forest and pasture, 3.5% commercial, 51% high-density development, 16% low-density development, and 8% roads and highway due to the redevelopment of the subwatershed (Allan *et al.*, 2010).

2.7.3 WEAP application

The Water Evaluation and Planning (WEAP) model was applied on the Oueme catchment that covers an area of 50 000 km^2 and is the major river system in Benin. The catchment is characterized by bimodal precipitation distribution in the southern part and is located in the Sudanian climate zone. Vollmert *et al.* (2003) reported that the annual rainfall in Benin was predominately below average since the 1970s which made the country vulnerable to water shortages. The continuous trend in declining precipitation in Benin allows opportunities to access deep groundwater to meet water demand during the year (Hollermann *et al.,* 2010). Several studies have concluded that access is limited due to occurrence of groundwater in preferential fractures of the crystalline aquifers in the area (Chilton & Foster, 1993; Faß, 2004; Barthel *et al.,* 2008, 2009). Furthermore, it is expensive to tap into those groundwater reservoirs and bears the risk of tapping into dry holes (Hollermann *et al.,* 2010). The dominance of small livestock in the southern part of Oueme catchment puts further stress on the available water resources (Gruber, 2008; Gruber *et al.,* 2009).

The study utilized the WEAP model to link supply and demand site requirements (Hollermann *et al.,* 2010). The model allows scenario analysis, changes in supply and demand structures that can be simulated to discover the effects of various management strategies and potential shortages (Yates *et al.,* 2005). The study aimed to close the gap between catchment hydrology and water management by addressing both socio-economic factors influencing the level of industrial, agricultural and domestic demand, and bio-physical factors affecting the river (Hollermann *et al.,* 2010). WEAP allows various methods to project the hydrology of the study. The hydrological processes can be either computed internally through the consideration of driving forces such as evapotranspiration and precipitation (Yates *et al.,* 2005). The differences in land and climate vary significantly within the Oueme river basin and this required subdividing the catchments into smaller sub-basins (Hollermann *et al.,* 2010).

The UHP-HRU model was used derive the input data for groundwater recharge, runoff and river discharge which was an input into WEAP (Giertz & Diekkrüger, 2006). The UHP-HRU is a spatially differentiated version of the UHP model which simulates groundwater discharge, interflow, runoff, infiltration and evapotranspiration and was developed especially for application in Benin (Bormann & Diekkrüger, 2004). The model can adequately simulate hydrological processes under climate at local and regional scales (Giertz & Diekkrüger, 2006). Furthermore, the model can simulate hydrological processes under land use changes (Giertz *et al.,* 2006, 2010a, b; Christoph *et al.*, 2008). The alluvial aquifers are only considered for the integrated groundwater model of the WEAP (Yates *et al.,* 2005). Consequently, the application of this method for the groundwater aquifers is limited to the study area as it consists mainly of fractured crystalline basement (El Fahem, 2008; Fab, 2004; Chilton & Foster, 1993; Barthel *et al.,* 2008, 2009). Groundwater was accounted for in the analysis since it presents a vital source in satisfying the water demands in Benin (Hollermann *et al.*, 2010). Hence, the study applied a simple storage approach to model groundwater which contrasted with other regional studies (Lévite *et al.,* 2003; SEI, 2006). Furthermore, reservoirs were considered as they provide an alternative to source surface water to meet water demands, and only the largest reservoirs in the study area were considered (Hollermann *et al.,* 2010).

2.7.4 PySWMM

The U.S. EPA SWMM has limited access to some simulated results in the model during simulation time. To address this challenge, several libraries have been developed over the last decade to read, parse, and run SWMM models (*.inp). Several programming languages including, *inter alia* Visual Basic, MATLAB, R and Python are used in the development of the library tools. Many libraries beyond simple SWMM interface include a collection of specific features for different applications. Some studies have shifted towards water quality modelling within their framework (Banik, 2014) whilst others have focused on model calibration (Leutnant et al., 2019) and optimization framework (Marco et al., 2019; Martínez-Solano et al., 2016; Pathirana, 2014). Riaño-Briceño et al. (2016) support modelling of real-time controls through extended functionality. Most of these developments generate a new *.inp (SWMM input) file through the use of a wrapper interface – which duplicates the data model, adding redundancy (McDonnell et al., 2020). During a simulation without having to read and write new *.inp files, the engineering and scientific communities significantly benefit from directly accessing the SWMM data model from a maintainability standpoint.

In support of the Open Water Analytics (OWA) open-source initiative, the ongoing development of the Open Water Analytics SWMM5 application programming interface (API) is used for parallelization with the PySWMM project. This initiative enables the development of Python interfacing wrapper to SWMM. PySWMM (along with the co-development of the SWMM5-API) is also being developed to enable rapid prototyping to access SWMM data and interact with the mode during simulation time. PySWMM retains backward compatibility and ultimately serves to augment what SWMM can do since it incorporates enhancements to the SWMM code base. Current mid-simulation capabilities include the ability to manipulate Low Impact Development (LID) parameters, load externally generated inflows and change hydraulic network settings. There is accessibility both during and after simulation time of LID statistics, sub catchment, link, node and results. PySWMM provides to the SWMM data model (setters and getters), which facilitates editing of hydrologic and network parameters through a single framework which encompasses a collection of low-level interfacing functions. This functionality allows engineers and researchers to more effectively address engineering and scientific questions related to water runoff quality and quantity through streamlining stormwater model optimization, controls, and result post-processing.

PySWMM is actively being used to address a range of topics in government, academia and industry such as asset optimization and real-time controls in industry. In academia, it has been used for studying the effects of model predictive control (MPC) and Real-Time Controls (RTC) of drainage systems (Li et al., 2019; Sadler et al., 2019). PySWMM is being used to model the precipitation driven transport of pollutants and contaminants in the EPA’s Office of

Research and Development for urban environments (Ratliff et al., 2018). Applications of EPA SWMM has been used widely for research applications (Niazi et al., 2017). Furthermore, it is accepted by the Federal Emergency Management Agency for National Flood Insurance Program purposes, and it is also being used for development of discharge permits (McDonnell et al., 2020). PySWMM enhances the capabilities and facilitates ease of use of EPA SWMM for these regulatory, engineering and research applications.

2.7.5 Csoft

All commercial hydraulic and hydrological software packages, such as MOUSE, HYSTEM-EXTRAN, INFOWORKS, XP-SWMM and SWMM 5.0, simulate extended or local reactive control with various levels of sophistication which allow the assessment of potential for Real-Time Control by incorporating some level dynamic flow regulation devices in their modelling packages (Colas et al., 2004). The Csoft software can serve as a Decision Support System (DDS) and simulate global optimal Real-Time Control to operate such a strategy online (Grondin et al., 2003).

Csoft was specifically developed by BPR CSO as a model-based decision support system to design and operate Real-Time Control systems (Grondin et al., 2003). Ranging from local reactive control to predictive global optimal control (GO RTC) (As discussed in section 2.7), a full range of real-time strategies can be simulated with all expert systems, intermediate stages of extended control, etc (Colas et al., 2004).

Two main components define the Csoft software. Firstly, optimal flow set points for all local control stations (controlled locally or system-wide) is determined by a model-based simulation and optimization module. The model uses inputs such as flows and water levels monitored in the sewers, rain distribution and rain depth using rainfall evaluation and/or rain gauge readings and forecasts from weather radar information, and status of flow regulators such as storage facilities, Water Pollution Control Plant (WPCP) capacity, fabric dams, gates, pumps, etc; for feedback adjustments. Secondly, a relational database providing multiple functions to handle extensive reporting/graphing capabilities, calculations, data validation, data organization, data storage and retrieval, and real-time data transfers. Parameters are defined both locally and globally in Csoft, in a manner that more sensitive areas may be protected better compared to less sensitive areas.

2.8 Stormwater harvesting efficiency assessment

A stormwater harvesting system can be evaluated using performance indicators under a range of different conditions. The performance of a water storage infrastructure has been assessed by several different performance indicators that have been developed over the past two decades. A comparative analysis of these performance indicators and their detailed appropriateness of application are provided by McMahon *et al.* (2006). The following performance indicators *viz:* volumetric reliability, time-based reliability, resilience, and overflow ratio are the most useful according to McMahon *et al.* (2006) and Mitchell *et al.* (2008) for the evaluation of a stormwater harvesting system's effectiveness:

- Volumetric reliability (R_v) or water savings efficiency is defined as the supplied volume of water divided by the total water demand during the period of simulation (Mitchell *et al.*, 2008). Water savings provided by the system can be measured using this performance indicator (Fewkes & Butler, 2000; Palla *et al.*, 2011).

  $$R_v = \frac{\sum_{t=1}^{T} Y_t}{\Sigma_{t=1}^{T} D_t}$$

  Where: R_v = volumetric reliability; Y = yield (m^3); D = water demand (m^3); T = total number of time-steps in the simulation period; t = time-step.

- Time-based reliability (R_T) reflects the proportion of simulation time-step interval in which the water demand is fully met during the entire period of simulation (McMahon *et al.*, 2006).

  $$R_T = \frac{N}{T}$$

  Where: R_T = time-based reliability; N = number of time-steps in which the target water demand was fully met; T = total number of time-steps in the simulation period.

- Resilience (ϕ) determines the ability of a storage unit to recover quicker from a period in which it was in failure (Hashimoto *et al.*, 1982; McMahon *et al.*, 2006). The result is sensitive to the chosen simulation time-step since resilience is a temporal measurement (McMahon *et al.*, 2006; Mitchell *et al.*, 2008).

  $$\emptyset = \frac{f_s}{f_d}\ f_d \neq 0$$

  Where: ϕ = resilience; f_s = number of continuous periods when the target water demand is not fully met; f_d = the total duration in which the target water demand is not fully met.

- Overflow ratio (O_T) is defined as the ratio of the storage unit that spills water in terms of volume to the volume of water entering the storage unit during the period of simulation (Palla *et al.*, 2011).

  $$O_T = \frac{\Sigma_{t=1}^{T} S_t}{\sum_{t=1}^{T} I_t}$$

  Where: O_T = overflow ratio; S_t = volume of water spilled by the storage unit (m^3); I_t = volume of water entering the storage unit (m^3); T = total number of time-steps in the period; t = time-steps.

When analysing stormwater harvesting systems, it was determined that volumetric reliability is the most applied performance indicator in industry compared to the other performance indicators listed above (Mitchell *et al.*, 2008; Palla *et al.*, 2011). Results of resilience and time-based reliability can vary significantly based on the time-step used during computation as they are both temporal performance indicators. In addition, the length of data records dictates the accuracy of resilience and time-based reliability estimates (McMahon *et al.*, 2006). When analysing performance indicators, Mitchell *et al.* (2008) recommends a ten-year climate time series to be the minimum length that should be used. Increasing the length of a time series will result in a convergence of temporal performance indicators towards a steady state (McMahon *et al.*, 2006).

2.9 Control of urban drainage system in general

2.9.1 Passive control and RTC

Control of urban drainage systems can be accomplished via RTC or passive approaches (Lund et al., 2018). In the passive approach, control of diversion elements including valves, gates and weirs is achieved by fixing each of the elements to a certain static setting. This setting can be adjusted to a better setting although considered permanent if, for example, there is a performance of an offline model-based optimization by the system (Vitasovic, 2006). In RTC, control of actuators such as pumps and movable diversion elements is done through conversion of real-time measurements from the system into operational decisions by algorithms and rules of varying complexity (Lund et al., 2018). This requires a combination of installing controllers and sensors in the system with the implementation of a telemetry system and a supervisory control and data acquisition (SCADA) system (Campisano et al., 2013; Cembrano et al., 2004; Puig et al., 2009).

RTC consists of control loops based on the difference between the controlled variable and set-point value. A controller changes the manipulated variable of an actuator with either discrete or continuous settings (Campisano et al., 2013; Schutze et al., 2003, 2004). The actuator site can be used to a place the sensor (Lund et al., 2018). Various control terms are described in Table 2-1.

Table 2-1: RTC terms (*after* Lund et al., 2018)

Terms	**Description**
Sensors	Monitor system stats, such as flow, water level, water quality.
Set-points	The desired state values for a certain place in the sewer system, such as a downstream pipe flow.
Controlled variables	The variables that should obtain a certain set-point.
Actuators	Controllable devices, such as pumps, gates, weirs, and valves.
Manipulated variables	The variables that can be changed actively in the control, such as a pump rate.
Controllers	Devices such as the programmable logic controller (PLC) and remote terminal unit (RTU) that adjust the actuators based on sensor values. These are the hardware on which different “software” controllers/algorithms can be implemented.
PID controller	A common controller for varying the settings of the actuator continuously is the proportional-integral-derivative (PID) controller
Two-point controller	A common controller for discrete settings is the two-point (on/off) controller that has only the option of being “on” or “off” (for example, for a pump) or “open” or “closed” (for example, for a gate).

There are various ways of performing control and categorization of control methods. In Table 2-2, various methods are presented that focus on timing input, RTC strategies, system-wise function, physical extension, degree of automation, and degree of control. RTC can generally be split into optimization-based and heuristic control (Garcia et al., 2015). The resulting control through heuristic approaches seems rational but it can be difficult to achieve an optimal solution (Cen & Xi, 2009; Garcia et al., 2015; Marinaki & Papageorgiou, 1999; Mollerup et al., 2013; Papageorgiou, 1983, 1988). Passive control results in difficulty to achieve optimal solution due to the dynamic loading of the system; evidence of this usually occurs during time-wise, and spatially unevenly distributed rainfall (Garcia et al., 2015; Lowe et al., 2016; Marinaki & Papageorgiou, 1998, 1999, 2001).

Table 2-2: Categorization of control methods (*after* Lund et al., 2018)

Category	**Control method**	**Description**
Degree of control	Passive control Real-time control (RTC)	Diversion elements are fixed to a static setting The settings of actuators are changed dynamically based on real-time measurements from the system.
Degree of automation	Manual Supervisory Automatic	An operator adjusts the actuators in the system. Actuators are adjusted automatically but the set-points or the direct settings of the actuator are specified/approved by an operator/supervisory system. The entire system is operated automatically.
Physical extension	Local Global	The control is performed independently for each actuator based on measurements from the immediate surrounding. The control is based on observations throughout the system and all actuators are regulated at once from a global perspective.
System-wise extension	System-wide control Integrated (system-wide) control Plant-wide control	Global control only considering the urban drainage system. Global control considering several subsystems alongside the urban drainage system; for example, wastewater treatment plants and receiving water bodies. Control only considering the wastewater treatment plant.
RTC strategies	Heuristic control Optimization-based control	The control is based on experience, which includes fuzzy-logic control, static rules optimized offline (rule-based control), or system that are controlled manually by an operator. The control is modelled as a dynamic optimization problem, which includes linear-quadratic regulators, evolutionary strategies, MPC and population dynamics-based control.
Timing of input	Reactive control Predictive control	The control is determined only based on measurements. The control is determined based on predictions of the future system state.

Urban drainage systems are most often controlled by rule-based (local) control, passive control, or manually by an operator (Lund et al., 2018). However, RTC can achieve a better control (Cen & Xi, 2009; Giraldo et al., 2010; Leirens et al., 2010; Lowe et al., 2016; Marinaki & Papageorgiou, 1998, 1999; Ocampo-Martinez & Puig, 2009a; Ocampo-Martinez et al., 2008; Papageorgiou, 1983, 1988; Pleau et al., 1996, 2005; Rauch & Harremoes, 1996, 1999). Hence, it is likely that many places around the word currently implement suboptimal control (Lund et al., 2018).

2.9.2 Operational goals for RTC

There are various reasons for control implementation and different metrics that can be used to quantify the resulting operational goals. Advanced RTC will often be performed in a system-wide urban drainage context to minimize one or more of the following:

- Combined sewer overflow (CSO) to the environment (measured in pollutant loads, water volumes, resulting oxygen concentration in recipient, risk, or damage cost)
- Urban landscape flooding (measured in pollutants loads, water volumes, risk, or damage cost)
- Operational cost or energy consumption (measured in energy cost or usage)
- Tear and wear of actuators for lifespan growth (measured in cost, usage, or settings variation)

In addition, limitation of water volume loss from rainfall and optimization of storage for stormwater harvesting (SWH) system can also be considered as potential operational goals.

2.9.2 Impediments to the implementation of RTC

Urban drainage systems have been implemented with RTC for more than 40 years, but there has been limitation in developing more sophisticated methods due to unreliable communication system, actuators and sensors, together with insufficient computational power. Implementation of more efficient control strategies such as model predictive control (MPC) can possibly overcome the above-mentioned limitations to certain degree. MPC is an adaptive control strategy for combined sewer systems where optimal control is recomputed recursively as new information about the sewer system state and new forecasts of rainfall become available (see Section 2.14). Additionally, automated operation of urban drainage system has attained increased interest (Meseguer & Quevedo, 2017). This originates from a stronger organization utility due to improved rainfall forecasts and corporatization of the water sector using numerical weather prediction (NWP) and weather radar models (Lund et al., 2018). Despite this, urban drainage systems that implement MPC as a control strategy, are limited to a few examples of real-life concepts and operations that are ready for application (see Fiorelli et al., 2013; Pleau et al., 2005; Vezzaro & Grum, 2014). This indicates that challenges that limit both further development and implementation of MPC techniques are still evident (Lund et al., 2018). These challenges include organizational issues such as lack of proper choice of control equipment; coorperation between operation and planning departments (Campisano et al., 2013) or lack of trust from operators (Vitasovic, 2006); adaptation to the limited computational uncertainty and power to facilitate an optimal solution through rigorously formulating the control problem mathematically (Dong et al., 2017); and linguistic uncertainties, which results in difficulty to exchange experiences and knowledge across research disciplines, institutes and industries (Lund et al., 2018).

2.10 Real Time Control Strategy

2.10.1 The General Strategy

The real time control strategy which is sometimes called global control is a system wide approach (Grum et al., 2011). RTC system allows to achieve several operational objectives in an urban drainage system: cost reduction, management of flows during a system disturbance (safety incidents, equipment failures, or work deviations), management of discharge peaks to the wastewater treatment plant (WWTP), flood prevention, and minimization of overflow volumes and frequencies (Bevilacqua et al., 2018).

RTC in urban drainage system is an efficient approach to reduce the impact on the natural water environment and improve performance (Rauch et al., 2002). In recent years, the spread of RTC systems' implementation has largely been due to technological innovations and theoretical studies (drainage system + RTC modelling) (Maiolo et al., 2020). Equipment and Methodologies are well adaptable and available for different urban drainage system uses (Vezzaro & Grum, 2014). Recent developments in radar now-casting has widened the applicability of these devices (Thorndahl, 2009); moreover, available computational capacity and online measurements have improved these tool's potential application field (Maiolo et al., 2020).

An RTC system dynamically regulates the drainage system to improve the system's overall performance by implementing a feedback loop based on online measurement to achieve specific objectives. Operational algorithms and strategies regulate the system operations according to the dynamic network and current state conditions detected in "real-time" (Campisano et al., 2013). An RTC system equipped with specific devices (actuators, controllers, sensors), can coordinate multiple functionalities such as (i) determining the physical actions on the final control actuators (ii) defining the settings of the control structures to achieve the wanted state (iii) comparing the current state against the wanted one and, (iv) monitoring the current state of the network (Maiolo et al., 2020). Thus, all the equipment allows the system's dynamic management according to the system's critical event and current conditions (Schilling et al., 1994).

2.10.2 The Radar Based Flow Forecast

Continuous radar-based flow forecasts can be established through the use of a well-tested approach that involves flow forecasting using the rainfall-runoff model with the forecasted radar data, dynamic calibration of simple rainfall-runoff models, radar forecasting and dynamic calibration of radar data against rain gauge measurements (Grum et al., 2011). The main principles of this approach have been described in Thorndahl et al. (2009), and are illustrated as shown in Figure 2-2.

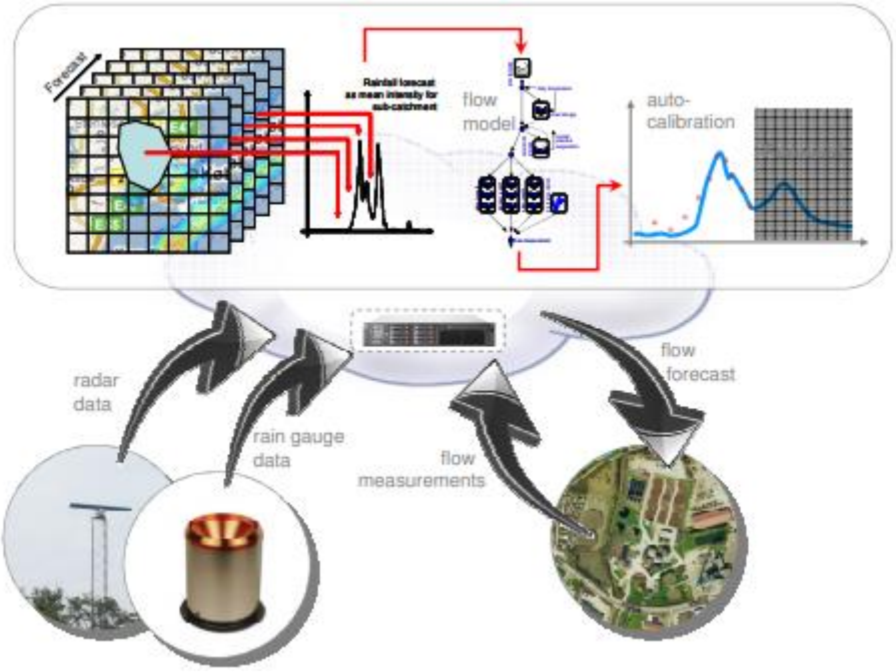


Figure 2-2: Illustration of the basic approach used to establish radar-based flow forecasts (Thorndahl et al., 2009).

The use of radar rainfall prediction introduces another element of reliability (Colas et al., 2004). The radar rainfall images provide rainfall evaluations over the entire area as if there was approximately one rain gauge per square kilometre of per square mile. Rainfall measurements obtained from all the rain gauges are used to globally calibrate the radar image. The use of radar rainfall images is more reliable due to the fact that the rainfall field is not always covered well by rain gauges, and because radar can still perform when one or two rain gauges fail. With regards to rainfall prediction, another reliability factor is that when Csoft computes interception set points, Csoft accounts for future rainfalls. Csoft improves reliability by making good use of radar rainfall predictions. The use of any of these features is naturally a matter of costs vs benefits. Nevertheless, there are minimal requirements that must be included for risk reduction, such as safety, reliability, adaptability and flexibility to consistently provide acceptable outcomes.

2.10.3 The Expected Cost

The core of the real time control strategy is the expected cost because the formulation of the expected cost ultimately dictates how the system will be operated (Grum et al., 2011). The expected cost can incorporate a wide variety of considerations such as the risk of endured environmental taxes, risk of sludge loss at the treatment plant, risk of lost bathing water, pumping costs, and risk of overflow and flooding.

In Grum et al. (2011), the expected cost for a section in an urban drainage system was defined as the product of cost of any given amount of overflow times and probability of occurrence. The endured cost was determined to be proportional to the volume of discharge for a given amount of overflow discharge. Hence, the integration of the product of the cost of a given overflow volume (for a given runoff amount) and the probability of occurrence of that runoff amount expresses the expected cost for a section, and this is illustrated in Figure 2-3.

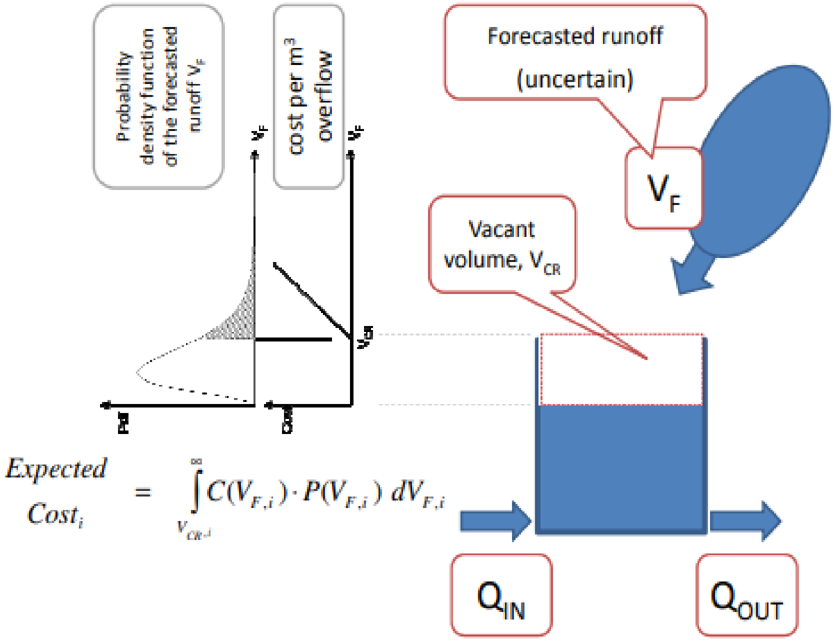


Figure 2-3: The expected cost or RTC (Grum et al., 2011)

2.10.4 Optimization Routine

Flows that minimize the expected cost as defined above was estimated using a genetic algorithm. The optimization problem is a classical non-linear programming problem with discontinuities with respect to the parameter (the estimated flows) in the objective function. Hence, failure to find optimal parameter set by the faster gradient-based methods often occur. Similarly, non-optimum flat points that real time control problems often encompass fool wandering methods such as downhill simplex. Additionally, a simple way of introducing constrains involving several parameters (flows) can be implemented using a genetic algorithm.

2.10.5 Connection to Local Control Units

It is essential to understand the main responsibilities of the overall and local controls in establishing the connection between the system wide dynamic risk based real time control strategy and the local control units at pumping stations or gates respectively. The local controls are typically responsible for keeping water levels combined sewer overflow weir levels and avoiding flooding whereas overall control is primarily responsible for optimizing storage utilization.

2.11 Level of Control

Any RTC system can be placed into one of three general classifications depending on its complexity according to several studies (e.g. Colas et al., 2004; US EPA, 2006; Vallabhaneni & Speer, 2011; García et al., 2015; Beeneken et al., 2013). Described in order of ascending complexity, these classifications are as follows:

- **Local control** – the simplest method of RTC is local control. If the adjustments made to the system are dependent solely on measurements taken at the same location at which the adjustments are made, then an RTC system is defined to be under local control. The use of automatic actuators or manual adjustments are used to make these adjustments (Colas et al., 2004; US EPA, 2006). Further, conventional Rule-based Controls (RBC) are typically used for the decision support system behind these adjustments in locally controlled RTC systems. RBC incorporate ‘if-then’ rules (i.e. do this if this has happened) and are generally straightforward (See section 2.12). Furthermore, RBC strategies incorporate control rules that are developed prior to implementation of the RTC system and are typically a function of measurement (García et al., 2015). Since local control RTC systems are simple to understand and operate, they are often favoured, yet their adjustments are limited to on-site conditions, essentially disregarding the conditions throughout the entire system. Conservative RBCs can result due to this limitation (US EPA, 2004; García et al., 2015).

- **Regional control** – the independency of management of storage facilities make the regional control management approach similar to the local control (Gaborit et al., 2013). The difference is the remote regulation, meaning that, adjustments to the system are remote to a location at which the adjustments are made which are based on measurements taken from the location or several locations (Colas et al., 2004; US EPA, 2004). Hence, a regional RTC control would not be suitable for a manually operated system with site-specific opening and closing of valves (US EPA, 2004). A remotely controlled regional communication such as Supervisory Control and Data Acquisition (SCADA) program located on a central server system are typically required for a regional RTC control system (Colas et al., 2004; US EPA, 2006). Furthermore, unlike local control, regional control RTC systems can function under either optimization-based algorithms or pre-defined RBCs. Optimization-based algorithms seek to reach a desired state of a system through manipulation in real-time (García et al., 2015). Either of these methods can be applied under the supervision of a system operator or automatically. Similar to local control, regional control RTC systems is limited as it only considers the conditions in the system where control logic is based rather than considering the conditions throughout the entire system (US EPA, 2006).

- **Global control** – global control RTC systems are incorporated to provide optimal operational efficiency, and are the most complex method of RTC (Colas et al., 2004). Data is centralised for global control RTC systems, so any measurement device that is part of the system can be used to make adjustments to the network at any point at which there is an actuator based on the data provided. The decision support system that either incorporate predictive forecasting, optimization-based algorithms, RBC or a

> combination of the aforementioned decision support system is used to make these adjustments (Colas et al., 2004; US EPA, 2006). For clarity, predictive forecasting is a method that uses forecasted rainfall to estimate future flows in the network and then adjusts the system accordingly *(ibid.)*. The global control RTC system, although the most complex demands the most understanding as it offers the greatest functionality. It requires supervisory control by an operator who has a good understanding of the system dynamics – as well rigorous network analysis and planning before it implemented (US EPA, 2004).

Utmost consideration must be given to what system complexity is appropriate when developing an RTC system. The US EPA stresses that implementation of an RTC system with a complexity level that the developers are capable of understanding and operating results to success. The success of RTC systems is more often hindered due to organisational or operational procedures rather than constrains by current technology such as technological issues. In addition, RTC may not always be cost-effective for all situations (Colas et al., 2004; US EPA, 2006), but is beneficial only in stormwater networks in which there is unused storage capacity during inter-event period.

Several components are required for RTC systems to function. As the complexity of the system increases, the number of components also increase, and this is illustrated in Figure 2-4. The typical components of an RTC system include: control systems (SCADA), data transfer structures, control devices (typically Programmable Logic Controllers (PLC)), actuators and measurement instrumentation (Beeneken et al., 2013).

Incorporation of RTC into stormwater conveyance network has gathered much interest in recent years although the technology it applies is not new. It was in the late 1960s when the first RTC prototype was introduced into an urban drainage system (García et al, 2015). Europe and North America in particular, have shown an increasing number of RTC systems that have been implemented into stormwater conveyance networks (García et al., 2015). Whilst research on RTC systems initially focused on the stormwater conveyance network to reduce sewer overflow through increasing retention time, more recent research has started to focus on increasing retention time in stormwater ponds for improvement on the water quality that RTC system provide (Fuchs et al., 2004; Muschalla et al., 2014; Vezzaro et al., 2014).

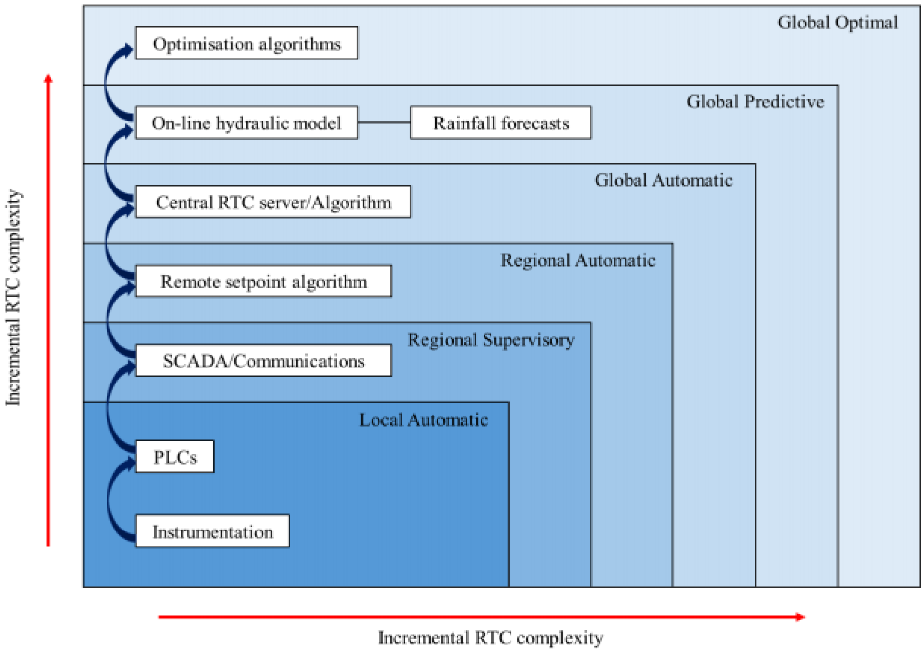


Figure 2-4: The various levels of complexity of Real Time Control systems (Vallabhaneni & Speer, 2011)

2.12 Rule-based RTC

Local, rule-based control (RBC) also known as heuristic control logic is the simplest form of automated RTC. In RBC, before the system is online, typically in the style of an 'if-then-else' logic structure, the control actions are set manually. This implies that, expert knowledge of the urban drainage system (UDS) for RBC systems design and implementation is required (Vitasovic, 2006). The reason why these systems are often developed in an iterative way is to pre-programme the control algorithm to handle all possible circumstances (Gaborit et al., 2013; Goodman & Quigley, 2015).

A study on rule-based control tested two 'extreme' control schemes (Jacopin et al., 2001). The first study aimed to prevent flooding during large storms by always maintaining maximum capacity of detention basins. The second study focused on promoting sedimentation during smaller events to detain water. It was concluded that both water quality and hydraulic control objectives can be met with RTC, but switching between the two strategies in the decision-making process was left to future research.

Simple control rules based on water accumulation, current precipitation measurements and pond depth are used to reduce large discharge rates in a detention basin and maximize hydraulic retention time of stormwater runoff (Gaborit et al., 2013). Further modelling of this system with a calibrated water quality model for nutrient treatment capabilities in a detention basin through application of RTC showed improvements (Muschalla et al., 2014), and the field experimentation of the system which was carried out for verification was successful (Carpenter et al., 2014). The application of RTC has been shown to improve water quality treatment through prolonged retention time in a variety of Best Management Practices (BMPs) such as wet ponds, constructed wetlands and green roofs (Bartos et al., 2017; Lefkowitz et al., 2016; Middleton & Barrett, 2008; Opti RTC & Geosyntec Consultants Inc., 2017).

In the work by Goodman & Quigley (2015), another heuristic control innovation was implemented to match post-development BMP to an approximation of pre-development runoff rates using flow-duration curve. This technique would allow for full flow-regime management which is shown to reduce unnatural erosion of waterways more efficiently rather than reducing the peak flow from low-frequency events, such as using multi-stage outflow risers to address 2-year and 10-year peak flows (Palhegyi, 2010; Tillinghast et al., 2011; Vietz et al., 2015). However, the curve-matching approach presented by Goodman & Quigley (2015) is a potentially expensive endeavour because it requires extensive modelling and many iterations. Additionally, the myriad definitions for “pre-development flow” given in US stormwater regulations has made it clear that the concept of pre-development flow has no universally accepted definition (USEPA, 2016).

Attempts have been made to apply regional coordination of RBC as the majority is implemented locally. McCarthy (1994) describes a simple technique to coordinate flows from two detention ponds so that they do not exceed the capacity of a downstream channel. Mullapudi et al (2017) prevented overflow and maximized treatment by balancing the discharges from two detention basins into a wetland. Releases from two detention ponds were alternated to create on-phase and off-phase interaction of flows at a downstream point in an experimental RTC set up (Mullapudi et al., 2018). For this method, experimentally-gathered travel time and shape of downstream hydrographs from each detention basin are used. However, interactions of more than two RTC elements in the same watershed is an area that remains poorly understood even though advances of important work are provided for coordination of several RTC elements. Thus far, there has been a shift towards global optimization-based control approaches by academics and UDS operators to address this problem.

2.13 Optimization-Based RTC

Many researchers have embraced optimization based RTC algorithms with capacity to predict the interactions of nonlinear complex systems typical in an urban drainage system (García et al., 2015; Lund et al., 2018). An optimization-based control algorithm minimizes costs and maximizes benefits costs for a system of inputs and outputs by employing mathematical techniques. This is referred to as global optimal real-time control (GO RTC) when applied for system-wide control. The algorithmic families loosely ordered from most to least prevalent, include Model Predictive Control (MPC), Linear Quadratic Regulators (LQR), Evolutionary Algorithms (EA), and Population Dynamics are most commonly applied for GO RTC of urban drainage systems (García et al. 2015).

MPC and LQR allow for the control logic to have a system-wide perspective since they incorporate an online system for their execution. Many advancements in LQR control have been developed for operation of irrigation canals (Balogun et al., 1988; Lemos & Pinto 2012) and reservoir routing (Wasimi & Kitanidis, 1983), but has been applied in both combined

(Marinaki & Papageorgiou, 2003) and separate (Wong & Kerkez, 2018) sewers for the control of urban drainage system. Future disturbances such as forecasted rainfall and runoff can be incorporated by MPC to allow for feedforward, as well as feedback, control. This use of predictive information is particularly relevant to urban drainage systems as it uses weather forecasts such as the drawdown of storage facilities before a large storm for anticipatory actions. Many scholars agree that the complexity of Model Predictive Control may hinder its great potential for optimal management of urban drainage systems (García et al. 2015; Lund et al. 2018). Lund et al (2018) reviewed applications of MPC in urban drainage system and found few examples of real operations actively implementing MPC. García et al (2015) concluded that MPC is one of the most used forms of GO RTC and this directly contradicts the study from Lund et al (2018). This contradiction may be due to hesitation by local governments to implement such an opaque and complex control strategy as current work in MPC has largely been theoretical and simulation based rather than applied.

Multi-objective optimization problems with nonlinear inputs are well suited for Evolutionary Algorithms (Muschalla, 2008). EA is used for offline analysis of urban drainage systems in most of the existing literature (Barreto et al., 2010; Cho et al., 2004; Muleta & Boulos, 2007; Muschalla, 2008), with limited examples for online real-time control utilizing EA (Vezzaro & Grum, 2014). Similarly, García et al (2015) pointed out that the application of Population Dynamics to RTC remains relatively unexplored. Work by Barreiro-Gomez et al. (2015) appears to be the only study that applied Population Dynamics for the control of an urban drainage system.

2.14 MPC basic principles

The prediction that warmer global temperatures will cause more intense storm events, increases the stress on stormwater systems (Berggren et al., 2012). Concurrently, sea level rise which reduces the already limited elevation head required to drain stormwater from streets to receiving bodies will likely decrease the effectiveness of coastal cities stormwater systems (Sadler et al., 2018). Alternatives are required to increase the effectiveness of coastal cities since significant changes to existing coastal cities stormwater infrastructure is often cost prohibitive. Kerkez et al. (2016) proposes a ‘smart’ system which can increase the effectiveness of stormwater infrastructure by actively managing the existing stormwater infrastructure.

The approach of a ‘smart’ system efficiently uses the existing infrastructure by increasing its effective capacity without increasing the actual capacity of the stormwater infrastructure (Sadler et al., 2018). The use of an automated valve at the outlet of a detention basin which can be closed or opened based on forecasts and conditions can be categorized as an example of active management of stormwater infrastructure.

The stormwater system ability to achieve its objective (e.g., minimize flooding, optimization of storage) can be largely impacted by the effectiveness of the actuators in the system. Model predictive control (MPC) can determine the optimum control policy for a system (i.e., which actuators can be modified, when to modify them, and to which modification/setting). Gelormino and Ricker (1994) focuses on urban drainage scenarios that effectively used MPC.

MPC is one way of performing advanced RTC of urban drainage systems (Lund et al., 2018). In the 1960s, MPC was first described theoretically, and its application was evident until the 1970s (Qin and Badgwell, 2003). The expansion of MPC application in some industries was based on the underlying fact that MPC concept is relatively easy to understand (Maciejowksi, 2002). It has been applied across a wide range of technical fields including food processing, chemical plants, production of pulp and paper, and aerospace and automotive industries (Qin and Badgwell, 2003).

The receding horizon principle and optimization are two key aspects of MPC (Lund et al., 2018). The receding horizon principle, which involves the repetition of optimizing the control recursively within a finite time horizon; and optimization, which selects the best possible sequence of control actions within this horizon. This optimization consists of an optimization model, an internal MPC model and an optimization solver.

In MPC, the internal MPC model computes the states of a system from the time of forecasts and into the future through the incorporation of input predictions in the form of runoff, rain, and/or sewage from relevant parts of an urban drainage systems (Figure 2-5). The optimization model defines the operational goals and, also from a basis on which the control actions are computed by the optimization solver. The optimized control is carried out in reality for only its first part; concurrently, a new optimization is performed. Every re-optimization can be utilized to incorporate new information about the input and state of the system.

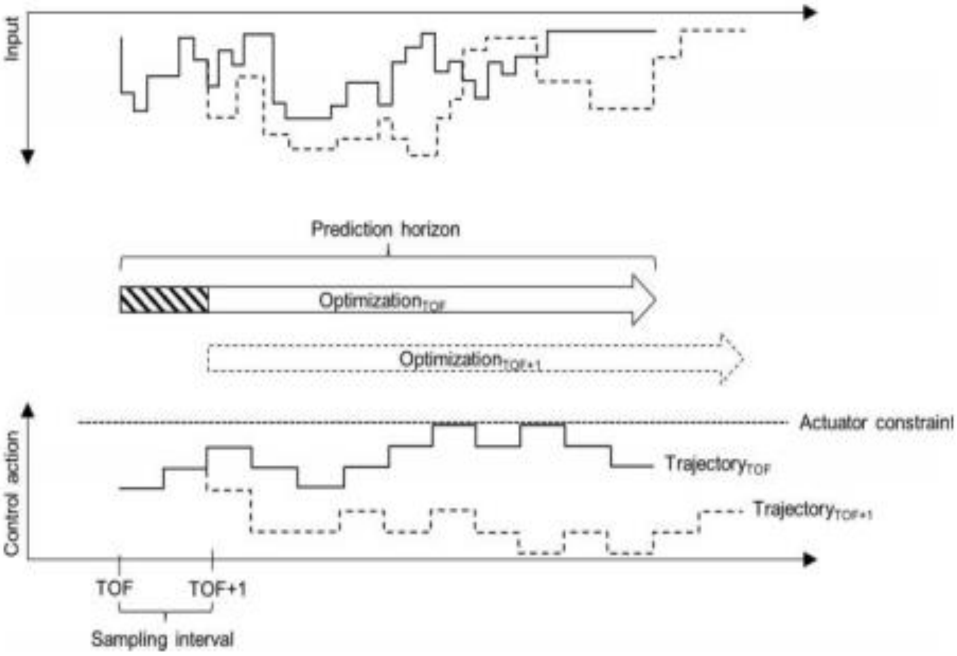


Figure 2-5: The concept of MPC, including the receding horizon principle and optimization. TOF D time of forecast (Lund et al., 2018)

In principle, MPC can deal with multivariable in complex systems considering operational and physical constraints such as pipe flow and actuator limitations. Hence, MPC can be applied globally and locally as a control scheme. MPC as a control strategy, is advantageous for complex and large urban drainage system with multiple wastewater treatment plants (WWTPs), multiple overflow structures, and a complex network of storage basins and actuators distributed in various parts of the sewer or SWH system, where constraints on water levels, volumes and flows are to be respected, and in a heterogeneously distributed rainfall case (Cembrano et al., 2004; Gelormino and Ricker, 1994; Ocampo-Martinez and Puig, 2009a, 2010; Pleau et al., 2005; Puig et al., 2009). MPC can anticipate a problem that arise from a limited capacity of structures based on the application of input predictions; therefore, the control becomes proactive (Duchesne et al., 2001, 2004; Garcıa et al., 2015; van Overloop et al., 2008; Puig et al., 2009; Schutze et al., 2004).

2.15 Procedure for Assessing the RTC for a given system

The criteria to assess the suitability of an RTC strategy for an urban drainage system concerning the specific system features are conditioned by several aspects rather complex to determine (Rossman, 2006). Several studies to establish the necessary standard and RTC application aspects were carried out (Maiolo et al., 2020). Erbe et al. (2007) is an example that provides RTC guidelines by the DWA (German Association for Water, Wastewater, and Waste). Moreover, some software tools such as the planning tool called PASST (Planning aid for sewer system real-time control) were developed for support during the decision-making process (Dirckx et al., 2011; Erbe et al., 2007).

The definition of a ‘control strategy’ arouse by critically analysing the above factors (Maiolo et al., 2020). The RTC possible configurations range from direct and simple controls accomplished at the “local” level (punctual or regional) to more complex “global” controls with an “optimal predictive global” configuration concerning the whole system (US EPA, 2006) as discussed in Section 2.12.

Many studies so far were concentrated on a centralized RTC’s approach (Beeneken et al., 2013; Pleau et al., 2005; Darsono & Labadie, 2007). However, given the huge amount of data to be read, managed and processed, this type of control system presents some problems although reliable (Maiolo et al., 2020). Generally, all data collected by sensors are sent to a central unit based on a specific strategy to produce a command for the actuators in this approach. Hence, a similar approach requires efficient connections among complex mathematical model and all elements (actuators and sensors) based on its functioning. Moreover, the behaviour of the whole system can be compromised due to failure of one node (Garafalo et al., 2017).

Recently, Kändler et al. (2020) have developed a new concept of a smart in-line storage system that can predict rainfall dynamics, and is easy to install and operate by real-time controlled actuators, and does not require an advanced centralized control system.

In the work by Erbe et al. (2007), guidance is provided to enable the engineer to assess the potential of Real Time Control by the DWA-M 180 guideline document. The document puts its main emphasis on technological-environmental aspects whilst giving valuable advice for the various stages of the planning and implementation process. Furthermore, legal and financial issues are also addressed in the document. The proposed procedure (Figure 2-6) consists of three main steps.

Step 1 – Initial considerations

The objectives of the urban drainage system under study are specified in the first step. As practice shows, this task may involve numerous discussions with the company operating the system relating to each other's financial objectives, environmental objectives and the consenting procedure, although this may sound trivial. Often, an evaluation of a multitude of objectives will have be considered for the suitability of real-time control for a given site. A point scoring table (contained also within PASST) that constitutes the first milestone of the procedure is used for evaluation.

Step 2 – Preliminary analysis

Some more information on the case study is required at this stage: Information should be collected on the availability of simulation models for the given system, existing sensor and control equipment, catchment data, detailed network layout, and the organizational, legal and regulatory framework. It is important to note that since the operational staff have expertise with the system which might not be documented in written form, discussions with the operational staff will also be required. In addition, the increase in the acceptance of any RTC system requires involvement of the operational staff because it has to be managed in the future. At this stage, any information required for the subsequent steps that is missing should be collected. When comparing any future operational scenarios against the present state, the description of the current state of the drainage system and of its current performance will also be invaluable. The preliminary simulation of the study is the core of this preliminary analysis. A simulation study should be carried out after an initial check on the potential for control obtained by doing simple mass balancing, using some indices or from an analysis of the behaviour of the existing system.

Step 3 – Detailed planning of the RTC system and its implementation

The next step will consist in detailed planning of the control system if the evaluation of various scenarios has resulted in RTC being the favoured option. The guideline document can provide only some general recommendations for this step due to boundary conditions and different dimensions within each particular system. The following aspects refer to the subsequent steps:

- Step 3.1 Detailed planning of control infrastructure
- Step 3.2 Detailed design of the control algorithm
- Step 3.3 Preparations for obtaining consent by the governmental authorities
- Step 3.4 Risk and failure analysis

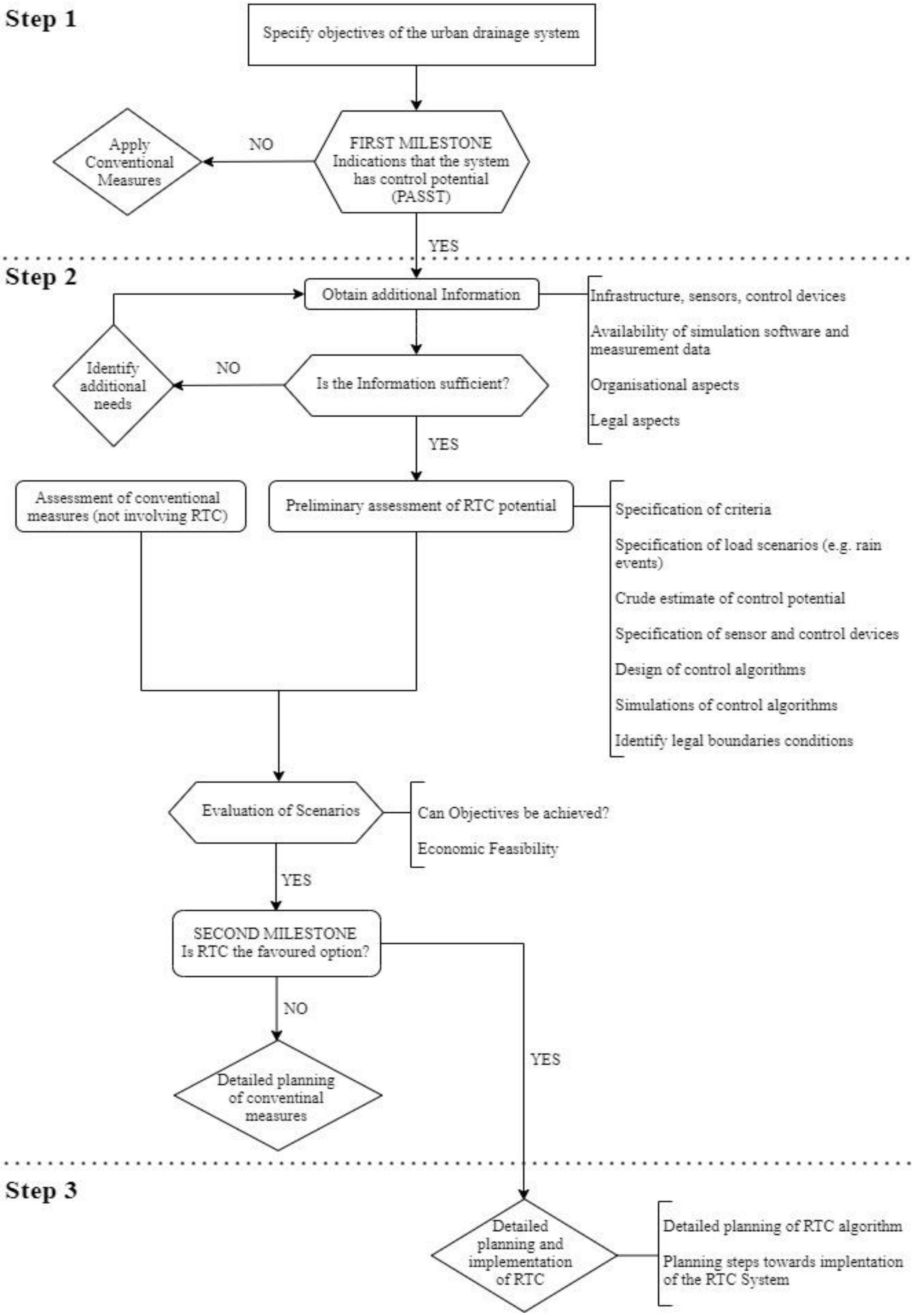


Figure 2-6: Flow chart of RTC planning procedure (*after* Erbe et al., 2007)

2.16 Urban drainage systems with Rule-based RTC

2.16.1 Diep River sub catchment

The study focused on discovering whether it was economically viable to use low complexity Real Time Control (RTC) techniques. The techniques were used to facilitate stormwater harvesting (SWH) from several existing ponds in the Diep River sub catchment (Cape Town, South Africa), without diminishing their capacity to attenuate downstream flood risk. The sub catchment experienced seasonal rainfall with wet winters, warm, dry summers and mild (WWO, 2016). Six SWH scenarios that were modelled for the study used three RTC strategies coupled with two alternative water demand alternatives for supply of selected developments with non-potable water.

For the study, it was assumed that the control of the outlets of all the existing ponds could be modified to retain runoff. All ponds were positioned directly in-line with the watercourse (on-line modelling) open storage facilities without impregnable linings. Hence, the ponds would be susceptible to water losses through infiltration and evaporation with an average of 18% modelled loss of volume (Rohrer & Armitage, 2017). The modelled storage volume of each pond was categorized into flood mitigation, active storage and dead storage (Figure 2-7).

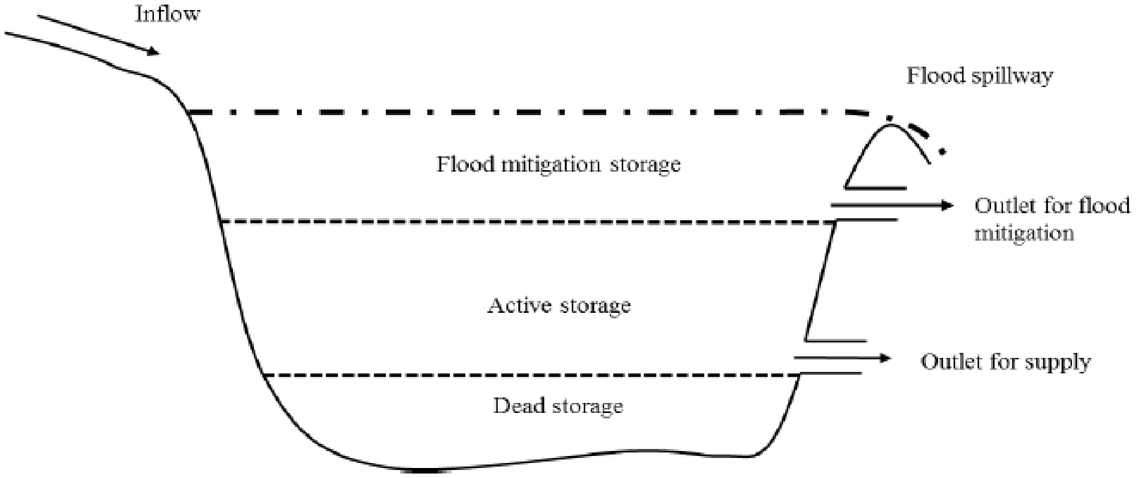


Figure 2-7: Conceptual design of an open storage stormwater harvesting system
(Mitchell et al., 2006)

Dead storage upholds the aesthetic value of the pond and represents sediment removal; active storage is the volume of water which can be supplied; whilst flood mitigation storage attenuates storm events through provision of additional volume over-and above spare active volume capacity of the pond. The six modelled scenarios of the study are shown in Figure 2-8. These consisted of three basic RTC strategies (A to C), each with two non-potable water demand alternatives that are different (WDA) (1 & 2).

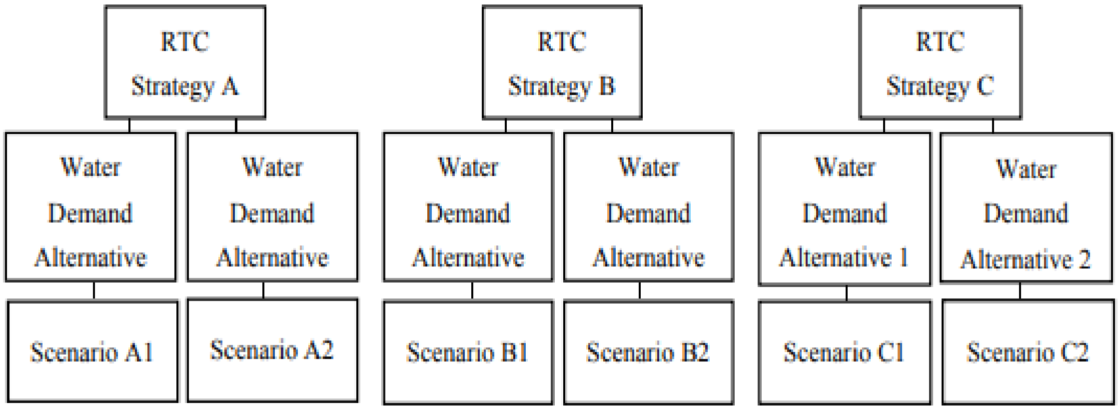


Figure 2-8: The six SWH scenarios – RTC strategy and Water demand Alternatives (WDA) – modelled (Rohrer & Armitage, 2017)

A stormwater pond could perform one of the three rules within each RTC strategy namely for: (i) storage of runoff only; (ii) storage and harvesting of runoff; or not used for SWH. Storage ponds were only used to store runoff which was then released to a downstream storage and harvesting pond according to various rules. Storage and harvesting ponds were only used to extract the stored runoff. Ponds that were neither used for harvesting and/or storage were not adjusted in any way, i.e., they retained their existing duty which was to reduce peak flows. Two separate residential non-potable water demands: WDA 1 (toilet flushing); and WDA 2 (toilet flushing, clothes washing and lawn irrigation) were used in the modelling of each RTC strategy.

There were 243 different possible RTC strategies that could be devised from the combination of the existing stormwater ponds and pond roles, assuming that Little Princess Vlei (LPV) which was the most downstream pond in the catchment was to only be used for the storage and harvesting of runoff. Modelling all of these RTC strategies was thus unnecessary as long as the most representative ones considered because most shared considerable similarities to one another. Hence, only three RTC strategies that represented the most extreme options coupled with the two WDAs (Figure 2-9) were modelled in an effort to streamline the study and massively save on computational effort.

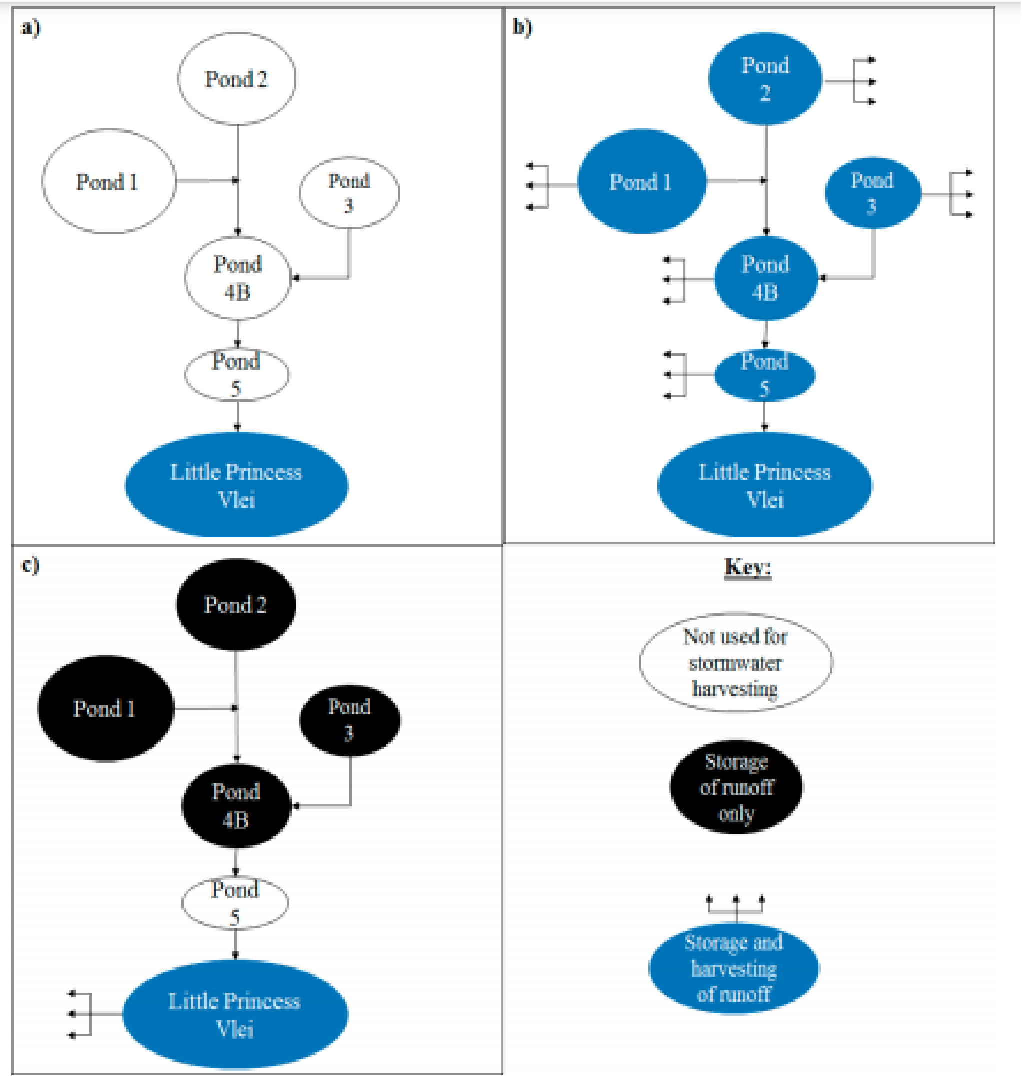


Figure 2-9: Schematic of RTC options: (a) RTC strategy A; (b) RTC Strategy B; (c) RTC Strategy C (Rohrer & Armitage, 2017)

RTC Strategy A considered only one pump in the system located at LPV and no control on the outlets of any ponds, which were the least possible modification to the existing stormwater ponds. This meant all ponds retained their existing function except for LPV which was utilized for harvesting and storage. This strategy was used as a 'benchmark' against which the other alternatives could be assessed. The following rules were used for RTC Strategy A:

- During periods in which there was a demand for harvested storage, the pump was turned on and it extracted water from the pond if the water level in LPV was above the dead storage depth. The pump was turned off if the water level in LPV was below the dead storage depth or there was no demand for harvested stormwater.
- RTC Strategy B considered a completely decentralised way of investigating the viability of harvesting stormwater. All the existing ponds were modelled for both harvesting and storage. Stormwater that is harvested in this way maximizes the potential for SWH but also costs the most resulting in a less economically viable solution. The

outlets and pumps in each pond were modelled for RTC operation except for the outlet at LPV under the following rule:

- Every pond in the catchment was able to pump water out. Each pond comprised of a pump which was independently operated based on the local conditions it serves, i.e., whether there was water available above the dead storage level and demand for harvested stormwater. The pump was turned off if the water level in a pond was below the pond's dead storage or there was no demand for harvested stormwater.
- When the water level in the ponds exceeded their active storage depth, the pond outlets were opened; otherwise, the outlets remained closed.
- RTC strategy C investigated, harvesting stormwater in a centralized manner at the most downstream pond in the catchment – LPV to maximize the storage within the catchment. It was assumed that four of the ponds; 1, 2, 3 and 4B which were modelled for storage only would best represent the benefits of utilizing RTC for improvement of the viability of SWH as it limited the maintenance, operation and capital costs whilst maximizing storage volumes. The following rules were used for RTC operation:
- The outlets of ponds 1, 2 and 3 were independently opened if their active storage depth was exceeded by the water level of the respective ponds. The outlets of ponds 1, 2 and 3 were also opened when the water level of the respective pond exceeded its dead storage depth whilst the water level of in pond 4B dropped below its dead storage depth. The outlets remained closed under operation of other conditions.
- When the water level in pond 4B exceeded its active storage depth, the outlet of the pond was opened. When the water level in LPV dropped below the dead storage whilst the water level in pond 4B exceeded the depth of its dead storage, the outlet in pond 4B was opened. The outlet remained closed under operation of other conditions.
- During periods in which there was a demand for harvested stormwater, the pump was turned on and water was extracted from LPV when the water level in the pond was above the dead storage depth. The pump was turned off if the water level in LPV was below the dead storage depth or there was no demand for harvested stormwater.

The program PCSWMM 6.2 was used to create and calibrate a SWMM5 catchment stormwater model for the study. The stormwater catchment network for a continuous ten-year period using a fifteen-minute time step and the hydraulic and hydrological runoff or behaviour within the catchment was simulated using the stormwater model. The Hargreaves method (Allen et al., 2006) was used to model evaporation whilst the Green-Ampt infiltration method (Chow et al., 1988) was used to model the infiltration within the catchment stormwater model.

Direct costs (*i.e.,* maintenance, operational and capital costs) were only considered to perform a Life-Cycle Cost Analysis (LCCA) for each RTC strategy to establish the effective unit supply cost of SWH and distribution, disregarding non-monetary aspects and indirect costs (Rohrer & Armitage, 2017). The conversion of all costs required to sustain the asset over its lifespan to an equivalent time period is a necessary process during an LCCA. Several studies were used as a guide to estimate costs for the study (Lampe et al., 2005; Woods – Ballard et al., 2007; WERF, 2016; Armitage et al., 2013). A real discount factor of 3.25% (Government ten-year bond minus inflation) was used to perform each LCCA for a fifty-year duration (HomeFinance, 2016; Investing, 2016). Armitage et al. (2013) proposed recommendations that were used for the study on the life span of each system component. The straight-line depreciation method that assumes that each component zero value at the end of its life cycle was implemented to complete residual values (Rohrer & Armitage, 2017). The Equivalent Annualised Cost (EAC) was used to reduce each scenario after the Life Cycle Cost was computed.

An optimal state in which the harvested volume of stormwater is traded off against costs, was required to create economically viable SWH system. Harvesting from multiple ponds (Scenario B1 and B2) in a decentralised manner maximised the harvested volume and increased the overall cost of the system due to increased maintenance, operation and capital costs, particularly associated with the requirement for dual reticulation systems and multiple treatment works. In comparison to harvesting from a single pond in (Scenario A1, A2, C1 and C2), the centralised system maximised infrastructure costs but with low yield. The estimated raw unit cost to supply harvested stormwater for each scenario, estimated average yield and total infrastructure cost were all considered in the study.

Options that considered WDA 2 in comparison to WDA 1 were clearly more economically viable. This was expected as SWH system supplying areas with a high-water demand concentration (i.e., water demand/area) are most likely to be economically viable due to the limitation of the extent at which dual water reticulation required, which results in lower infrastructure costs (Fisher-Jeffes, 2015). Cost per cubic metre to supply harvested stormwater comparable to the typical maximum tariffs (29.03, 23.51 or 15.81 ZAR/m^3) which the City of Cape Town used as a ‘rising-block’ tariff scheme depending on the demand to bill residents within the catchment for their potable water usage at the time of the study (Rohrer & Armitage, 2017). When comparing results of the estimated raw unit cost to supply harvested stormwater for each scenario with the results of the estimated yield; single, centralised, pump, treatment and distribution systems (Scenario A1, A2, C1 and C2) essentially outweighed the loss in effective storage in comparison with the decentralised system (Scenario B1 and B2) due to lower costs. However, it was possible to achieve the economic benefits of centralised system whilst obtaining yields in comparison to these obtained by decentralised system through the use of RTC for distribution of storage amongst upstream ponds (Scenario C1 and C2).

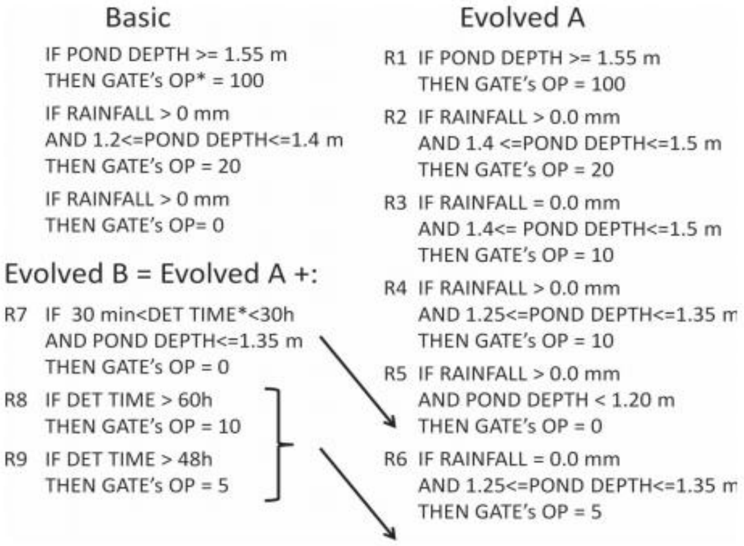
The study demonstrated that the use of rudimentary RTC techniques can secure considerable additional storage capacity within an existing stormwater pond system pond system without significantly impairing the existing pond’s ability to mitigate downstream flood risks. Harvesting stormwater in a centralised manner was clearly more economically attractive despite the lower stormwater yields in comparison to decentralised SWH system which maximised the available storage. However, the use of rudimentary RTC techniques in centralised systems for distribution of stored runoff amongst upstream ponds nearly yielded stormwater volumes as large as those obtained by decentralised system at unit costs comparable to a completely centralised system, therefore offering a good reference between both approaches which have favourable aspects. Hence, existing stormwater ponds to store runoff amongst distributed ponds which be enabled through the use of rudimentary RTC techniques has the potential to overcome some of the storage limitations in urban area associated with SWH, thus making this a viable water source.

2.16.2 Québec city catchment

The case study was conducted in a grassy, dry, on-line stormwater detention pond located in Québec city (Canada) at the outlet of a residential catchment. The catchment covered 15.3ha with an average slope and imperviousness estimated to about 3.5 & 33% respectively (Gaborit et al., 2013). The catchment was equipped with a separate dual drainage sewer system for stormwater which utilized the streets as the major conveyance and an underground sewer system as the minor one. The maximum outflow of the detention pond was fixed to 0.35 m^3/s. The urban catchment sewer conveyance system's geometrical and land use properties were precisely known, as well as the storage capacity of the pond and wet surface as a function of height.

The runoff volume and quality exiting the small urban catchment, including its dry detention pond was simulated using the open-source Storm Water Management Model (SWMM) version 5. The SWMM5 build-up/wash-off representation was used to simulate the runoff quality. A storage curve (representing the area as a function of height) which can describe a non-linear, completely mixed reservoir was used to simulate the dry detention pond. Control rules to manage the routing of the flow in the sewer conveyance system can be defined using SWMM5.

Trial-and-error was used in the decision-trees presented for the study for threshold values. The RTC methodology for the study focused strictly on developing rules that rely on measurements of rain intensity and on water heights in the pond rather than on flow information, because technical problems are more likely to occur with velocity sensors than with water height sensors. The gate's opening percentages were based on an analysis of the pond's drawdown time when completely filled to allow a wide variety of possible discharge flows. Control rules were associated to a corresponding priority order in the SWMM5 model that can be performed by choosing two different control actions when system states led to simultaneous but contradictory pre-defined resulting actions. The rules are presented in decreasing order of priority (Figure 2-10 and 2-11).



Basic

IF POND DEPTH >= 1.55 m
THEN GATE's OP* = 100

IF RAINFALL > 0 mm
AND 1.2<=POND DEPTH<=1.4 m
THEN GATE's OP = 20

IF RAINFALL > 0 mm
THEN GATE's OP= 0

Evolved B = Evolved A +:

R7 IF 30 min<DET TIME*<30h
AND POND DEPTH<=1.35 m
THEN GATE's OP = 0

R8 IF DET TIME > 60h
THEN GATE's OP = 10

R9 IF DET TIME > 48h
THEN GATE's OP = 5

Evolved A

R1 IF POND DEPTH >= 1.55 m
THEN GATE's OP = 100

R2 IF RAINFALL > 0.0 mm
AND 1.4 <=POND DEPTH<=1.5 m
THEN GATE's OP = 20

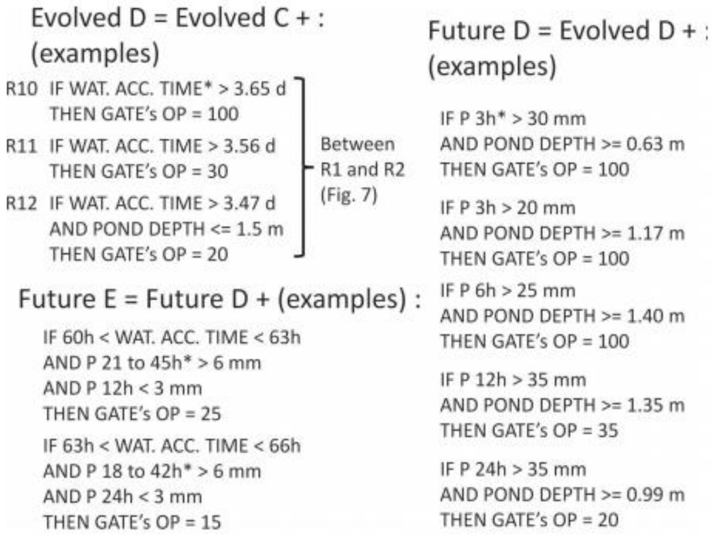
R3 IF RAINFALL = 0.0 mm
AND 1.4<= POND DEPTH<=1.5 m
THEN GATE's OP = 10

R4 IF RAINFALL > 0.0 mm
AND 1.25<=POND DEPTH<=1.35 m
THEN GATE's OP = 10

R5 IF RAINFALL > 0.0 mm
AND POND DEPTH < 1.20 m
THEN GATE's OP = 0

R6 IF RAINFALL = 0.0 mm
AND 1.25<=POND DEPTH<=1.35 m
THEN GATE's OP = 5

Figure 2-10: Rules of the first three developed RTC scenarios. OP = opening percentage; DET TIME = detention time (Gaborit, 2013)



Evolved D = Evolved C + :
(examples)

R10 IF WAT. ACC. TIME* > 3.65 d
THEN GATE's OP = 100

R11 IF WAT. ACC. TIME > 3.56 d
THEN GATE's OP = 30

R12 IF WAT. ACC. TIME > 3.47 d
AND POND DEPTH <= 1.5 m
THEN GATE's OP = 20

Between
R1 and R2
(Fig. 7)

Future E = Future D + (examples) :

IF 60h < WAT. ACC. TIME < 63h
AND P 21 to 45h* > 6 mm
AND P 12h < 3 mm
THEN GATE's OP = 25

IF 63h < WAT. ACC. TIME < 66h
AND P 18 to 42h* > 6 mm
AND P 24h < 3 mm
THEN GATE's OP = 15

Future D = Evolved D + :
(examples)

IF P 3h* > 30 mm
AND POND DEPTH >= 0.63 m
THEN GATE's OP = 100

IF P 3h > 20 mm
AND POND DEPTH >= 1.17 m
THEN GATE's OP = 100

IF P 6h > 25 mm
AND POND DEPTH >= 1.40 m
THEN GATE's OP = 100

IF P 12h > 35 mm
AND POND DEPTH >= 1.35 m
THEN GATE's OP = 35

IF P 24h > 35 mm
AND POND DEPTH >= 0.99 m
THEN GATE's OP = 20

Figure 2-11: Rules of the ''evolved D'' strategy and examples of rules of the RTC scenarios relying in addition on forecast information; WAT. ACC. TIME = time spent with water accumulated in the pond (water accumulation time); P xxh = total rainfall depth forecasted over the next xx hours; Pxx to yyh = total rainfall depth forecasted between the next xx and yy hours (Gaborit et al., 2013)

Real-Time control objectives to manage a dry pond included *inter alia* avoiding any overflow while maximizing the detention time; retaining runoff as soon as it starts entering the pond to deal with a possible first-flush effect; performing a smooth drawdown when discharging the pond if there is no need to hurry in order to minimize re-suspension and hydraulic shocks induced to receiving water bodies, were taken into consideration to evolve control from a "basic" scenario to the "evolved A" one as shown in Figure 2-10. As soon as the water height fell below some warning levels, the "evolved A" scenario allowed diminishment of the pond's outflow. The pond's overflow safety which relates to the conditions of the rules were able to limit their instability by depicting some dead bands in their involved level threshold values. To avoid abrupt changes in the gate's opening percentage which would result in induced hydraulic shocks to the receiving river, the "evolved A" case had to consist of more control rules than the "basic" scenario.

The 'evolved B' case specified minimum and maximum detention time rules (Figure 2-10). Vallet (2011) justified a minimum detention time, where 30 hours was considered for the study and was in accordance with the minimum detention time. Vallet (2011) noticed that first-flush Suspended Solids (SS) accumulated near the outlet of the basin during its filling, and it took about 20 hours to significantly decrease and homogenize the Total Suspended Solids (TSS) concentration in the pond. In the rules, the condition of the minimum detention time was associated to a water height of the pond limitation above which the rule was not taken into consideration (Gaborit et al., 2013). This was done by considering the overflow safety to prevent closing the outlet gate in the dead bands of the rules. At only 30 min after the end of the last rain event, the minimum detention time was thus considered. The value of 30 min was selected due to the lag time of the basin being 15 min in order to prevent the closing of the outlet gate when runoff volume of the last rain event had not yet reached the detention basin.

Vallet (2011) proposed maximum (useful) detention times which were integrated in the study. Vallet (2011) noticed that, beyond 40 hours of retention (settling), almost no more quality was achieved. Hence, the pond's maximum hydraulic capacity was recovered by smoothly emptying the pond which was preferable for such a case (Gaborit et al., 2013).

The 'evolved B' scenario was modified to create the 'evolved C'. When the rainfall of the last 5 min was greater than 0, a rainfall event was detected while resetting the dry time to 0 for the "evolved C" scenario. The "evolved C" considered a rainfall event only when the following conditions were met in order to prevent closing the outlet gate for negligible rainfall depths: if rainfall of the last 25 min was greater than 0.6 mm, rainfall of the last 10 min was greater than 0.4 mm, or rainfall of the 5 min was greater than 0.3 mm (more than rain bucket tip). This refinement captured the first flush runoff as it allowed a sufficiently rapid closing of the outlet. It thus reduces the frequency of oscillations between the dry and rainy status of the system as it contributes to a reduction in the number of operations applied to the gate. Following the same, the minimum detention time (assumed equal to dry period) in the "evolved C" was reset to 0 only when the rainfall depth of the last 25 min was greater than 0.6 mm.

Accumulation of water in the pond was limited to 4 days for mosquito prevention (Santana et al., 1994; Knight et al., 2003) in the "evolved D" scenario. Hence, rules were added directly before or after level-based rules with the same resulting gate's opening percentages to the decision tree (Figure 2-11) of the "evolved C" scenario (Gaborit et al., 2013). When the water level exceeded 0.055 m, water accumulation time in the pond was initialised and stopped when it fell below 0.045m. The results of simulated water heights of the RTC of the "evolved D" scenario were able to maximize detention time while avoiding any overflow than the static "basic" control case.

Rainfall forecasts were accounted for in the study since they may provide the necessary information for overflow risk reduction. The Environment Canada (EC) provided forecasts that were used in the study, and the forecasts covered a 3-month period of the autumn of 2010. The forecasts consisted of their Global Ensemble Product (GEP) that has a spatial resolution of 100 x 70 km (7000 km^2 at mid-latitudes), maximum prediction horizon of 240h, a 3-h timestep, two updates per day and 21 members. Maximum horizon of 72 hours was used for the study, which allowed enough anticipation time for the small urban (Quebec) catchment. The 15.3ha (0.153 km^2) small urban catchment was inappropriate for the GEP resolution. Hence, the original GEP's rainfall forecast spatial disaggregation which derives products with 6 km resolution as performed by Gaborit et al. (in press) and exploiting the downscaling technique proposed by Perica & Foufoula-Georgiou (1996), were used for the study.

Rainfall nowcasts up to 6-hour horizon can be allowed through extrapolation in time of radar rainfall maps (Pierce et al., 2004). The available rainfall forecasts that originate from meteorological models could be coupled with nowcasts if longer lead times are required (Bowler et al., 2006). The pond's hydraulic capacity was anticipated using the meteorological data (Gaborit et al., 2013). The current pond water level and its remaining volume capacity were measured at any given time. Based on the rainfall forecasts and associated runoff coefficient, the future incoming volume of runoff was calculated. This coefficient was defined, based on a few (but varied) observed rainfall events and their associated simulated runoff volumes (accounting for the constant base flow), as a function of the duration and volume of rainfall implied in the event. In addition, the coefficient was found to vary between 35% and 61%. Then, the gate's opening percentage was computed based on the volume to be evacuated and the time remaining before the predicted overflow will occur, only if a hydraulic capacity excess was forecasted.

The total rainfall depths predicted over the next 3, 6, 12, and 24h were taken into consideration at each given time by the forecasts. A duration equal to half of the horizon length and hence respectively fixed to 1, 3, 6, and 12h was used as a target, so as for the rainfall depth forecasted over a given horizon to correlate with the duration. This way, a correction was done when the rainfall volume was to be included in the shorter horizon forecasts, only if a fraction of the incoming runoff volume was underestimated because of an overestimation of the rain duration.

The time left before the occurrence of a forecasted overflow coincided with its associated rain event duration. This relies on the principle that if a security warning was caused by the 6-hour horizon forecast, and so on, there was at least 3 hours to discharge the pond if no hydraulic capacity warning was issued by the 3-hour horizon capacity.

The following methodology was used to translate the aforementioned philosophy in the SWMM5 control rules: the gate was opened when at the next higher threshold percentage; if the incoming runoff volume forecasted by a rainfall forecast was greater than the pond's maximum volume minus the current volume and minus the volume of water which can be discharged by a gate's opening y% in the remaining time. However, maximum water level heights (instead of the current pond volume plus the volume which can be discharged with a given gate's opening) and forecasted rainfall depths (instead of predicted volumes) were used to the write the rules in SWMM5. More precisely, this was achieved using four different possible gate opening percentages of 10, 20, 35, and 100%, eight different rainfall depth thresholds from 0 to more than 40 mm (with increments of 5 mm), and rainfall forecasts with four different possible horizons.

Enhanced RTC scenarios of a dry detention pond were proposed in the study as described above. A high potential of improvement of the pond's performance was revealed through the many different strategies implemented. In all implemented RTC strategies, TSS (and associated pollution) of the pond increased from 46% to about 90%. The rules indeed allowed simultaneous prevention of overflow and maximization of induced hydraulic shocks to the receiving water bodies while maximizing the detention time of water. Mosquito breeding issues were avoided by respecting the constraint relative to a maximum time of 4 days with water accumulated in the pond. Even if meteorological forecasts are, of course, not error-free; taking rainfall forecasts into consideration can further reinforce the safety of the management strategies. Such strategies are interesting because they do not require an on-line implementation of the model (i.e., no simulation has to be performed in real-time) since they allow consideration of forecasted information. For smaller return period events, it is envisioned to use a dry pond for design to draw more precise conclusions about the pros and cons of the (scenarios considering) different forecast products by increasing the frequency of potential overflow situations. Sophisticated scenarios as such, may be too costly for implementation in practice since they rely on remotely controlled actuators, data acquisition system and automatic sensors. Scenarios which rely on rainfall forecasts, only on the pond's depth at the of the adjustment and on one (manual) adjustment per day of the pond's gate opening; are all currently being tested.

2.16.3 Tehran drainage system

The study focused on a main drainage system of Tehran, the capital of Iran which is located in the southern part. The network covered an area of 156 km^2 which included 42 sub-catchments and 132 conduits (Jafari et al., 2019). The drainage network consisted of 116 km underground tunnels approximately 15.6 km which lacked the capacity to safely transfer stormwater runoff of a 50-year design rainfall. The studied system, which is a detention reservoir, applied on-line RTC with controllable and uncontrollable gates and openings was built to temporarily store excess storm runoff due to lack of hydraulic capacity of the drainage network. The model performance on the detention reservoir was examined using six severe historical events.

The operation model focused on reducing flood inundation at downstream of the system by discretizing the maximum depth of a detention reservoir with an outflow gate located at B meters above the surface (Figure 2-12) into n levels. In this considered case, the outflow gate was crucial in the control of flood. Hence, a policy on how to regulate gate openings which considers decision variables was used to solve the optimization problem of system's operation performance. In other words, the gate opening percentage were represented by decision variable (G_j) which corresponded to water levels within the interval [d_j, d_{j+1}) (Figure 2-13).

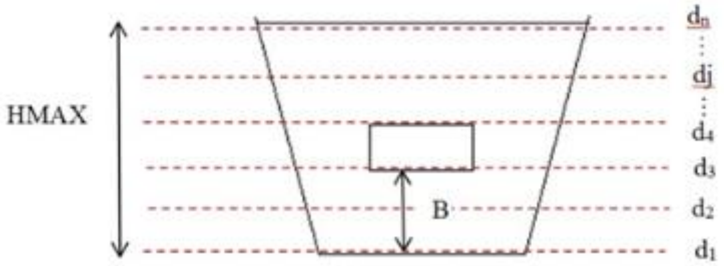


Figure 2-12: Discrete water level in the detention reservoir (Jafari et al., 2019)

G_1	G_2	G_3	…	G_j	…	G_m

Figure 2-13: Decision variable vector (Jafari et al., 2019)

Height B controlled the number of decision variables because as the water level exceeded the bottom edge elevation of the gate, the gate began to function. Obviously, addition of more gates would have resulted in an increase in the number of decision variables. Optimal real-time operation (RTOP) model was used to obtain an operation policy (gate openings percentage) for evacuation of water out of the system.

The operation policies of regulators were updated periodically in the RTOP model, so that the horizon D is divided into a number of decision time intervals T_i, and each decision time corresponded to a particular control rule R_i which was derived. Consequently, time horizon D was used to determine finite sequence of operating R_1, R_2, …, R_i, …, R_H where during the interval T_i, each R_i alludes to a vector of optimal policies for gate operation to be applied. Presented below is the model formulation of RTOP.

RTOP model formulation

$$MIN : \sum_{T=T_i}^{T_H} F_T \qquad (2.2)$$

Subject to:

$$F_T = f(R, h_t, G_j, \ldots)_{T_i} \qquad (2.3)$$

$$0 \leq h_t \leq HMAX \qquad (2.4)$$

$$h_t = f(h_{t-1}, Q_{in,t}, G_j)_{T_i} \qquad (2.5)$$

$$[G_j]_{T_i} = \begin{cases} 0 & if\ h_t \leq B \\ \sum_{Z=1}^{11} Z_z \times P_z & otherwise \end{cases} \qquad (2.6)$$

$$\sum_{Z=1}^{11} Z_z = 1 \qquad (2.7)$$

In the evaluation of the objective function (Equation 2.2), it was important to note that the formulation represents a multi-period optimization model since it considers the state of the current decision time T_i to the end of horizon time T_H. however, application of the found optimal operation rule was only for decision time interval T_i.

F_T is the total volume of the flood in the period T_i in the above formulation, and is a function of a number of variables such as gate operational policy (decision variables), the water level at the detention reservoir h_t, rainfall amount and characteristics R, and other parameters that were determined using flow routing and rainfall-runoff simulation model. Each objective function (Equation 2.3 to 2.5) represents the SWMM simulation module of the model that must be performed. G_j is the percentage of the gate openings that corresponds to water levels within an interval $[d_j, d_{j+1})$ which was accounted via Equation 2.6 in which Z_z is a binary number, and P_z is an integer variable that takes a value among [0, 10, 20, …, 100%]. H_t is the reservoir's water level at which time t; which is a function of G_j, the water level at the previous time step (h_{t-1}), and inflow discharge to the detention reservoir at the time t ($Q_{in,t}$).

The aforementioned optimization problem was solved using the popular metaheuristic harmony search (HS) algorithm. Trial runs of the HS algorithm for several flood scenarios were computed to determine suitable values of optimization algorithm parameters.

SWMM was used to develop the simulation model of the system using the aforementioned system's characteristics, features and data collected by MG consulting Engineers (MGCE, 2011a). The network was divided into two-sub models to reduce the executing runtime (Jafari et al., 2019). In this manner, for each decision time, the downstream sub-model was called for each function evaluation and the upstream sub-model was run just one time. The model was divided into two sub-models based on the assumption that the gravity flow is formed in the upstream model and, the inflow to the separated node is independent of the performance of the gate.

The studied system (detention reservoir) contained eight openings, three sluice gates, and operations that were crucial in flood reduction. The detention reservoir was considered to have an allowable maximum water depth of 7.5 m which was separated into 15 discrete values with 0.5 m increments. Each discrete water level corresponded to decision variables that were considered as opening percentages.

The following three operational scenarios were defined to investigate the importance of each gate operation:

Scenario 1:

All the openings and gates were fully open all the time without the use of any control rule, and this procedure is currently used in practice.

Scenario 2:

RTOP model was used to control sluice gates, but eight openings at an elevation of 4.5 m were fully open without the use of any control rule.

Scenario 3:

RTOP model was used to regulate all openings and sluice gates. In other words, all the openings and gates were assumed to be controllable in the system.

Efficient use of the system's regulation capacity was influenced by the ability to regulate all controllable elements in the system. Application of scenario 3 led to the optimal utilization of the reservoir capacity where excess water was temporarily stored, which can be later used for other purposes such as irrigation of urban green landscape.

Additionally, partial control of the system (Scenario 2) compared with a fully controlled case (Scenario 3) led to 17% increase in flood inundation.

2.17 Urban drainage systems with optimization based RTC

2.17.1 The case study of Norfolk, Virgina USA

The main objective of the study was to create an open-source implementation of MPC for SWMM5 (Sadler et al., 2018). Since a computationally expensive metaheuristic approach was required, an additional objective was performed to leverage parallel computing. The open-source Python programming language was used in conjunction with SWMM5 to accomplish these objectives. A simplified use case study was utilized to evaluate the MPC implementation. Comparison of results applied to the same use case study for three scenarios were conducted. The three scenarios are namely: (1) No active control (passive); (2) Rule-based; and (3) MPC.

Three main Python libraries of the Python programming language viz: PySWMM, Distributed Evolutionary Algorithms for Python (DEAP), and Scalable Concurrent Operations in Python (SCOOP) can be used to design MPC implementation for SWMM5. The SWMM5 model which is written in the C programming language receives a python interface that is provided by the PySWMM library. A SWMM5 model can be run step-by-step through PySWMM so that the best control policy can be found at each control time step as this is a critical functionality for MPC. An evolutionary algorithm of the DEAP library was used to select the best control policy. The evolutionary algorithm can be executed through parallelizing which is a function provided by the SCOOP library.

The Python MPC workflow (Figure 2-14) shows that system states are used from ‘reality’ for each control time step. The ‘reality model’ simulates ‘reality’ with a SWMM5 model. The heads at each node and flows at each link in the system represents system states that are read from the ‘reality model’. The ‘process model’ which is another SWMM5 model captures these states. An evolutionary algorithm in the DEAP library was used to select the practically optimum policy. To achieve this, many simulations run must be executed in the process model (one for each control policy) although they are computationally expensive. This process can be parallelized using the functionality provided by the SCOOP library since the model runs are independent. The evolutionary algorithm selects the policy which is then returned to the ‘realty model’ and implemented. If the next step is executed, then the process repeats.

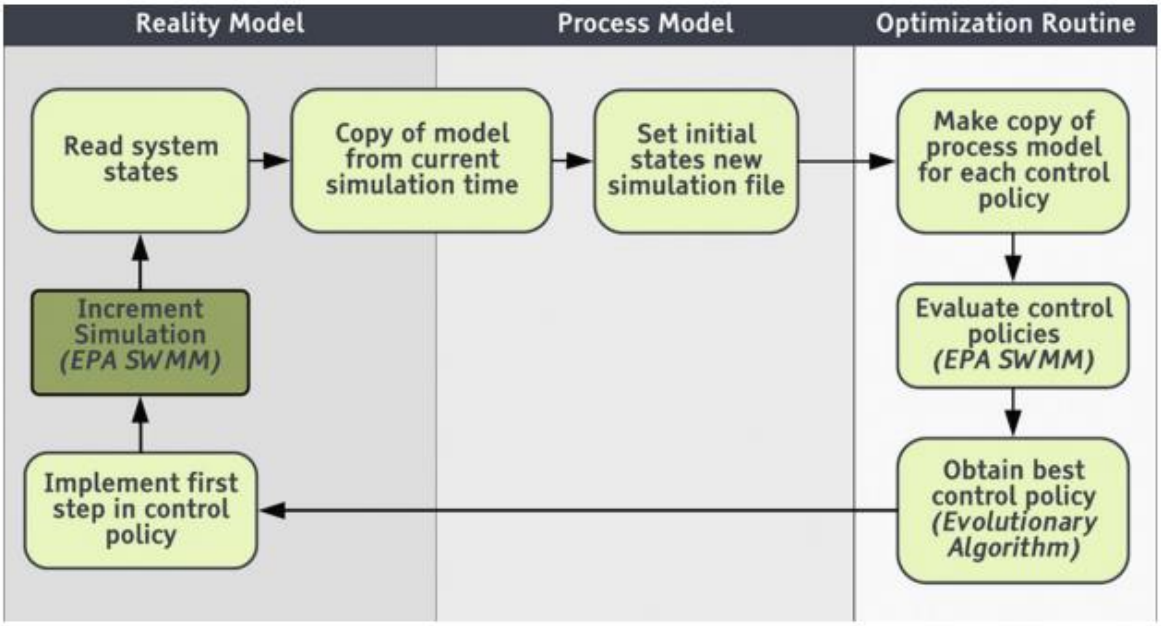


Figure 2-14: MPC workflow (Sadler et al., 2018)

To evaluate the MPC implementation, a simple use case motivated by an actual flood-prone area in Norfolk, Virgina USA was used. The study consisted of a detention pond that was upstream from a node at which flooding was to be minimized. An "orifice" structure in SWMM5 which can have a setting between 0 (completely closed) and 1 (completely open) was used to simulate the active control of the pond outlet. An array of settings between 0 and 1 were used for the control policies of the simplified use case, one setting for each control time step in the control horizon. Settings were limited to be even tenths (e.g., 0.1, 0.2) to reduce the number of possible controls setting to be evaluated by the evolutionary algorithm which is computationally expensive. An arbitrary synthetic rainfall event was simulated. A control time step of 15 mins was used in a control horizon of 6h. An evaluation of 8 generations and initial generation population of 80 individual policies for the evolutionary algorithm were computed. The control policies for the use case were evaluated based on the following objective in SWMM5:

$$Cost = \alpha F_{st} + \beta F_{ds} + \theta D_{st} \quad (2.8)$$

Where F_{st} is the total volume of flooding from the storage node in millions of gallons (1 gallon = 3.785 L), F_{ds} is the total volume from the downstream node in millions of gallons, and D_{st} is the average deviation from a target level for the detention pond in feet (1 foot in this case) (1 foot = 0.3048 m). The α, β and θ values are weight coefficients. The values used for the study were 100, 100, and 0.05, respectively. These chosen values aimed at adding more weight to flooding than deviation from the target level at the storage unit.

The use of multiple processing cores through the SCOOP library and MPC implementation were successful at running as described above. The control policy resulting from the MPC in the evaluation use case reduced 0,05 million gallons of flooding compared to 0,01 million gallons of the passive control scenario at the downstream node. In addition, the rules-based approach was not able to maintain the depth at the storage node closer to the target value, something the MPC policy was able to accomplish. The performance of the rule-based and MPC approach were able to retain water in the detention pond efficiently than the passive control approach that could later be used for irrigation purposes.

The development, implementation, and evaluation of an open-source for MPC for the United States Environmental Protection Agency's (EPA) Stormwater Management Model (SWMM) was achieved through Python programming language and key Python libraries for step-by-step running of the model, parallel computing, and use of evolutionary algorithms. The resulting control policy of the MPC implementation significantly reduced flooding in comparison to the no active control (passive) scenario for the simple, simulation use case. MPC for any control in a SWMM5 model can be performed using the MPC implementation described above, could be a useful tool in understanding the potential utility of smarter stormwater systems. Adjustments of weights in the objective function and ensuring consistency between the reality and process model by taking advantage of SWMM5's hotstart file capabilities, are open for future improvements.

2.17.2 Simple case study of two retention basins and sub catchments

The software framework BlueM.MPC was developed for the case study (Heusch & Ostrowski, 2011). The scope of the study implemented the software BlueM.Opt (Muschalla et al., 2009) which uses various optimization algorithms. The following algorithms were implemented: solving real valued problems using an evolutionary algorithm (Muschalla, 2006) including multi-threading capacity; solving real valued problems using a hill-climbing algorithm (Hooke & Jeeves, 1961); solving global optimization using a hybrid evolutionary algorithm as an evolutionary strategy; and solving local optimization using a hill-climbing algorithm including multi-threading capability (Kerber, 2009), and an n-dimensional continuous global optimization algorithm known as the dynamically dimensioned search (DDS) (Tolson & Shoemaker, 2017).

Evolutionary algorithms have a particular advantage due to their ability to make use of parallelization features (Heusch & Ostrowski, 2011). MPC applications in computers seems to be a particularly promising feature as latest developments in computers have shown that standard PCs can include several CPU cores.

SWMM5 was integrated as a process model with the focus on the application of dynamic flow routing models within MPC systems. Practitioners, researchers, and many datasets that are already available recommend SWMM5 as a reliable software.

The setup and workflow of BlueM.MPC is depicted in Figure 2-15. information for the control time step and for the durations of three horizons was provided for the application of the MPC module. The same workflow applied to every control step once the control process started. A dynamic link library (SWMM.dII) or an executable (SWMM5.exe) was used to simulate the optimization module that generates SWMM5 datasets. Simulation results were taken either by analysing time series data or from the resulting report file. The optimization module which consequently generates a new dataset to continue with the optimization process was used to evaluate the results. This approach strictly separates optimization modules and hydrodynamic simulation. It is a derivative-free optimization method (black box optimization) since it is not based on numerical derivations of the dynamic flow equations.

Calculations with a simple case study were performed to confirm the functionality of BlueM.MPC. The system contained two retention basins and two sub catchments. The two retention basins consisted of an upper and lower basin. The upper retention basin outflows were controlled. Definition of the objective function consisted of overflow minimization from both storage basins. The system was forced to empty the basins whenever possible by applying additional penalty functions for stored volumes. DDS algorithms were used for the results obtained. The same results were obtained through the use of other optimization algorithms, which led to the conclusion that a simple case study cannot be used as a basis to judge the strengths and weaknesses of the particular algorithms.

Even though the overall system contained only minor control potential for the water levels, the study showed the functionality of the MPC system from both basins. The water levels at the beginning of the simulation period for both retention basins demonstrated the system’s functionality where excess water was temporarily stored, which can later be used for other purposes such as irrigation.

Additionally, the water levels in the upper basin were kept low by filling the lower basin using the MPC functionality system, for smaller overflow volumes to occur. For the total simulation period, the MPC system decreased overflow volumes at approximately 3% which is adjacent to the theoretical maximum decrease.

In conclusion, the study utilized SWMM5 which is a public domain and widely used distributed dynamic rainfall-runoff model to simulate the non-linear dynamics of the urban drainage system. The non-linear dynamics were simulated as an “opaque” model meaning that the model did not consider the mathematical form of the governing equations to evaluate the control policies. The approach precluded the possibility of guaranteed optimality (like using metaheuristic such as an evolutionary algorithm to find a “practical optimum”), but the non-liner dynamics of the system were maintained. Although the study developed software that implements MPC with SWMM5, the approach had some drawbacks including the availability and sustainability of the software which was closed source and is no longer available.

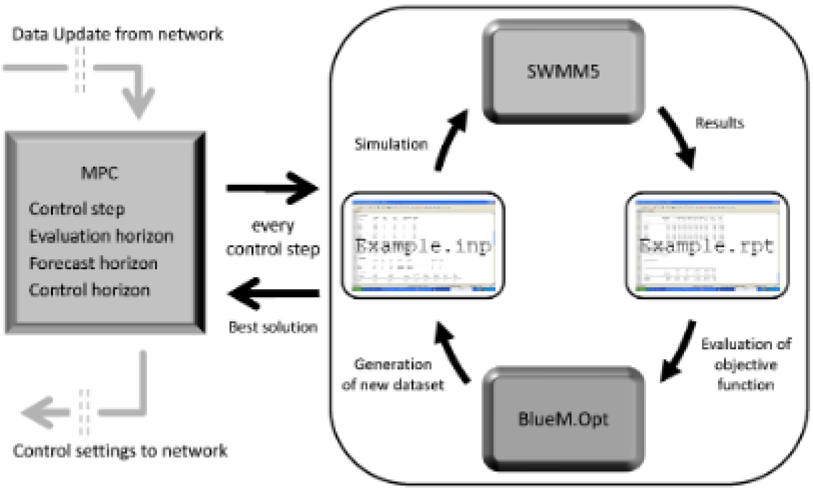


Figure 2-15: Setup and workflow (Heusch & Ostrowski, 2011)

2.17.3 Ann Arbor, Michigan urban headwater catchment

A choice must be made with respect to the spatial scales at which real-time control technologies will first be implemented and analysed when retrofitting urban watersheds (Wong & Kerkez, 2018). The study contends the scale of urban headwater catchments should be the focal point at which real-time control strategies are analysed. These sub-catchments usually cover an area of up to 5 km^2 and can be found in most suburban and urban communities, large and small (Emerson et al., 2005; Lee et al., 2012; Zhen et al., 2004). Overall, a number of practical and fundamental factors motivated the choice to focus on this scale (Wong & Kerkez, 2018). Fundamentally, smaller-scale systems first have to be analysed and understood for the scalability of real-time watershed control (Lee & Bang, 2000). The control of smaller catchments will ultimately underpin the control of larger watersheds if feasible at these scales (Wong & Kerkez, 2018).

Practically, valves should be added one-by-one or as controlled clusters rather than retrofitting an entire city with control valves all at once. Decisions to upgrade or build stormwater infrastructure are often driven by new commercial or residential development projects in the United States which impacts flows at the scale of local stream and pipes network (Grigg, 2012; Kessler, 2011). Given the recent emphasis on distributed stormwater management, these measures often include basins, ponds and wetlands at precincts, neighbourhood, subdivisions and commercial complex (Wong & Kerkez, 2018). Rainfall forecasts were integrated with real-time control for the since the study covered an area of 4 km^2 as most existing gage and radar rainfall products are offered at 1-5 km^2.

Coupled hydrologic-hydraulic approach are used to simulate most modern physicallybased models of urban watersheds such as EPA's Stormwater Management Model (Gironàs et al., 2010), where hydrologic dynamics such as infiltration and runoff, are represented via empirical or physical sub-models. Nonlinear *Saint-Venant* equations for shallow flow are typically used to model flows which are subsequently routed using a hydraulic engine (Rossman, 2010). The application of formal control and optimization approaches becomes intractable due to the high degree of detail, complexity and nonlinearities inherent in these models (Wong & Kerkez, 2018). Fortunately, perfect models are not necessary to achieve desirable control outcomes for many complex control systems such as those on factory processes and autopilots (Schütze et al., 2004). A control model that approximates the dynamic dynamics of the underlying system for model-based controllers such as model predictive controllers and linear quadratic regulators is often sufficient as long as it satisfies stability criteria since the actual control actions will often steer the system back into domains where the approximations hold true (Francis & Wonham, 1976). This is often achieved via linearizing the system dynamics around desired setpoints (e.g. flood stages, flows, etc.) in feedback control after application of modern control techniques (Wong & Kerkez, 2018). Examples of approximated models for the specific control of water flows in canals and pipes included linear tank models (Ocampo-Martinez et al., 2013), Muskingum (Gill, 1978), reduced Saint-Venant (Xu et al., 2011), integrator delay zero models (Litrico & Fromion, 2009) and the integrator delay (Schuurmans et al., 1995).

A state-space representation of the hydraulic dynamics as an *integrator delay model* (Schuurmans et al., 1995), was used as an approach to simulate the control model for the study. Xu et al (2011) focused on the use of this representation for control of water levels in irrigation canals that are connected in series. However, there is no clarity on the efficiency of the use of this formulation for stormwater system control as it presents additional complexities for urban watersheds (Wong & Kerkez, 2018). These included the need to accommodate complex and interconnected infrastructure topologies (parallel storage nodes or treelike networks), and hydrologic effects (antecedent moisture, runoff, etc.) as well as rainfall. The choice to adopt this approach was based on the expectation it was to sufficiently capture shallow-water and hydrologic flow dynamics to enable feedback control. Most importantly, however, the watershed physical features which include the distance between storage nodes and their curves can be used to fully parameterize the matrix-based representation. Prior studies have shown to be very cost effective and ubiquitous on this formulation which only relies on water level measurement for implementation (Bartos et al., 2017; Wong & Kerkez, 2014). The integrator delay model for the study conceptualized an urban watershed as a system of interconnected storage nodes (Figure 2-16a) as a linearized state-space representation (Wong & Kerkez, 2018). The approach of the study used a linear-quadratic regulator (LQR) once the linear representation of the catchment was formulated, to set the outflows from each controllable storage node for any given timestep (Figure 2-16b). The approach compared the input of the desired system states such as height at each storage node to the corresponding heights throughout the actual system, and then pushed the system toward these desired setpoints by calculating the necessary outflows at each controlled node.

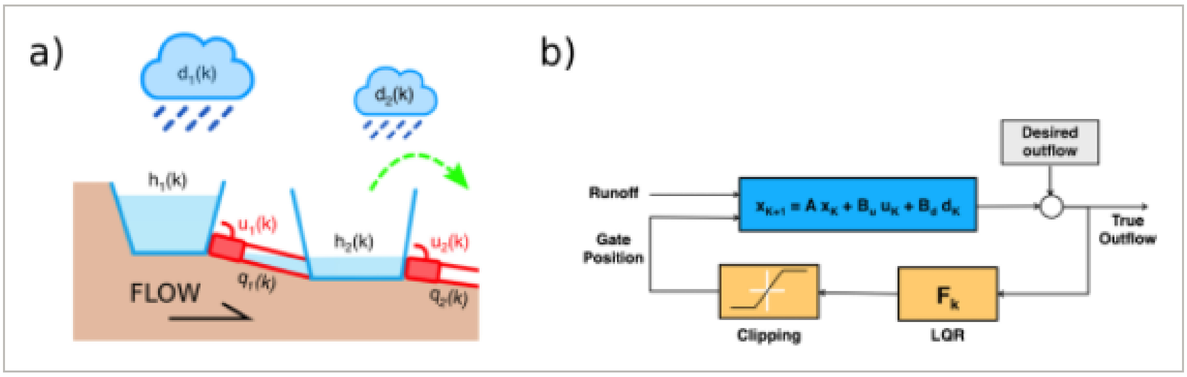


Figure 2-16: Graphical representation of (a) an integrator-delay model and (b) the block diagram of the feedback controller (Wong & Kerkez, 2018)

Linear-quadratic (LQ) control is a matrix-based, closed-loop feedback control method that aims to accomplish desired setpoints through incorporation of open-loop dynamics (Malaterre & Baume, 1998). LQR is suitable for real-time control which makes it possible to run even on modern microcontrollers since the matrix computations are relatively fast (Wong & Kerkez, 2018). LQR minimizes a quadratic cost function that uses a control input based on the latest sensor measurements to control a linear dynamic system (Dorato et al., 1995).

Many studies often use the linear models they are based on to evaluate the performance of control algorithms (Wong & Kerkez, 2018). However, it may give the impression that the controller performs better than it actually would in the real-world if this simplified linear model does not adequately capture the physical hydraulic-hydrologic dynamics. The approach of the study applied the linear controller to a physically-based model to address the above concern. In this fashion, the physically-based model reflected what could be expected reality whilst the linearized model was used to make control decisions.

The US Environmental Protection Agency (EPA) Stormwater Management Model (SWMM) was used to evaluate the control performance. The SWMM model was not designed for system-level control algorithms such as the one in this study although it provides rudimentary control rules (e.g. site-scale water level control) and a powerful simulation engine. To that end, a customized modelling framework that uses the SWMM engine was implemented to execute the model in a stepwise fashion n (Mullapudi et al., 2017; Riaño-Briceño et al., 2016). The model was halted every timestep after which the states was extracted and an external logic module (an LQR controller for the study) was used rather than running the model for the duration of an entire system to set the states of valves and gates across the entire system (Wong & Kerkez, 2018). The control input was updated every five minutes or simulation steps to more realistically match the sampling frequency of sensor nodes whilst the routing step in the SWMM was set to five seconds.

The framework of the physics engine which is written in the *C* programming language is implemented as a stand-alone library provides a wrapper to SWMM with popular and modern languages including *Matlab* and *Python*. This requires no need to implement the controller in the original SWMM model itself because the framework allows for the seamless interaction of control libraries and modern computational with the physically-based modelling of SWMM. More importantly, implementation of this methodology does not necessarily depend on SWMM. SWMM is instead used as an evaluation engine for the controller. This, in fact, is much more comprehensive than most control approaches that uses the simplified linear model to evaluate a control algorithm that the controller is based on.

A 4 km^2 catchment in Ann Arbor, Michigan was used to evaluate the proposed control approach which was being retrofitted for real-time control. This particular catchment called for improved means to reduce flows at the outlet of the watershed as it has been of interest to local officials due to stream erosion (Lawson et al., 2017, Pratt, 2016). The catchment consisted of 11 storage basins with variation in volume from 370 m^3 to 32000 m^3 (Wong & Kerkez, 2018). The city managers provided a calibrated SWMM model of the catchment reflecting the up-to-date knowledge of the real system. For representation of valves, each storage node in the model located at the bottom of the storage node was retrofitted with an adjustable 0.1 m^2 orifice. All conduits between storage nodes were circular in geometry ranging in length from 40 m to 400 m and Manning roughness coefficient of 0.01, and each orifice had a higher invert elevation than the overflow height of all downstream storage nodes. The choice to use this modelled catchment as a case study reduces one element of uncertainty when conducting the initial evaluation of the proposed control algorithm for managing stormwater runoff due to the catchment's low baseflow and limited influences of groundwater effects (HRWC, 2013). The soil types are some type D and largely type C according to USDA and USGS soils data and the soil infiltration in the subcatchments were modelled using the Green-Ampt model (Rawls et al., 1983). CDM Smith (2015) last calibrated the model in 2015. A linear model was formulated from the SWMM model and the model was simulated at a five second resolution, control actions were constrained to five-minute windows to be consistent with the control and sensor networks currently being deployed (Wong & Kerkez, 2016a).

The modelled catchment which corresponded with the time period during which the SWMM model was calibrated was evaluated under rainfall data collected from April 1 to December, 2013 (CDM Smith, 2015). A long-term simulation offers additional insight into performance under rainfall variability as opposed to using individual events by allowing initial model conditions to settle toward realistic values throughout the duration of the simulation (Gironás et al., 2009). Long-term rainfall data served as the rainfall timeseries for each of the simulation which were sampled at a five-minute resolution (Wong & Kerkez, 2018). The control algorithm was feedback-based rather than predictive which means that current conditions were used for control decisions and not subjected to weather uncertainty. Nonetheless, an additional analysis was carried out to evaluate performance under uncertainty by injecting virtual sensor noise into the water levels retrieved from the physically based model. Noise levels were parameterized based on water level sensors sampled at each timestep from a standard deviation $\sigma = 2.5$ mm and Gaussian distribution of mean zero. The realistic noise levels were amplified by 5 and 10 times to investigate the impact of two larger noise levels, this was done to evaluate the robustness of the algorithm under high levels of measurement uncertainty.

A baseline was first established by assessing the response of the uncontrolled system to a relatively small event (2-year, 24-hour storm) to evaluate the performance of the LQR-based feedback controller. During this storm, the peak flows in the catchment reached 0.3 m^3/s at the outlet and there were no overflows at any of the storage nodes. It was then evaluated if during larger events, the controlled system could reach the same baseline performance. However, it would be over design for an infrastructure designed for 100-year, 24-hour events that can perform efficiently for a 2-year, 24-hour storm. This was intended to reflect the benefits of retrofitting existing infrastructure with valves and gates for coordination when operated to limit flows and improve the use of existing storage throughout the network rather than continuing to build bigger storage nodes or dig up pipes.

On average, the LQR based control approach outperformed the uncontrolled system when all the storage nodes (SNs) were controlled both at the scale of the individual sites as well as the watershed outlet. Specifically, only one SN had an overflow event and outflows at each SN did not exceed the critical flow level of 0.3 m^3/s when evaluated on a 10-year, 24-hour. The outflow hydrographs from the controlled sites exhibited dynamics with lower flows over longer period of time, whereas the outflows of the uncontrolled SNs exhibited the familiar hydrograph shape with a distinct peak and recession period. Hence, water was held within the SNs so as to not exceed the outflow threshold which resulted in longer retention times.

2.18 Summary of literature review

Increased water demand for consumption and occurrence of drought alongside growth of urban population lead to water scarcity. Water crises in many countries around the world has led to various investigation of non-traditional water sources such as stormwater for the supply of non-potable water demands including *inter alia* garden irrigation and/or toilet flushing (Mitchell, *et al*., 2008). Stormwater harvesting (SWH) is the collection, storage, and use of runoff from urban surfaces such as roads and drains that would otherwise drain to a water body (DECNSW, 2006; O'Connor *et al.*, 2007; NRMMC *et al*., 2009a; Akram *et al.,* 2014). Challenges with respect to resource shortages, environmental degradation and water management are evident in a developing country such as South Africa (RSA) (Kok & Collinson, 2006; Turton, 2008; DEA, 2010; UNEP, 2010; RSA, 2011a, 2011b; Fisher-Jeffes *et al*., 2012; DWA, 2013). Fisher-Jeffes (2015) found that although there was significant climate variation across South Africa, SWH had the potential to reduce the total residential potable water demand of the Liesbeeck River Catchment in Cape Town. The performance of SWH systems can be improved through the application of Real-Time Control (RTC). RTC is generally defined as using collected data and monitoring the function of a system for optimal performance by controlling certain aspects of the system (Schutze *et al*., 2004). Extensive investigations around the RSA for implementation of alternative water resources including, *inter alia,* desalination facilities, exploiting aquifers, raising dam walls and new dams have been considered. However, only Rohrer & Armitage (2017) and Okedi (2019) have considered the application of Real Time Control (RTC) to enhance stormwater harvesting as a viable resource in the context of South Africa. In this study, the various case studies in literature were used to develop the concept required to assess the performance of SWH with RTC configurations. The assessment was undertaken with model simulations using data based on rainfall forecast in Cape Town. Rainfall forecast was used to initiate pre-storm release in real-time to enable the enhancement of SWH performance with RTC configurations. The two RTC configurations (RTC-1 and RTC-2) used for the study are reactive *i.e.,* based on existing conditions, and locally implemented using PySWMM.

Table 2-3: Summary of comparison of salient features of the urban drainage system case studies and methodology adopted for the study

Urban drainage systems	**Salient features**	**Publication derived**
Diep River sub-catchment	Pumps, outlets, multiple ponds	Rohrer & Armitage (2017)
Quebec City catchment	Outlet gate, detention pond	Gaborit et al (2013)
Tehran drainage system	Openings, sluice gates, detention reservoir	Jafari et al (2019)
The case study of Norfolk, Virgina, USA	Orifice, detention pond	Sadler et al (2018)
Simple case study of two retention basins and sub-catchments	Outlet, two retention basins	Heusch & Ostrowski (2011)
Ann Arbor, Michigan urban headwater catchment	Valves, sensors, multiple storage basins	Wong & Kerkez (2018)
The UCT watershed	Sensors, actuated valves, dam	This study

3 Methodology

3.1 Overview

In this study, the prospects for RTC techniques to enhance stormwater harvesting (SWH) based on rainfall forecast were investigated using the University of Cape Town (UCT) dam. Various RTC techniques explored as discussed in the literature review and potential to enhance the efficiency and functionality for SWH was determined. Section 3.2 presents the study area and model development. Section 3.3 discusses data acquisition including *inter alia* catchment topography, soil infiltration, rainfall, evaporation, and water demand. Section 3.4 highlights the stormwater model construction. Section 3.5 presents the calibration processes undertaken and Section 3.6 comprises of static simulations. Section 3.7 features simulations of a Real-Time control retrofit. Section 3.9 highlights the economic analysis such as the LCCA while section 3.10 details the summary of the method. An overview of the method is presented in Figure 3-1.

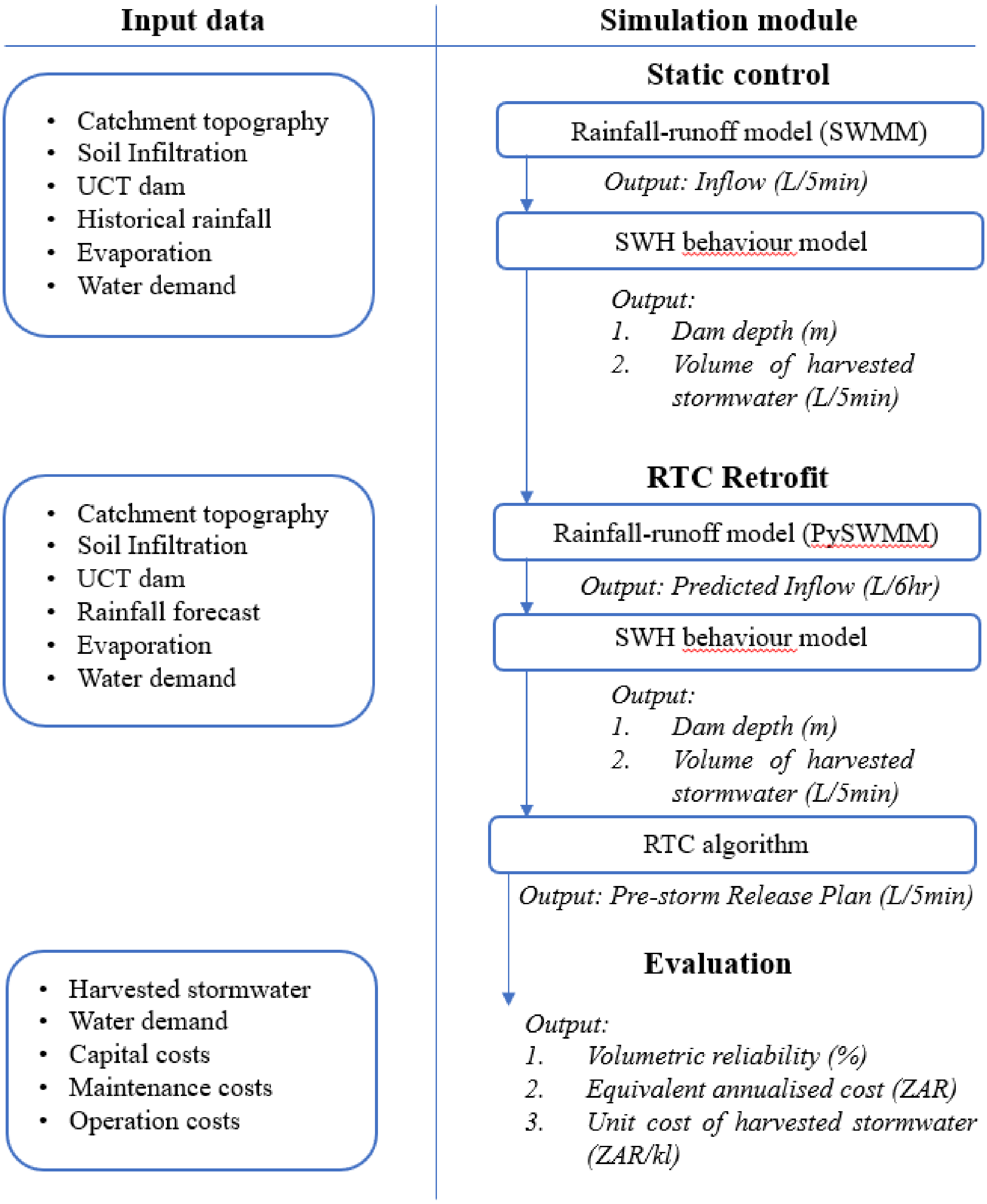


Figure 3-1: Conceptual framework for the adopted research approach

3.2 Study area

Two main considerations for the selection of a suitable catchment to used in the study were based on the availability of data to model the hydrological processes and storage required for the economic exploitation of SWH through RTC. The City of Cape Town (CoCT) is situated in the south-western part of South Africa (Figure 3-2) whilst the UCT dam is located in the western part of CoCT (Figure 3-3).

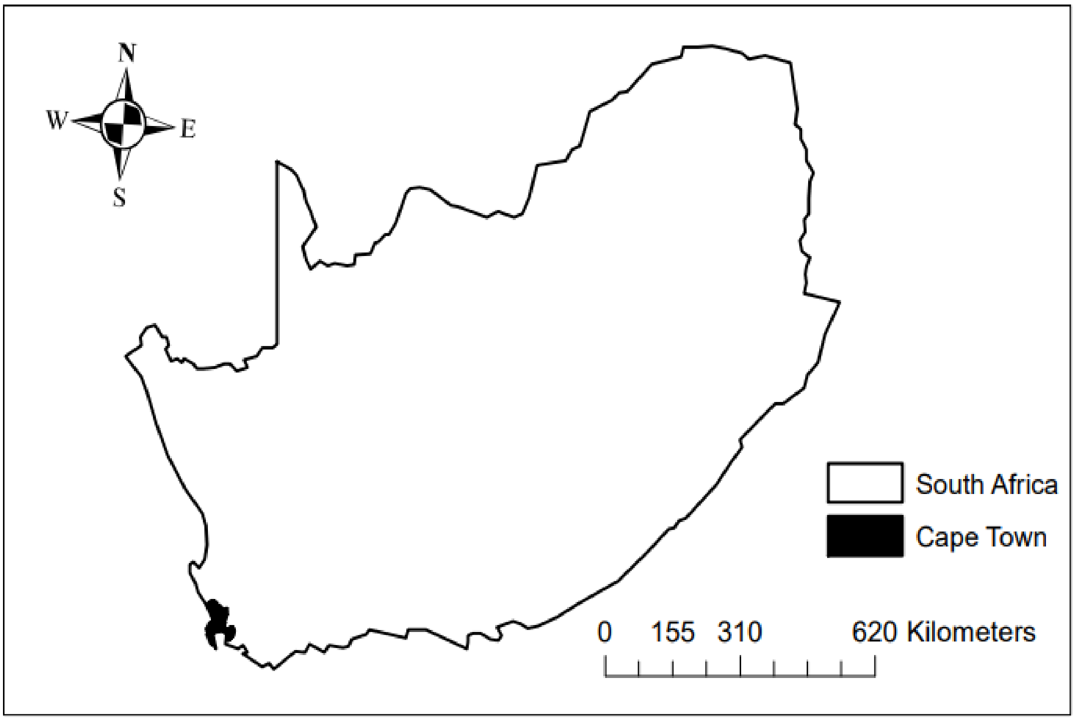


Figure 3-2: The City of Cape Town in South Africa

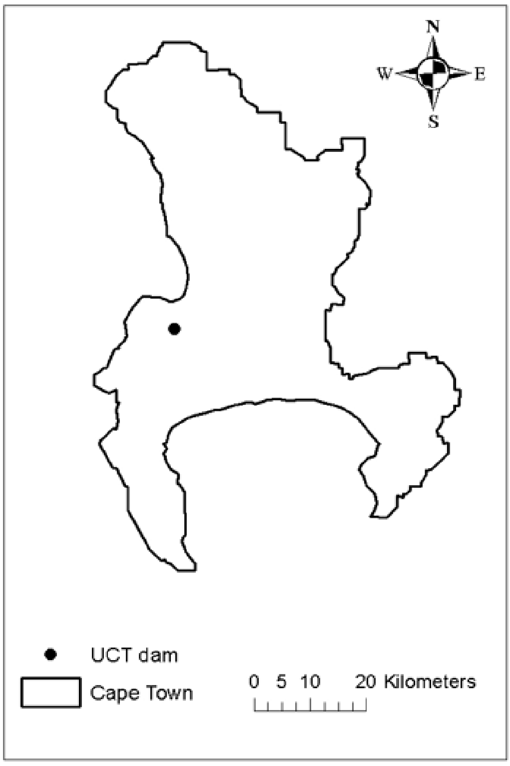


Figure 3-3: The UCT dam in Cape Town

Mediterranean climate such as mild, wet winters and dry, warm summers are prevalent in the CoCT (Rohli & Vega, 2011). WMO (2014) states that the average rainfall in the CoCT is 515 mm/yr; however, the presence of mountainous topography within the City's boundaries results in high variable rainfall and evaporation across CoCT. The UCT watershed which is located within the Liesbeek River Catchment is affected by the presence of the Peninsula Mountain to the west. The Liesbeek River Catchment is characterized by an annual average precipitation and evaporation that varies from 600 to 1500 mm/yr and 1150 to 1550 mm/yr respectively (Fisher-Jeffes, 2015).

3.3 Model development

The UCT dam and associated catchment was chosen to represent a typical storage reservoir used for irrigation. The catchment area is about 0.33 ha, of which 98% is pervious, with a land use composed of an open greenfield area. 100% of the catchment drains into the UCT dam with a storage capacity of 47500 m^2 and a surface area of 0.82 ha (Figure 3-4).

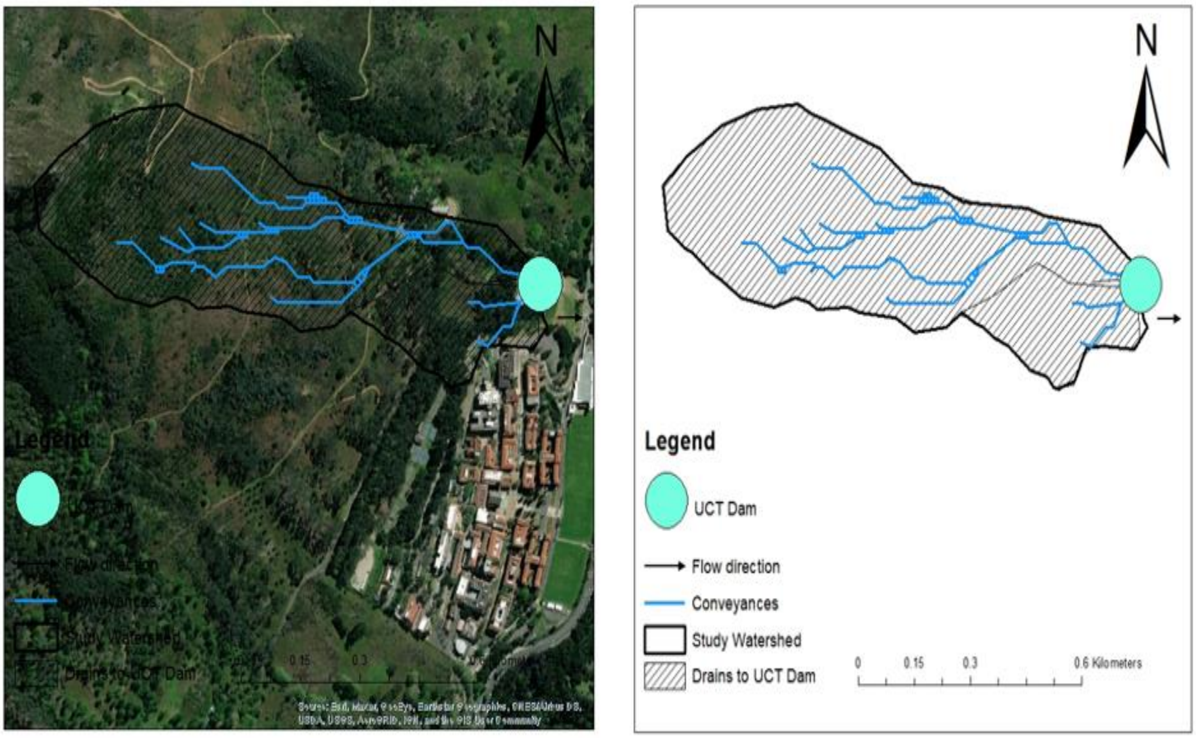


Figure 3-4: The UCT watershed

EPA SWMM 5.1, an open-source program for hydraulic and hydrologic simulation from the U.S. EPA (Rossman, 2015), was used to model the rainfall-runoff mechanisms in the study area. SWMM is commonly used for RTC simulations as control algorithms can be applied externally via a programming wrapper or programmed directly into the model as described in various studies such as (Joksimovic & Sander, 2016; Gaborit et al., 2016, 2013; Goodman & Quigley, 2015; Muschalla et al., 2014; Degrave et al., 2013; Heusch & Ostrowski, 2011; Wong & Kerkez, 2018) discussed in the literature review. The default SWMM Runoff method was used to model the runoff (Rossman, 2015). A dynamic wave routing of conduit lengthening and routing time step of 15 seconds, each; was used to represent the hydraulics of the system.

3.4 Data acquisition

To model the various aspects of a stormwater harvesting system, substantial amount of data was required. For modelling process, the following was acquired:

- Catchment topography
- Soil Infiltration data
- UCT dam
- Rainfall data
- Evaporation data
- Water demand

3.4.1 Catchment topography

Digital Elevation Model (DEMs) with a spatial resolution of 10 m was obtained from the City of Cape Town (CoCT) to accurately represent the catchment topography. A DEM is generally described as a geo-referenced data set, that allows to encode the topography for environmental modelling purposes (Toz & Erdogan, 2008). In the last 20 years, DEMs have become a widely used tool in various disciplines such as land planning, hydrology, and remote sensing. DEMs aid in better interrogating and visualizing features. In addition, a DEM that has adequate resolution can represent complex terrain units and are directly compatible with remotely sensed data sources. The DEM obtained from the CoCT represented the height above mean sea level of the water surface rather the ground surface, and this resulted in limitations for the channel section computation.

3.4.2 Soil Infiltration data

To model infiltration component which occurs when stormwater runoff flows over pervious surfaces reducing the volume of runoff (Mitchell *et al.*, 2007), it was necessary to assess the soil properties of pervious the areas in the catchment. Green-Ampt infiltration model in SWMM 5.1 was used to model infiltration as the model requires soil parameters, which are widely available in literature. The study determined appropriate soil parameter values from literature such as James *et al.* (2010).

Borehole logs of the New Lecture Theatre and New Engineering Building of the University of Cape Town produced by Kantey & Templer consulting engineers were used to identify the soil conditions (Upper soil type zones) of the watershed. As the Green-Ampt model determines infiltration that occurs in the upper soil zone, the borehole logs were useful in estimating infiltration parameter.

3.4.3 UCT dam

Information that detailed the infiltration parameters, outlet structures and storage capacity were required. This infiltration was derived from sources which included: a report on the UCT dam; and as-built drawings of the UCT dam. The storage capacity of the dam was modelled using a storage curve (depth versus area) as shown in Table 3-1 in SWMM 5.1. The storage curve of the dam were generated in the following:

- The maximum depth of the dam was determined from the as-built drawings
- The storage curve was developed from the storage volume below the dam's maximum depth using a report produced Zutari (2020).

The information provided by the as-built drawings were used to model the outlet structure of the UCT dam. The as-built drawings provided information on the type of outlet structure and dimensions. The discharge coefficient of the outlet structure was estimated from literature by Xu *et al.* (2018).

Table 3-1: Depth – Area curve

Depth (m)	**Area (m^2)**
1.5	7
2.5	113
3.5	346
4.5	707
5.5	1195
6.5	1810
7.5	2552
8.5	3421
9.5	4418
10.5	5542
11.5	6841
12.5	8200

3.4.4 Rainfall data

Mitchell *et al.* (2008) recommends that when analysing a continuous simulation of a stormwater system, a rainfall time series of ten years should be minimum length of rainfall. Mitchell et al., (2008) further states that accurate estimates of performances indicators, particularly (described in Section 2.5) are produced using longer rainfall records, whilst significant estimation inaccuracies could be produced with shorter records (e.g., one- or two-years length time series). When analysing a stormwater harvesting system, the chosen time-step is important. Coombes & Barry (2007) found that stormwater yields were significantly under-estimated for simulations that used daily time-steps instead of six-minute time-step.

Five-minute time-interval data is preferred, as it accounts for response time of the smallest subcatchments for continuous simulation models: however, fifteen-minute or hourly time-interval data can be used to produce acceptable estimations.

Historical rainfall data (5-min time-interval) from 2015 to 2022 was obtained from the South African Weather Services (SAWS) that monitors the Kirstenbosch station in Western Cape. Unfortunately, the rainfall record that was obtained for the study did not match the level of detail recommended by Mitchell *et al.* (2008) and Coombes & Barry (2007).

3.4.5 Evaporation data

For this study, it was necessary to model evaporation which incurs water losses from the system. As there was no operating evaporation gauging station positioned within the UCT watershed, it was not possible to obtain evaporation data. As a result, SWMM 5.1 which derives evaporation totals using Hargreaves's method was used to compute daily evaporation data. The Hargreave's method is an empirical equation that computes evaporation totals using temperature. Satisfactory results have been evident using this method (Xu & Singh, 2001; Allen *et al.*, 2006). Hence, historic temperature data (daily time-interval) from 2015 to 2022 was obtained from the Kirstenbosch station.

3.4.6 Water demand

Availability of data on the use of water for irrigation at UCT is limited. The UCT dam is only used to irrigate the soccer fields on Lower Campus, cricket fields on Middle Campus and rugby fields on Upper Campus (Figure 3-5). Historically, the storage volume of the dam has met the sports field irrigation demand (Zutari, 2020). However, this had to be augmented with municipal potable water in recent years (during drought) as the yield of the dam could not meet demand. This was not surprising as Cape Town was affected severely by the drought. Estimations of irrigation demand were based on an irrigation demand model (Table 3-2).

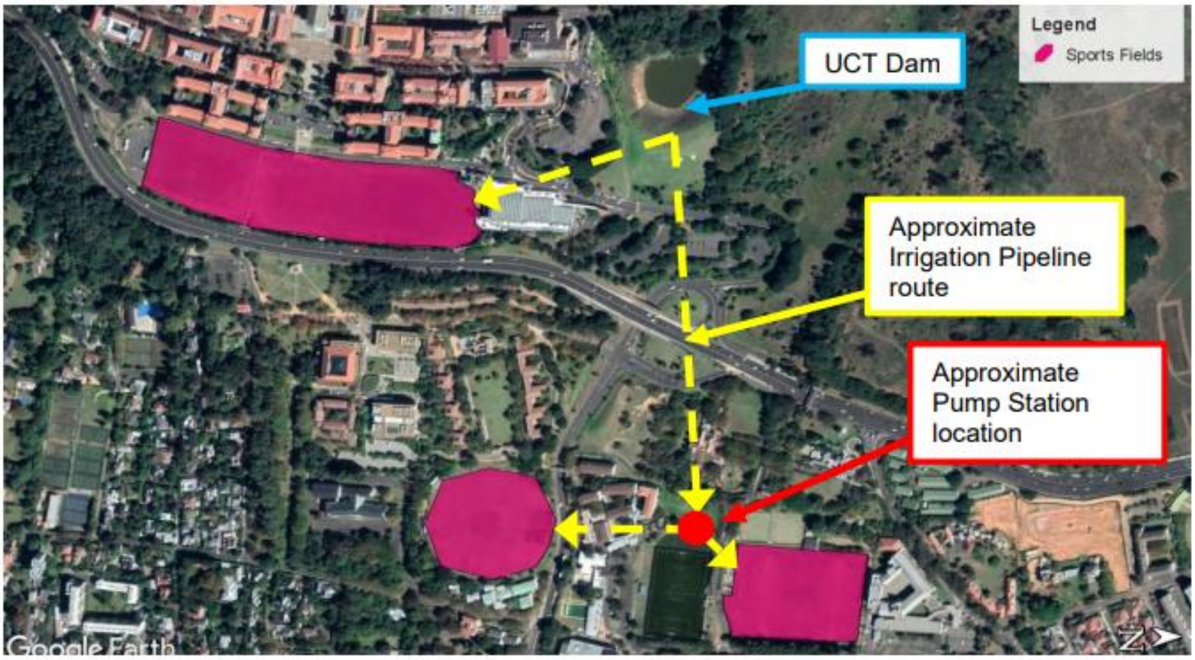
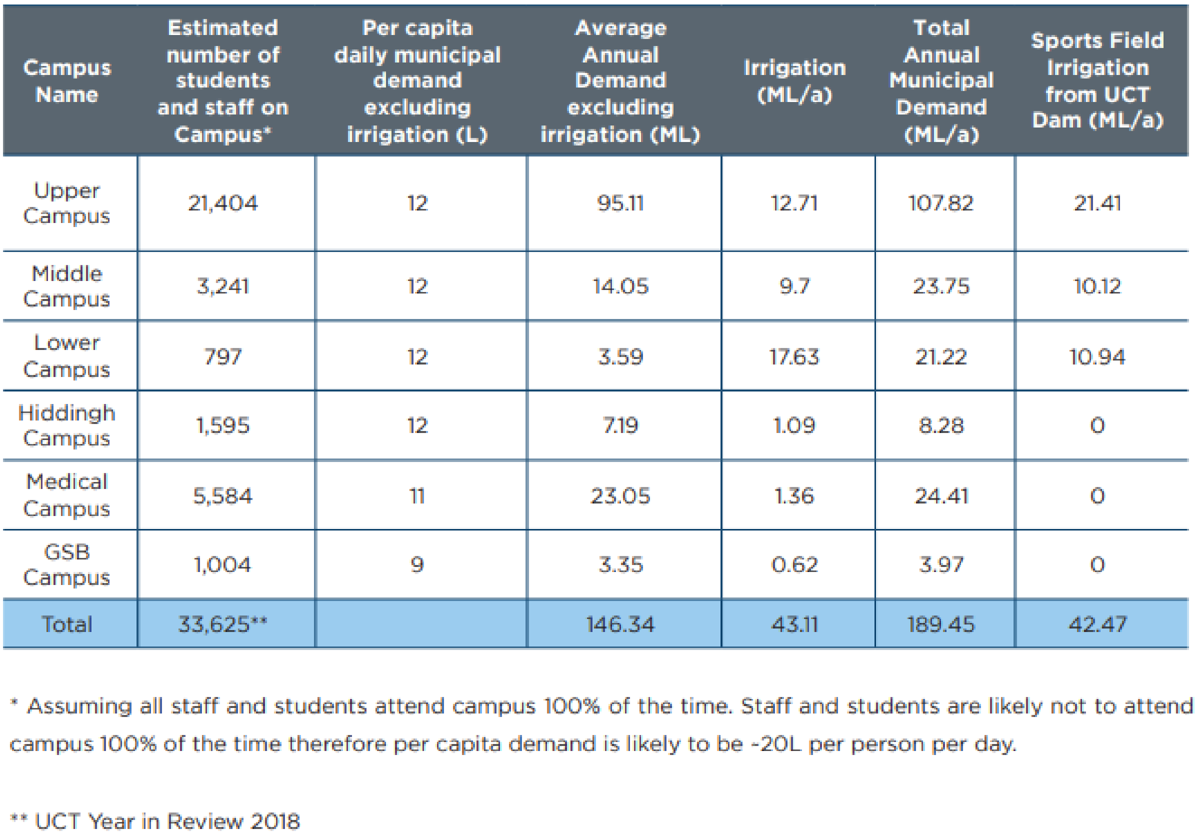


Figure 3-5: Proposed irrigation pipeline route and pump station location (Zutari, 2020)

Table 3-2: UCT Campuses Status Quo Results (Zutari, 2020)



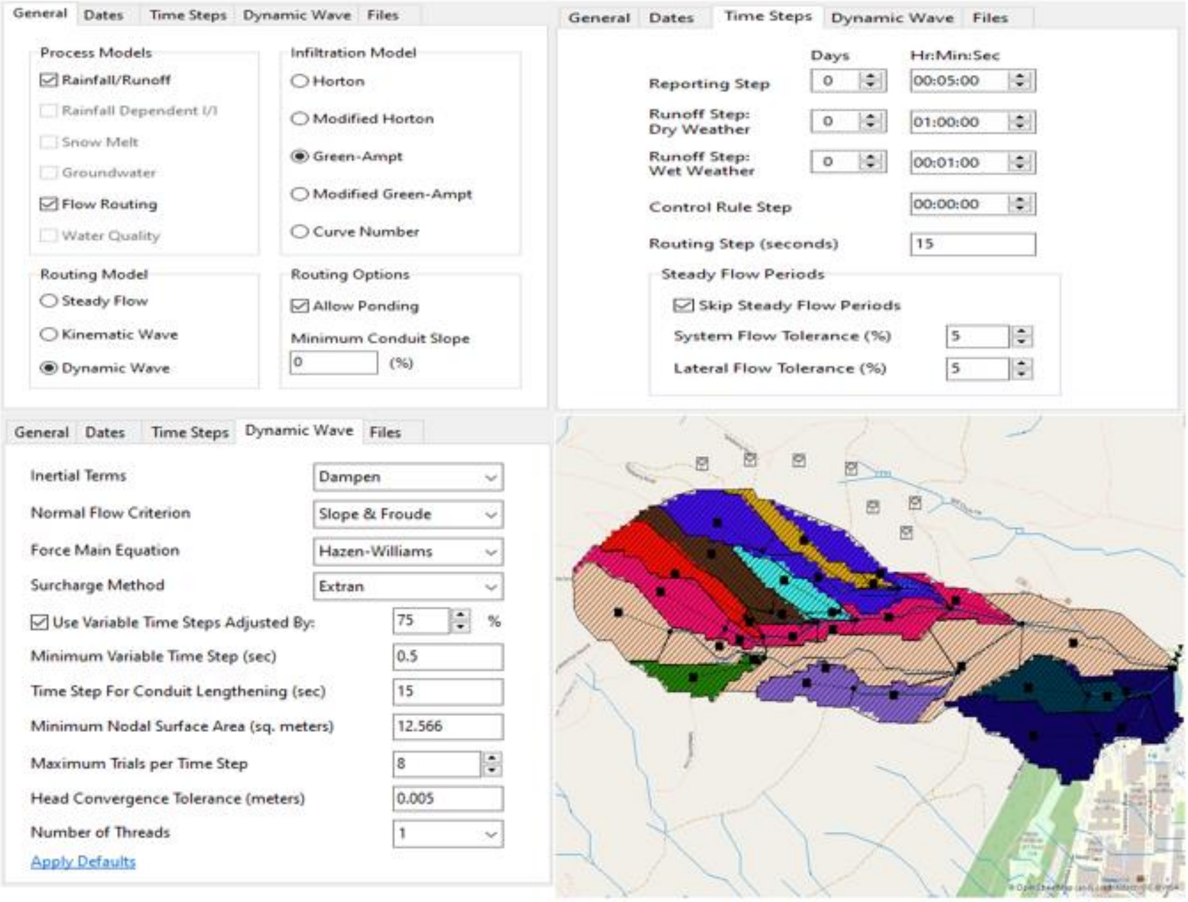
Campus Name	Estimated number of students and staff on Campus*	Per capita daily municipal demand excluding irrigation (L)	Average Annual Demand excluding irrigation (ML)	Irrigation (ML/a)	Total Annual Municipal Demand (ML/a)	Sports Field Irrigation from UCT Dam (ML/a)
Upper Campus	21,404	12	95.11	12.71	107.82	21.41
Middle Campus	3,241	12	14.05	9.7	23.75	10.12
Lower Campus	797	12	3.59	17.63	21.22	10.94
Hiddingh Campus	1,595	12	7.19	1.09	8.28	0
Medical Campus	5,584	11	23.05	1.36	24.41	0
GSB Campus	1,004	9	3.35	0.62	3.97	0
Total	33,625**		146.34	43.11	189.45	42.47

* Assuming all staff and students attend campus 100% of the time. Staff and students are likely not to attend campus 100% of the time therefore per capita demand is likely to be ~20L per person per day.

** UCT Year in Review 2018

3.5 Stormwater model construction

The hydrological catchment (the UCT watershed) was delineated using *ArGIS's* watershed tool. This tool determines the entire contributing area upstream of the drainage outlet by specifying the common drainage outlet using a DEM – described in Section 3.3.1. In addition, the UCT watershed comprised of smaller contributing areas (sub-catchments) that were identified using the watershed tool in *ArcGIS* (ESRI, 2016a). The UCT watershed was then divided into 31 sub-catchments (Figure 3-6). The stormwater conveyance network of the watershed consisted of open natural channels. The DEM used incorporated stormwater channels; the dimensions of section profile were determined using the '3D – Analyst profile graph'. Then, the dimensions were incorporated into SWMM 's '*transect creator*'tool.



Process Models
☑ Rainfall/Runoff
☐ Rainfall Dependent I/I
☐ Snow Melt
☐ Groundwater
☑ Flow Routing
☐ Water Quality

Infiltration Model
○ Horton
○ Modified Horton
● Green-Ampt
○ Modified Green-Ampt
○ Curve Number

Routing Model
○ Steady Flow
○ Kinematic Wave
● Dynamic Wave

Routing Options
☑ Allow Ponding
Minimum Conduit Slope 0 (%)

	Days	Hr:Min:Sec
Reporting Step	0	00:05:00
Runoff Step: Dry Weather	0	01:00:00
Runoff Step: Wet Weather	0	00:01:00
Control Rule Step		00:00:00
Routing Step (seconds)		15

Steady Flow Periods
☑ Skip Steady Flow Periods
System Flow Tolerance (%) 5
Lateral Flow Tolerance (%) 5

Inertial Terms	Dampen
Normal Flow Criterion	Slope & Froude
Force Main Equation	Hazen-Williams
Surcharge Method	Extran
☑ Use Variable Time Steps Adjusted By:	75 %
Minimum Variable Time Step (sec)	0.5
Time Step For Conduit Lengthening (sec)	15
Minimum Nodal Surface Area (sq. meters)	12.566
Maximum Trials per Time Step	8
Head Convergence Tolerance (meters)	0.005
Number of Threads	1

Figure 3-6: SWMM Simulation Options and Map

3.6 Calibration

A substantial amount of parameter estimation was required to model both the hydraulic and hydrology capacity of a catchment as this is evident from the preceding sections. Data on the catchment conditions were used to derive appropriate parameters; however, to provide the most 'useful' representation of the catchment, it was essential to calibrate these parameters (Sangal *et al.*, 1994; Singhofen, 2001; James, 2005). Several techniques have been developed to optimise the calibration process of a stormwater model such as: Nash-Sutcliffe efficiency (NSE), per cent bias (PBIAS), and the Root Mean Square Error (RMSE) according to Moriasi *et al.* (2007). To reasonably estimate the harvestable stormwater volume, a hydrological model was developed and calibrated. The stepwise calibration was as follows:

- The rainfall data measured at five-minute time intervals was used for the model development and calibration to represent the rapid runoff processes that result in short response times in urban catchments. The water level data for the dam required for calibration and validation processes was limited to 10 June 2022 to 7 August 2022 taken at fifteen-minute interval with no observed values from 2 to 15 July 2022. The water level data was obtained using water depth sensors courtesy of a fellow master's student (Roberto De Oliveira) The simulated values as seen in Figure 3-7 gives a representation of the behaviour of the actual conditions for the period with no observed values which is from 2 to 15 July 2022.
- Calibration was based on water levels taken from 28 to 30 July 2022 while validation was performed from 10 to 17 June 2022 as seen in Figure 3-8 and Figure 3-9. Figure 3-8 estimates high and low phenomena based on either an underestimation or overestimation of the catchment hydrological parameters while Figure 3-9 shows a validation period that results in NSE > 70% which is reasonable.
- The water levels were found to be the most sensitive to saturated hydraulic conductivity. Parameters in SWMM such as depth of depression storage for impervious surfaces (DStore – Imperv), depth of depression storage for pervious surfaces (DStore – Perv) and Manning's n for pervious surfaces (N – Perv) which were found to be sensitive according to various studies were not calibrated (Jewell *et al.*, 1978; Zaghloul, 1983; Liong *et al.*, 1991; Tsihrintzis & Hamid, 1998; Barco *et al.*, 2008).
- Visual inspection was used to select suitable values for the sensitive parameter by trial and error to achieve mimicry between model and observed water levels.
- The calibrated parameter conformed to acceptable range defined by James (2005).

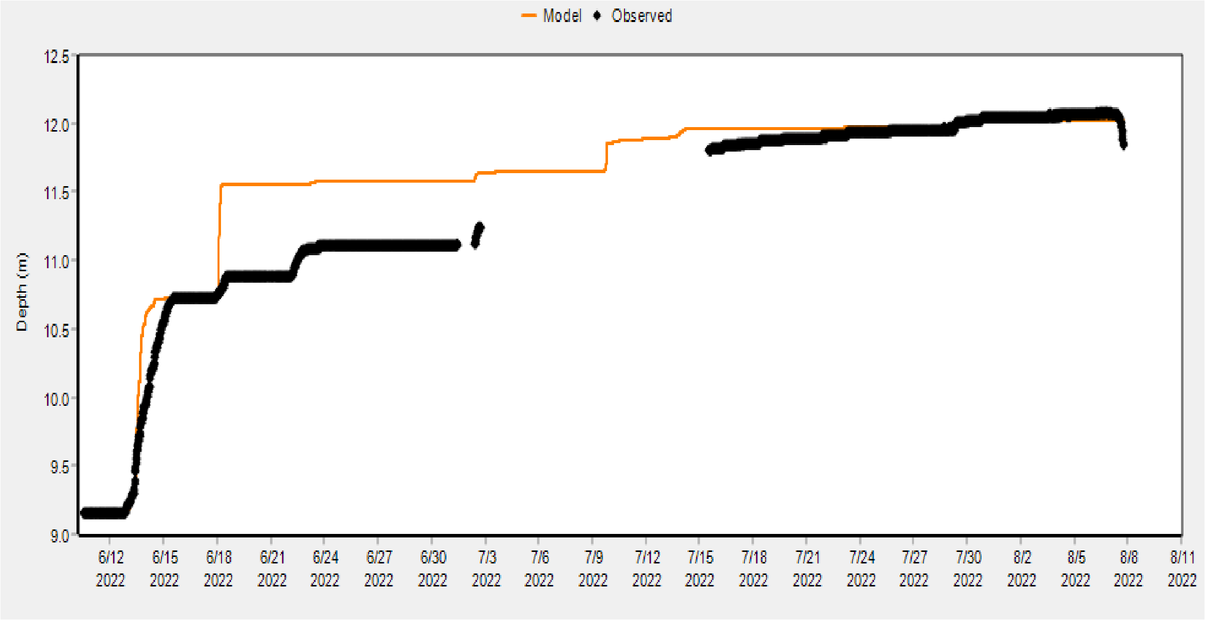


Figure 3-7: Observed and simulated water levels

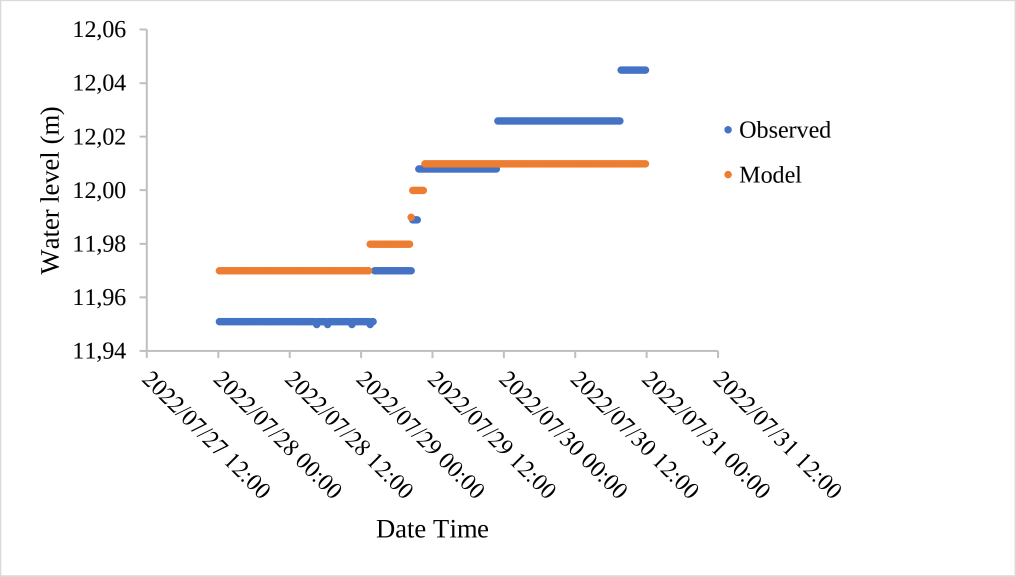


Figure 3-8: Observed and simulated water levels (calibration period)

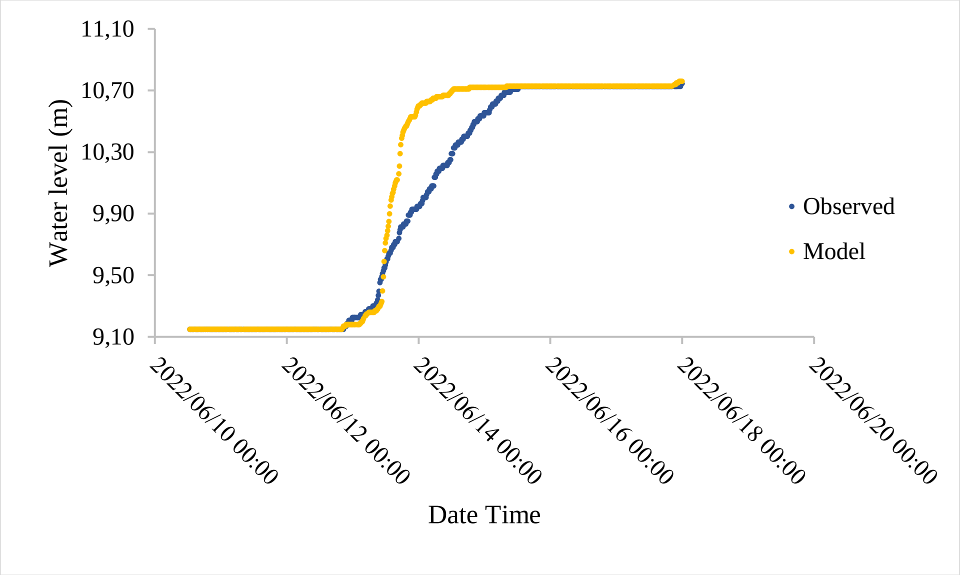


Figure 3-9: Observed and simulated water levels (validation period)

Nash-Sutcliffe values of 0.74 and 0.91 respectively for calibration and validation periods were computed according to Gaborit *et al.* (2013). Schmitt *et al*. (2020) computed NSE values 0.91 for both calibration for certain events. In addition, Moriasi *et al.* (2007) recommends that model calibration provide reasonable results when NSE > 0.5. The summary of the results from the calibration process including runoff quantity continuity error and flow routing continuity error are shown in Table 3-3.

Table 3-3: Calibration and validation results of water levels

	Observed vs Calibrated	Observed vs Validation
Nash Sutcliff Efficiency	0.74	0.91
Runoff quantity continuity error (%)	-0.003	
Flow routing continuity error (%)	3.75	
Highest continuity error at nodes	Node 12 (4.26%)	

3.7 Static control simulations

Two static control configurations were applied to the UCT dam *viz:* static control 1 and 2 (SC1 and SC2) in SWMM 5.1. SC1 (baseline scenario) is a procedure that is currently in practice and, SC2 the recommended improved static practice assuming that the stormwater system can adequately convey runoff into the dam and dredging undertaken to remove sediment and maximise storage. SC1 shortfall is that when the dam falls below a depth of 6m, the UCT management uses municipal water which is costly to irrigate the fields. Additionally, Zutari (2020) states that it is uncertain as to what the long-term sustainable yield of the dam is. The orifice is only opened between 08h00 and 13h00 for irrigation of the sports field for both configurations.

```
STATIC CONTROL 1 (SC1):
If Simulation clocktime  > 08:00:00
And Simulation clocktime < 13:00:00
And 6m <= UCT dam depth <= 12.5m
Then Open orifice to meet demand
Else close orifice
```

```
STATIC CONTROL 2 (SC2):
If Simulation clocktime  > 08:00:00
And simulation clocktime < 13:00:00
And 3m <= UCT dam depth <= 12.5m
Then Open orifice to meet demand
Else close orifice
```

3.8 Simulations of a Real-Time Control Retrofit

The simulation of RTC for SWH in the UCT watershed considered actuator settings, control rules and rainfall data. Rainfall forecast data used for RTC application for the study was acquired from the Global Forecast System (GFS) model managed by the National Centre for Environmental Prediction (NCEP). Global forecasts of up to two weeks prediction can be provided by a GFS model in a spatial form (described in section 2.3). A six hourly temporal resolution of a rainfall forecast time series provided by the NCEP was used for the study. The available GFS forecast data in the study area at latitude 34° 00' S and longitude 18° 31' E were extracted for the period 2015 – 2022 for RTC simulations. The extracted GFS forecast data was compared with measured data as shown in Figure 3-10. The measured data was extracted at latitude 33° 59' S and longitude 18° 25' E. It was determined that there were some differences in the magnitude of the events and the timing of the peak (shift in peak times). In addition, some peaks in recorded data were 40% higher than GFS data due to poor quality of forecast. The disadvantage of an underestimation in the forecast would be no release from the storage (UCT dam) with subsequent occurrence of a flood. The quality of forecast can be improved by implementing forecast with smaller time-steps (i.e., five or fifteen hourly temporal resolution) and forecast revision for better water management in the context of South Africa. Forecast are revised when the difference between the actual conditions and forecast are such that public safety and security are at risk and/or when inconvenience to the public is thought to be extensive. In addition, precipitation should be accounted when the chance of precipitation is equal to or greater than 30 per cent.

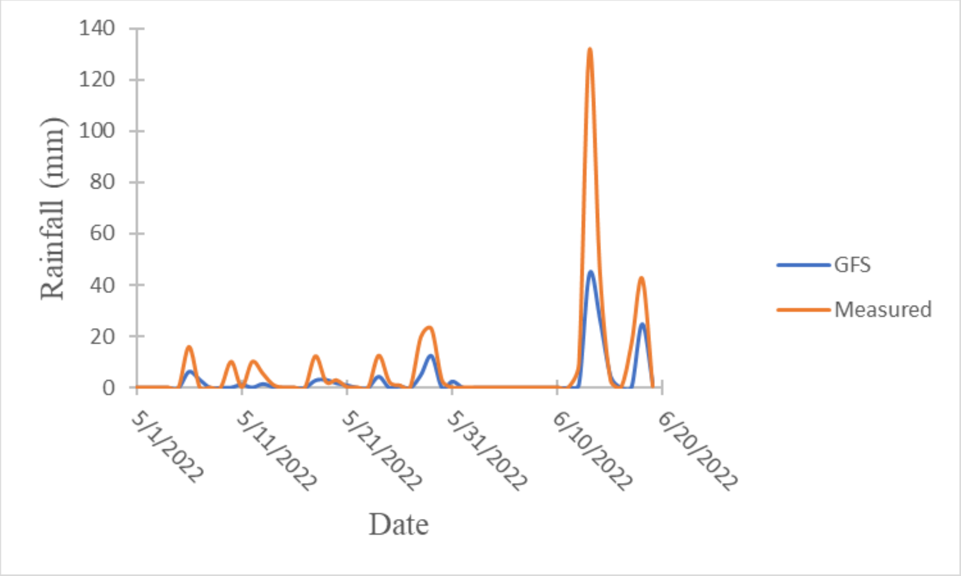


Figure 3-10: Comparison of GFS and measured rainfall data (NOAA, 2022; SAWS, 2022)

PySWMM which is a Python programming language package that allows for the step-wise observation and modulation of SWMM models as they execute, was used in the study to simulate Real-Time control of the test watershed model (McDonnell et al., 2016). In the SWMM model, PySWMM tools have the ability to observe and manipulate nearly any parameter; however, only data that could be feasibly monitored in a real-world application was used for RTC application to create a realistic scenario (Schmitt et al., 2020). The model was set up with the listed components required to dynamically manage storage as recommended by the study:

- Depth sensors in the UCT dam
- Actuated valves in the UCT dam outlet
- Rain gauge (one for entire test watershed)

The depth sensors were housed in an IP64 compartment which is waterproof as a protective measure to ensure that the sensors were not damaged during typical flood flows. Real time data was captured from the sensors to the server via LoRa network and then processed using Things network and Things speak. A 5-minute time step was used to execute the control algorithm, which maintains a realistic interval to receive and transmit data and control commands whilst allowing for adequate temporal resolution (Bartos et al., 2017).

PySWMM interrupts the SWMM simulation and retrieves the relevant measurements (precipitation, current depth, etc.) at the aforementioned interval (Schmitt et al., 2020). The control algorithm was fed this information, to decide on the opening's percentage for the UCT dam outlet valve. The actuator was set to the required position by PySWMM, and the SWMM simulation continues until the following time step. Real-Time control of the UCT dam outlet valves was simulated through the application of RTC-1 and RTC-2 algorithms as shown in Figure 3-11 and 3-12. The primary objectives of RTC-1 and RTC-2 algorithms were to improve the performances of SC1 and SC2 respectively.

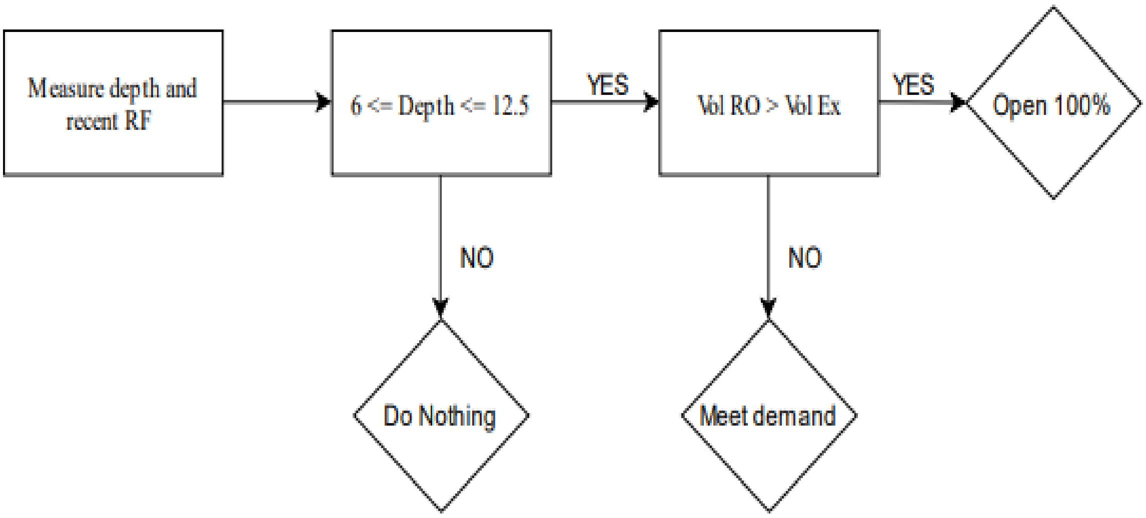


Figure 3-11: RTC-1 algorithm, executed every five minutes. RF = rainfall. Vol RO = volume of runoff estimated from an equation taken from Woods-Ballard *et al.* (2007). Vol Ex = maximum volume – current volume of water in the UCT dam.

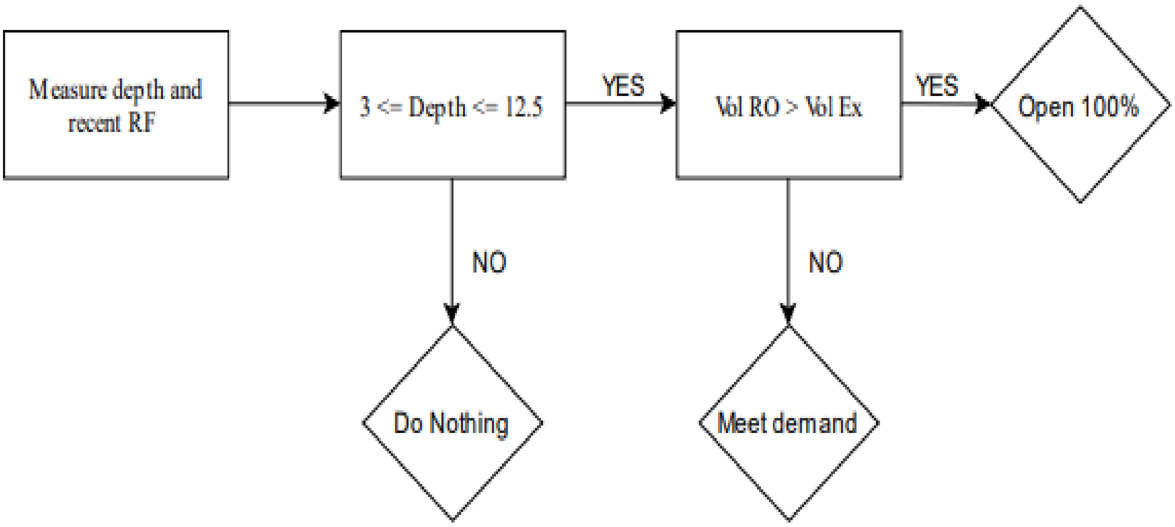


Figure 3-12: RTC-2 algorithm, executed every five minutes

3.9 Economic analysis

3.9.1 Capital costs

Capital costs (Excl. VAT) were based on Kantey & Templer Consulting Engineers estimates that entailed:

- Remediation works associated with the stormwater channels at the UCT earth dam.
- Slope stability analysis of the UCT earth dam after the recent fires.
- Drilling investigation for slope stability.

Additionally, capital costs of actuators and depth sensors required for Real-time control were obtained from RS Export Solutions and Hafei WNK companies respectively.

3.9.2 Maintenance costs

It is essential that a stormwater harvesting system receives frequent maintenance to function optimally. Maintenance costs (Excl. VAT) were based on kantey & Templer Consulting Engineers scope of work that entailed:

- A site visit to visually inspect the slopes of the earth dam with a particular concern of mudslides during the winter season.
- Site visit conducted by a Civil engineer, Dam engineer and Geotechnical engineer.
- An assessment report with recommendations submitted after the site visit.

3.9.3 Operation costs

Operational costs (Excl. VAT) of a stormwater harvesting system were accounted for this study. Operational costs were based on energy costs to run the system. The time for which the system was in operation was multiplied by the CoCT's electricity tariff as seen in Table 3-4 to determine the energy cost required.

Table 3-4: Electricity Tariffs (CCT, 2022)

Small Power User (<500kVA)	**Units**	**Small Power Users 1 (>1300kWh/month)**	**Small Power Users 2 (<1300kWh/month)**
Service	ZAR/day	69.96	5.52
Energy	ZAR/kWh	1.99	3.50

3.9.4 Life Cycle Cost Analysis

The total cost of implementing each stormwater harvesting control was computed using a Life Cycle Cost Analysis (LCCA). LCCA is an economic evaluation method which is commonly used by considering all costs incurred by an asset over its period of service (WERF, 2011; Armitage *et al*., 2013). Developers can use LCCA to make informed comparisons about initial capital costs versus maintenance and operation costs of various systems (Swamee & Sharma, 2008). In addition, a monetary appraisal (direct/indirect costs) or an economic appraisal (costs/benefits caused by environmental influences) can be performed by using LCCA; thus-making the tool beneficial. It was decided that only direct costs (i.e., capital costs and maintenance and operational expenses) would be considered for the study; thus, disregarding an economic appraisal which can be difficult to determine as it requires placing a monetary value on subjective factors such as aesthetic amenity or ecological services. Additionally, indirect costs and non-monetary aspects were not considered.

During a LCCA, the total cost Life Cycle Cost (LCC) is computed by converting all costs incurred by the asset over its lifespan to an equivalent period (i.e., convert future costs to a present value). Future costs are converted to their present value using Equation 3.1 whilst Equation 3.2 is used to compute the discount factor. Equation 3.3 was used to compute the LCC.

$$PV_n = FC_n \times DF_n \quad (3.1)$$

Where: PV = present value for year, n (ZAR); FC = total future monetary costs in year, n (ZAR); DF = discount factor in year, n; n = number of years from present year

$$DF_n = \frac{1}{(1+i)^n} \quad (3.2)$$

Where: DF = discount factor for year, n; i = real discount rate; n = number of years from present year

$$LCC = \sum_{n=0}^{No.\ years} (PV_n)_{costs} \quad (3.3)$$

Where: LCC = Life Cycle Cost (ZAR); No. years = total number of years in life cycle analysis; n = number of years from present year; PV = present value for year, n; Res = residual cost (ZAR)

The following aspects were considered during the LCCA of each stormwater harvesting control:

- Discount rate – *'The discount rate is the rate used to convert all future costs all future costs and benefits to present value so that they can be compared'* (Lampe et al., 2005). In addition, the difference between a government 10-year bond and inflation (Consumer Price Index) is considered to be the discount rate (Fisher-Jeffes, 2015). Shown in Table 3-2 are the values used to determine the discount rate in line with the National Treasury (2004) recommendations which stats that *'For practical purposes, the discount rate is assumed to be the same as the risk adjusted cost of capital to government. The government bond yield has been used by some institutions as the discount rate for a particular project over a comparable period. The argument in favour of using the government bond yield is that it reflects the actual cost to government of raising funds at any given time. This ignores a number of factors that are difficult to quantify, including: various risk margins relating to increased government borrowing; various tax implications of diverting funds from private to public consumption; and government's time preference of spending'.*

Table 3-2: RSA bond yields and inflation

Analysis period	Government 10-year bond (%)	Inflation (%)	Discount rate (%)
2012 - 2022	10.5	7.6	2.9

*Trading Economics (2022) **StatsSA (2022)

- Life cycle duration – the LCCA was performed for a fifty-year duration as this better represented the actual lifespan of a stormwater harvesting system. Annual estimates such as the stormwater yield and each system's energy cost were based on the hydrological period of analysis.
- Life span of a system components – this establishes each system's future capital costs as well to compute residual values at the end of the life cycle duration. Information on a component's lifespan were based on Mackenzie (2010).

The Equivalent Annualised Cost (EAC) – shown in Equation 3.4, represents the cost per year of ownership and operation of an asset. In addition, the unit cost (ZAR/k*l*) of harvesting stormwater per year for each stormwater harvesting control was computed.

$$EAC = \frac{i(1+i)^n}{(1+i)^n-1} \times LCC \quad (3.4)$$

Where: EAC = equivalent annualised cost (ZAR); i = real discount rate; n = number of years from present year; LCC = life cycle cost (ZAR)

3.10 Summary of the method

The chapter focused on the key components of the method used including overview, study area, model development, data acquisition, stormwater model construction, calibration, static simulations, simulations of Real-Time Control retrofit and Economic analysis. For this study, a substantial amount of data was required to model the various aspects of the stormwater harvesting system. Unfortunately, there were limitations in terms of obtaining data at the required level of detail. Hargreaves's method was used to estimate daily evaporation as evaporation data was not available for the catchment. Furthermore, a stormwater model of the UCT watershed was constructed and calibrated using SWMM 5.1. RTC-1 and RTC-2 algorithms were implemented to enhance performances of SC1 and SC2 respectively. Results (Chapter 4) of the performances of the static and RTC configurations are presented.

4 Results and discussion

4.1 Overview

This chapter presents the results that were obtained after modelling Static and RTC configurations and discusses the benefit of applying RTC on annual yield and volumetric reliability of the UCT dam. The results presented in this chapter include the Static and RTC configurations modelled using rainfall records from 2015 – 2022 with fifteen-minute timestep (Section 3.3.3) and from 2015 – 2022 with a six-hourly timestep (Section 3.7) respectively. The routing continuity error for all configurations ranged between -0.8% to 0.1% whilst the runoff continuity error equalled – 0%. James (2010) states that a continuity error below 10% is tolerable *i.e.,* thus the errors are considered acceptable. Section 4.2 presents the impact of RTC on average annual yield and volumetric reliability. Section 4.3 focuses on the unit cost of harvested stormwater. Section 4.4 discusses on the impact of Real-Time Control technology whilst section 4.5 details the cost of implementing RTC technology.

4.2 Impact of RTC on annual yield and volumetric reliability

The modelled SWH system configuration with RTC was improved significantly in terms of average annual yield and volumetric reliability. The ability to enhance average annual yield and volumetric reliability was evident in the comparison between RTC algorithms and static controls (Figure 4-1 and 4-2). RTC-1 exhibited approximately 2.1 ML and 5.2% better average annual yield and volumetric reliability in comparison to SC1. RTC-2 exhibited about 1.1 ML and 2.5% better average annual yield and volumetric reliability in comparison to SC2. Hence, the application of RTC-1 and RTC-2 algorithms on the UCT dam provided a capacity (*i.e.,* extended detention required for SWH) of 2.2 ML (about 5.1% of SC1 mean annual stormwater yield) and 1.1 ML (about 2.6% of SC2 mean annual stormwater yield) respectively. Zutari (2020) estimates UCT residences taps (Potable water) demand at 11ML/a. Hence, RTC-1 and RTC-2 approaches has the potential meet about 6.4% and 10.9% of the residences potable water respectively whilst satisfying irrigation demands if stormwater could be fully treated. SC1 was the only configuration that failed to meet the average annual volume of harvested stormwater demanded. In addition, volumetric reliability of at least 70%, which is the minimum level of service required was achieved by the storage configurations.

In the comparison of the water levels variation for static control and RTC configurations in Figure 4-3 and 4-4. Anticipated flow from forecasted rainfall was accommodated by dropping the water depth rapidly *i.e.,* flooding was avoided by setting RTC control rules to allow for pre-emptive drawdown of water levels to provide for capacity in the UCT dam.

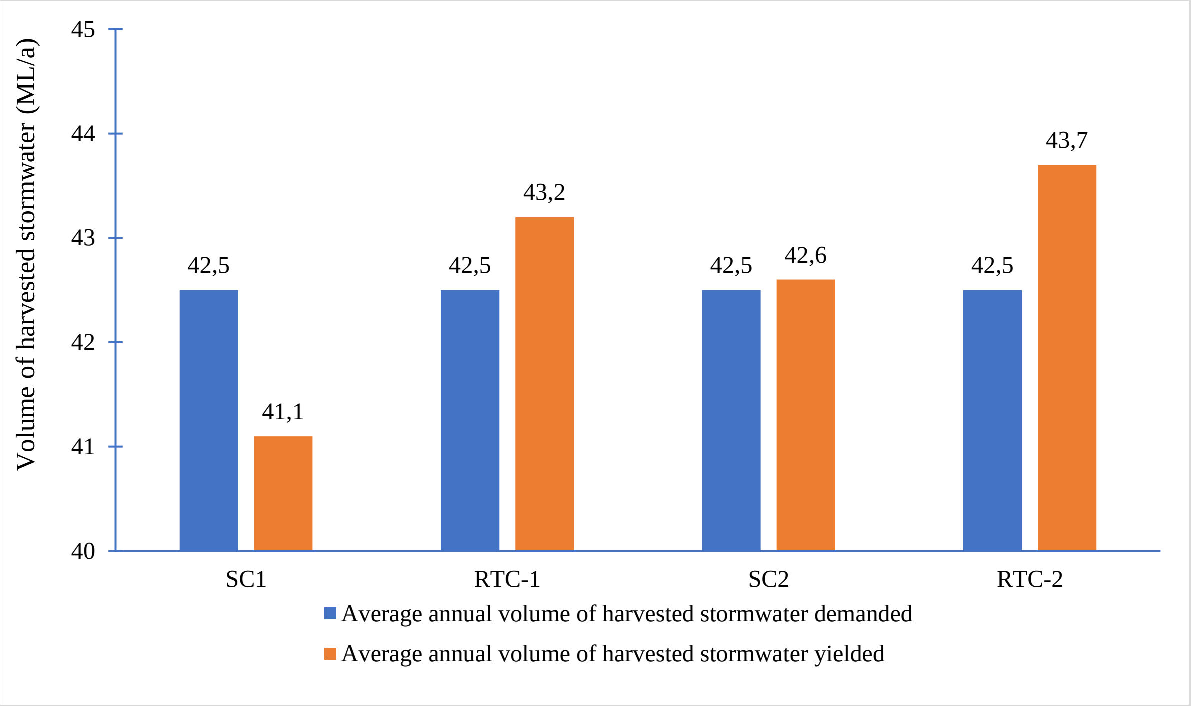


Figure 4-1: Average annual yield per configuration

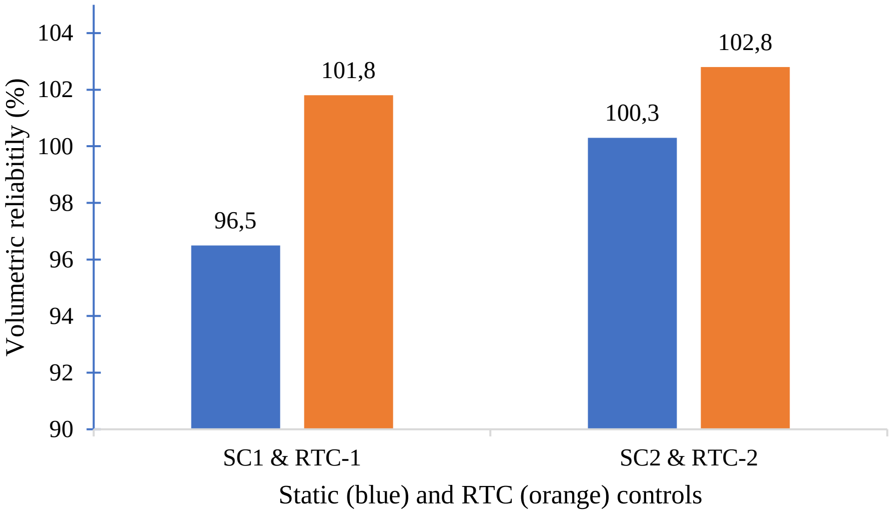


Figure 4-2: Volumetric reliability per configuration

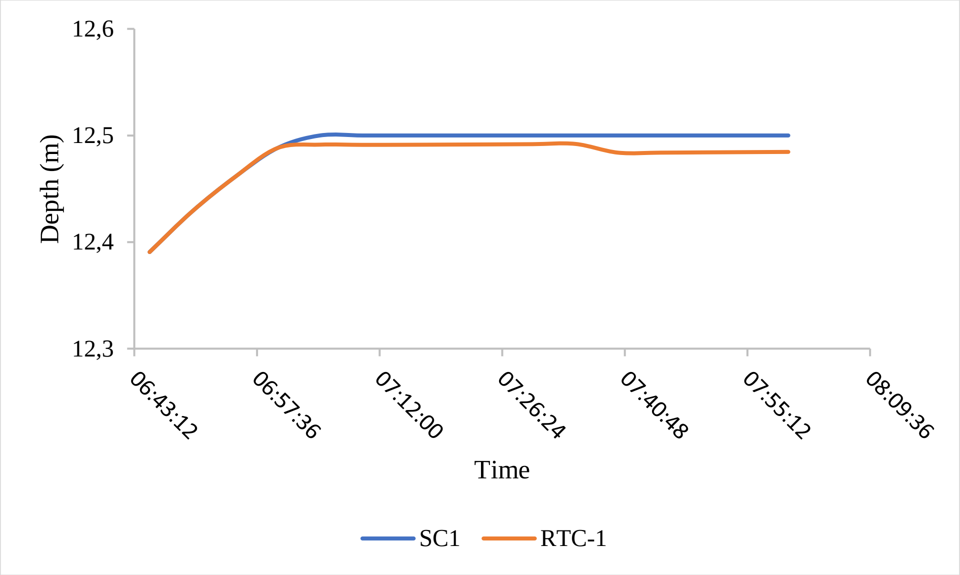


Figure 4-3: Water level in the UCT dam (12,5m maximum depth) during 23 July 2019

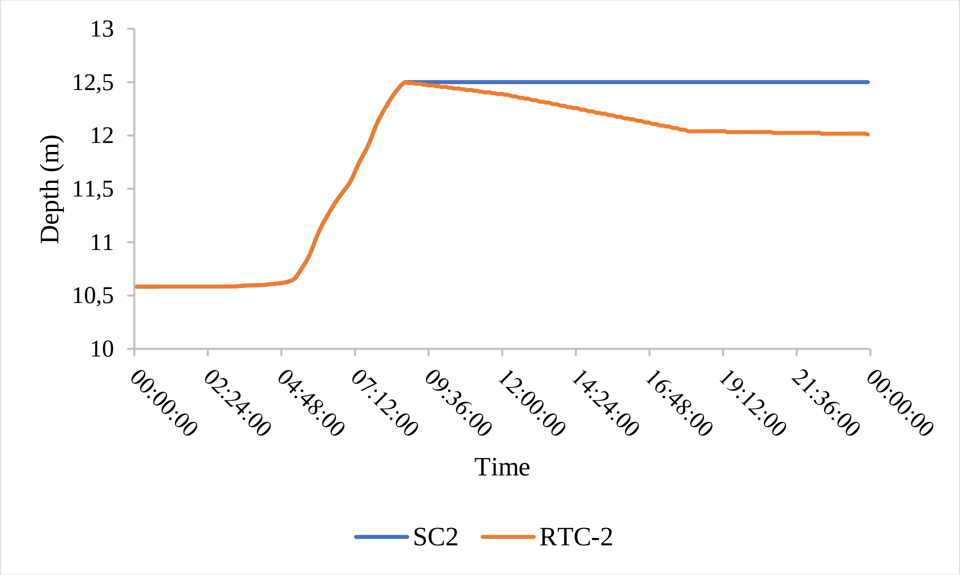


Figure 4-4: Water level in the UCT dam (12,5m maximum depth) during 10 October 2019

4.3 Unit cost of harvested stormwater

The unit cost of harvested stormwater for each configuration was computed by dividing the scenario's Equivalent Annualised Cost (EAC) as seen in Figure 4-5 by the average annual yield of harvested stormwater (determined over the ten-year hydrological analysis period). The unit cost of harvested stormwater for each configuration can be seen in Figure 4-6.

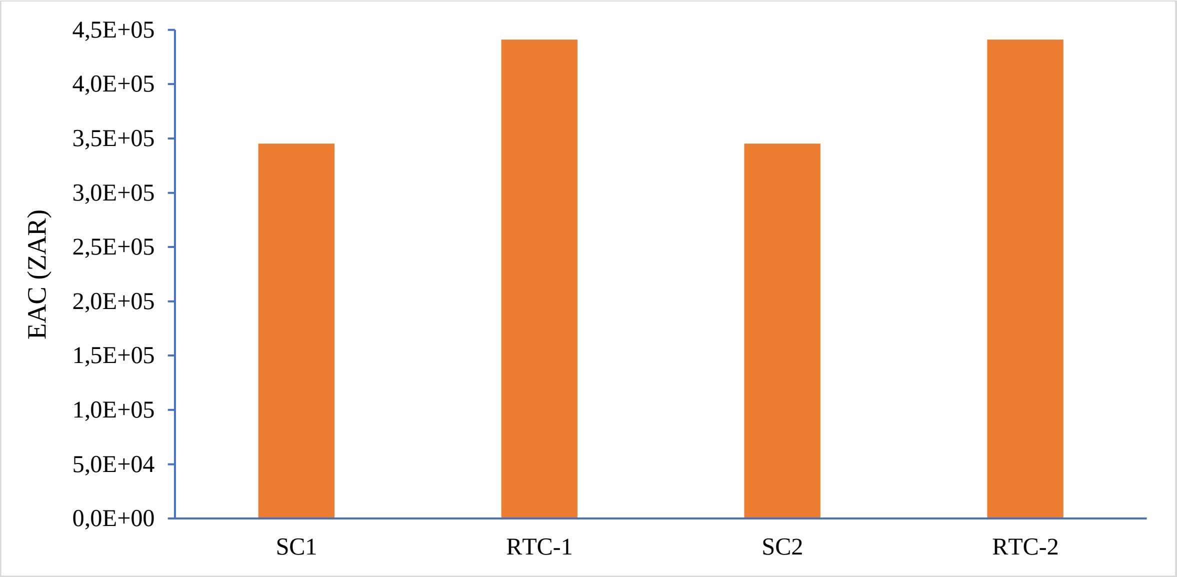


Figure 4-5: Equivalent annualised cost for each configuration

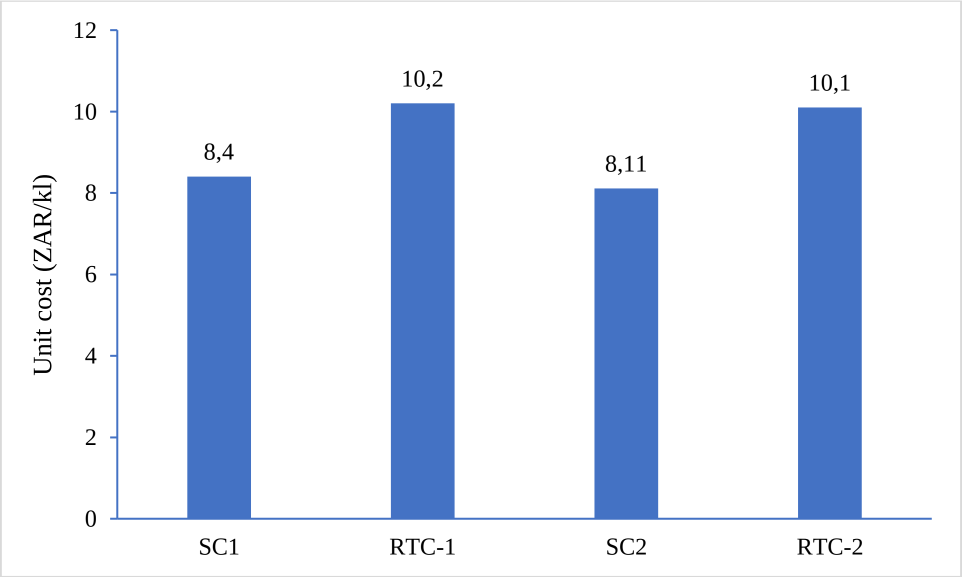


Figure 4-6: The unit cost of harvested stormwater for each configuration

Water usage by sports bodies in the CoCT is billed at flat rate (Excl. VAT) of 29.55 ZAR/kl (CCT, 2022). The CoCT increases the tariff for water usage during scarce events. Figure 4-6 reveals that Static and Real-Time configurations harvested at a unit cost that is comparable to the cost per kilolitre that the UCT management typically pay the CoCT for their water usage. The cost of supplying harvested stormwater to the UCT sports fields for irrigation varied insignificantly between the four configurations. Static and Real-Time configurations harvested at a unit cost lower than what the UCT management are typically charged by the CoCT. In addition, Static (SC1 & SC2) and Real-Time (RTC-1 & RTC-2) configurations harvested stormwater at a cost approximately one-fourth and one-third the rate of what CoCT charges for water bodies respectively. As expected, Real-Time configurations harvested stormwater at a cost comparable to Static configurations due to the inclusion of depth sensor in the UCT dam and actuated valves in the valves in the dam outlet. SC1 and SC2 results in water savings of up to 21.15 ZAR/kl and 21.45 ZAR/kl respectively whilst RTC-1 and RTC-2 could save up to 19.35 ZAR/kl and 19.45 ZAR/kl. Thus, Static configurations results in water savings approximately in comparison to RTC. Hence, Static configurations harvested stormwater at a relatively lowest unit cost in comparison to RTC configurations.

It can be argued that an economically efficient stormwater harvesting system manages to minimize costs while maximizing the stormwater it harvests. This optimal state cannot be obtained by solely focusing on maximizing stormwater yields whilst minimizing costs. For example, RTC configurations harvested more stormwater than Static configurations but Static configurations harvested stormwater at a relatively low unit cost in comparison to RTC.

4.4 Impact of Real – Time Control Technology

The results suggest that the average annual yield and volumetric reliability of SWH system can be substantially improved by using RTC technology. This accomplished by pre-storm release *i.e.,* collecting rainfall forecasts in real-time and discharging water from the system prior to the occurrence of a rainfall. The use of pre-storm release can contain upcoming storm runoff which gives the system additional capacity. In addition, pre-storm release can reduce uncontrolled system overflow (*i.e.,* flood attenuation). The rainfall depth of forecasts was generally lower than real-time which often produced underestimated volume of pre-storm release for this study (described in Section 3.7). Thus: during pre-storm release, a small volume of water was discharged on occasion for the RTC system. Hence, this has the possibility of diminishing performance for water supply. This ‘underestimation’ can be improved by using a more accurate and smaller time-interval rainfall forecast data which optimizes the system.

4.5 Cost

The results of this study have shown that Static configurations harvested stormwater at a lower cost unit in comparison to Real-Time configurations. However, Rohrer & Armitage (2017) demonstrated that scenarios which modelled the greatest percentage of the total non-potable demand per residential property were economically viable. Furthermore, Rohrer & Armitage (2017) concluded that the cost of a stormwater harvesting system water distribution infrastructure highly influences it’s economic viability.

Rapid development of technology in recent times such as methodologies, tools and improved devices greatly reduce the cost of RTC technology. An RTC system can minimize adverse impacts of urban runoff on the environment whilst providing private and public benefits to water consumers at a relatively low cost. Uptake of such environmental technologies through this combination of private and public benefits are vital.

5 Conclusions and Recommendations

5.1 Overview

This chapter presents concluding remarks of the study and contribution (Section 5.2), challenges and recommendations (Section 5.3).

5.2 Study Contribution

The study identified and reviewed South African weather companies such as SAWS, CSAG and the NWS that runs a GFS model which is appropriate to RSA. It was found that SAWS do not focus on rainfall forecast and CSAG's forecast has been discontinued in 2016. Hence, this study used a GFS model that model provides time series rainfall forecast at a six-hourly temporal resolution. It was determined that there were some differences in the magnitude of the events and the timing of peak (shift in peak times). In addition, some peaks in the historical data were 40% higher than GFS data. In this study, a continuous simulation was conducted to model the ability of two types of SWH system, namely a conventional (static) and RTC system (dynamic) to deliver non-potable water for irrigation. The study determined that the implementation of RTC can significantly improve the annual yield and volumetric reliability performance of a SWH system. The dynamic management of the UCT dam with RTC-1 and RTC-2 approaches increase yield by 2.1 ML and 1.1 ML respectively. Additionally, RTC-1 and RTC-2 approaches increase volumetric reliability by 5.3% and 2.5% respectively whilst maintaining the required level of service of a stormwater harvesting system. SC1 and SC2 results in water savings of up to 21.15 ZAR/kl and 21.45 ZAR/kl respectively whilst RTC-1 and RTC-2 could save up to 19.35 ZAR/kl and 19.45 ZAR/kl. Thus, Static configurations results in water savings approximately 9% in comparison to RTC. In addition, Static configurations harvested stormwater at a relatively lowest unit cost in comparison to RTC configurations. Hence, RTC approaches increase yield and volumetric reliability with relatively low-cost implications. In addition, RTC-1 and RTC-2 approaches has the potential meet about 6.4% and 10.9% of the residences potable water demand respectively whilst satisfying irrigation demands if stormwater could be fully treated. It can be concluded that RTC-1 and RTC-2 provide guidance on the dynamic management storage to enhance SWH. The RTC system exhibits a great potential in reshaping stormwater harvesting system to simultaneously deliver water conservation and stormwater management. The ability of an RTC system to provide centralised control and failure detection, which can be readily adapted to variation of climate and local conditions over both the short and long term opens up possibilities of delivering a system that is more stable and reliable.

5.3 Recommendations for future research

This research mainly focused on the application of Real-Time control to enhance stormwater harvesting by assessing the average annual yield and volumetric reliability in the UCT dam for water supply.. The key challenge for the study was availability of long time series data for modelling the environment and water demand.. The areas recommended for future research are as follows:

- Future studies should consider climate change with variations in rainfall intensity, temperature, and other control algorithms (*e.g.*, optimization-based control, predictive control.
- Future research in RTC applications should consider the significance of sampling (time) interval for the efficiency of the RTC strategy and the potential error in results when designing control algorithms.

Finally, this study represents only a part of a greater effort to reuse urban stormwater in a water sensitive precinct or campus. These real-time tools combined with RTC retrofitting can pave the way for the future of smart stormwater management.

6 References

Abdul-Aziz, O.I, and Al-Amin, S. (2015). Climate, land use and hydrologic sensitivities of stormwater quantity and quality in a complex coastal-urban watershed. *Urban Water J,* 13, 1–19.

Akhter, M. S., and Hewa, G. A. (2006). “The Use of PCSWMM for Assessing the Impacts of Land Use Changes on Hydrological Responses and Performance of WSUD in Managing the Impacts at Myponga Catchment, South Australia.” *Water.* 511(8), 1-17. doi:10.3390/w8110511

Allan, C.J., J. Diemer, and V. Gagrani, (2010), Beaverdam Creek Watershed Monitoring Report. Charlotte, North Carolina.

Allen, R. G., Perreira, L. S., Raes, D., & Smith, M. (2006). Crop Evapotranspiration.

Armitage, N., Vice, M., Fisher-Jeffes, L., Winter, K., Spiegel, A., & Dunstan, J. (2013). South African Guidelines for Sustainable Drainage Systems. ISBN: ISBN 978-1-4312-0413-7.

Armitage, N., Fisher-Jeffes, L., Carden, K., Winter, K., Naidoo, V., Spiegel, A. “Mugsy,” Mauck, B., & Coulson, D. (2014). *Water Sensitive Urban Design (WSUD) for South Africa*: Framework and Guidelines. Water Research Commission. Cape Town. ISBN: 9781431205301.

Bakker, K. (2013a). “Constructing “public” water: The World Bank, urban water supply, and the biopolitics of development.” *Environment and Planning D: Society and Space*. 31(2):280–300. DOI: 10.1068/d5111.

Bakker, K. (2013b). “Neoliberal versus postneoliberal water: Geographies of privatization and resistance.” *Annals of the Association of American Geographers*. 103(2):253–260. DOI: 10.1080/00045608.2013.756246.

Balogun, O. S., Hubbard, M., and Devries, J. J. (1988). “Automatic control of canal flow using linear quadratic regulator theory.” Journal of Hydraulic Engineering, 114(1), 75–102.

Banik, B., Di Cristo, C., & Leopardi, A. (2014). SWMM5 toolkit development for pollution source identification in sewer systems. *Procedia Engineering*, 89, 750–757. doi:10.1016/ j.proeng.2014.11.503

Barco, J., Wong, K.M., & Stenstrom, M.K. (2008). “Automatic calibration of the US EPA SWMM model for a large urban catchment.” *J. Hydraul. Eng*, 10.1061/(ASCE)0733-9429(2008)134:4(466), 466–474.

Barnett, S.R., and Rix, R. (2006). *Southern Fleurieu Groundwater Assessment;* Department of Water, Land and Biodiversity Conservation: Adelaide, Australia

Barreiro-Gomez, J., Obando, G., Riano-Briceno, G., Quijano, N., and Ocampo-Martinez, C. (2015). “Decentralized control for urban drainage systems via population dynamics: Bogotá case study.” 2015 European Control Conference, ECC 2015, 2426–2431.

Barreto, W., Vojinovic, Z., Price, R., and Solomatine, D. (2010). “Multiobjective evolutionary approach to rehabilitation of urban drainage systems.” Journal of Water Resources Planning and Management, 136(5), 547–554.

Barthel, R., Jagelke, J., Götzinger, J., Gaiser, T., Printz, A. (2008). Aspects of choosing appropriate concepts for modelling groundwater resources in regional integrated water resources management— examples from the Neckar (Germany) and Ouémé catchment (Benin). Phys Chem Earth 33 (1–2):92–114

Barthel, R., Sonneveld, B. G. J. S., Götzinger, J., Keyzer, M. A., Pande, S., Printz, A., Gaiser, T. (2009). Integrated assessment of groundwater resources in the Ouémé basin, Benin, West Africa. Phys Chem Earth 34(4–5):236–250

Bartos, M., Wong, B., and Kerkez, B. (2017). “Open storm: A complete framework for sensing and control of urban watersheds.” *Environmental Science: Water Research and Technology*, Royal Society of Chemistry, 4(3), 346–358.

Beeneken, T., Erbe, V., Messmer, A., Reder, C., Rohlfing, R., Scheer, M., Schuetze, M., Schumacher, B., Weilandt, M., Weyand, M., & Group, G. D. W. A. W. (2013). Real time control (RTC) of urban drainage systems - A discussion of the additional efforts compared to conventionally operated systems. *Urban Water Journal*, 10(5), 293–299. doi:10.1080/1573062x.2013.790980. ISBN: 1573-062X. ISSN:1573-062X. Retrieved from ://WOS:000325048000002

Behle, C. (2005) Ländliche Trinkwasserversorgung in Benin unter besonderer Berücksichtigung der nationalen Versorgungsstrategie “Alimentation en eau potable et assainissement en milieu rural”. Dissertation, University of Bonn. Available at http://hss.ulb.uni-bonn.de/diss_online/ landw_fak/2006/behle_cornelia/0598.pdf. Accessed 12 January 2010

Berggren, K., Olofsson, M., Viklander, M., Svensson, G., and Gustafsson, A. M. (2012). Hydraulic impacts on urban drainage systems due to changes in rainfall caused by climatic change. *J. Hydrol. Eng.*, 17, 92–98. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000406

Bevilacqua, P., Mazzeo, D., and Arcuri, N. (2018). Thermal inertia assessment of an experimental extensive green roof in summer conditions. *Build. Environ.*, 131, 264–276.

Blignaut, J., and Heerden, J. (2009). The impact of water scarcity on economic development initiatives. *Water SA*, 35(4), 415–420. ISBN: 03784738. ISSN:18167950.

BOM. Climate Data Online. Available online: http://www.bom.gov.au/climate/data/ (accessed on 26 August 2015).

Bormann H., and Diekkrüger, B. (2004). A conceptual hydrological model for Benin (West Africa): validation, uncertainty assessment and assessment of applicability for environmental change analyses. Phys Chem Earth 29(11–12):759–768.

Bowler, N. E. H., Pierce, C. E., and Seed, A., (2006). STEPS: A probabilistic precipitation forecasting scheme which merges an extrapolation nowcast with downscaled NWP. *Quarterly Journal of the Royal Meteorological Society*, 132, 2127–2155.

Brayshaw, D. J. (2018). Weather, Climate and the Nature of Predictability. In: Troccoli A. (eds) Weather & Climate Services for the Energy Industry. Palgrave Macmillan, Cham, 85-95.

Buetow, D., (2008). Lake Monitoring Report, Mecklenburg County Water Quality Program (MCWQP), Mecklenburg County, North Carolina

Carpenter, J. F., Vallet, B., Pelletier, G., Lessard, P., and Vanrolleghem, P. A. (2014). "Pollutant removal efficiency of a retrofitted stormwater detention pond." Water Quality Research Journal of Canada, 49(2), 124–134.

Campisano, A., Cabot Ple, J., Muschalla, D., Pleau, M., and Vanrolleghem, P.A. (2013). Potential and limitations of modern equipment for real time control of urban wastewater systems. *Urban Water Journal*, 10, 300–311. doi:10.1080/1573062X.2013.763996.

Carden, K. (2013). *A measure of sustainability in the context of urban water management in South Africa*. PhD Thesis. University of Cape Town.

CCT. (2022). Annexure 6 Tariffs, fees and charges book. Retrieved from Tariffs: Electricity and Sundry Electricity (capetown.gov.za).

CCT. (2022. Annexure 6 Water and sanitation tariffs. Retrieved from capetown.gov.za

CDM Smith (2015). City of Ann Arbor stormwater model calibration and analysis project—Final report. Retrieved from https://www.a2gov. org/departments/systems-planning/planning-areas/water-resources/Documents/A2_SWM_Report_20150601.pdf

Cembrano, G., Quevedo, J., Salamero, M., Puig, V., Figueras, J., and Marti, J. (2004). Optimal control of urban drainage systems. A case study. *Control Eng. Pract.*, 12, 1–9. doi:10.1016/ S0967-0661(02)00280-0.

Cen, L., and Xi, Y. (2009). Aggregation-based model predictive control of urban combined sewer networks. *In Proceedings of the 7th Asian Control Conference*, Hong Kong, China, 1308–1313

CHI. Calibrating a SWMM5 Model Using the SRTC Tool. Available online: http://support.chiwater.com/ support/solutions/articles/29894-calibrating-a-swmm5-model-using-t (accessed on 4 October 2015).

Chiew, F.H.S., A.J. Pitman, and T.A. McMahon, (1996). Conceptual Catchment Scale Rainfall-Runoff Models and AGCM LandSurface Parameterisation Schemes. *Journal of Hydrology* 179(1-4): 137-157, doi: 10.1016/0022-1694(95)02877-3.

Chilton, P. J., Foster, S. S. D. (1993). Hydrogeological characterisation and water-supply potential of basement aquifers in tropical Africa. Hydrogeol J 3:36–49

Chisadza, B., Mushunje, A., Nhundu, K., & Phiri, E. E. (2020). Opportunities and challenges for seasonal climate forecasts to more effectively assist smallholder farming decisions. *S Afr J Sci*, 116(1/2),1-5. https://doi.org/10.17159/sajs.2020/4649

Cho, J. H., Seok Sung, K., and Ryong Ha, S. (2004). “A river water quality management model for optimising regional wastewater treatment using a genetic algorithm.” Journal of Environmental Management, 73(3), 229–242.

Chow, V., Maidment, D., and Mays, L. (1988). *Applied Hydrology*; McGraw-Hill: Singapore.

Christoph, M., Fink, A. H., Diekkrüger, B et al. (2008). IMPETUS: implementing HELP in the Upper Ouémé Basin. *Water SA* 34:481–490

Chuang, H. Y., & Sousounis, P. J. (2000). A technique for generating idealized initial and boundary conditions for the PSU-NCAR Model MM5. *Monthly Weather Review*, 128: 2875–2882.

Colas, H., Pleau, M., Lamarre, J., Pelletier, G., & Lavallee, P. (2004). Practical perspective on Real-Time Control. Water Quality Research Journal of Canada, 39(4), 466–478. ISBN: 1201- 3080.

Conserve Energy Future. (2018). *What is water shortage*. Available: https://www.conserveenergy-future.com/causes-effects-solutions-of-water-shortage.php [2018, August 30].

Cook, C., Reason, C. J. C., & Hewitson, B. C. (2004). Wet and dry spells within particularly wet and dry summers in the South African summer rainfall region. *Clim. Res*., 26: 17–31.

Coombes, P., & Barry, M. (2007). The effect of selection of time steps and average assumptions on the continuous simulation of rainwater harvesting strategies. Water Science and Technology, 55(4), 125–133.

CRCCH (Cooperative Research Centre for Catchment Hydrology), 2005. Model of Urban Stormwater Improvement Conceptualization (MUSIC), Ver. 3 User Manual. Monash University, Victoria, Australia.

Darsono, S., and Labadie, J. W. (2007). Neural-optimal control algorithm for real-time regulation of in-line storage in combined sewer systems. *Environ. Model. Softw*., 22, 1349–1361.

DEA. (2010*). South African Country Report for the Eighteenth Session of the United Nations Commission on Sustainable Development (CSD-18)*. Retrieved April 3, 2014, from http://www.un.org/esa/dsd/dsd_aofw_ni/ni_pdfs/NationalReports/south_africa/SouthAf r icanCSD18CountryReport.pdf.

DeChant, C. M., & Moradkhani, H. (2014). Toward a Reliable Prediction of Seasonal Forecast Uncertainty: Addressing Model and Initial Condition Uncertainty with Ensemble Data Assimilation and Sequential Bayesian Combination. *Journal of Hydrology*, doi: http://dx.doi.org/10.101/j.jhydrol.2014.05.045.

DECNSW. (2006). *Managing Urban Stormwater: Harvesting and Reuse*. Department of Environment and Conservation NSW. Sydney South, Australia. ISBN: 1741378753. Retrieved May 22, 2012 from www.environment.nsw.gov.au.

Degrave, R., Schoorens, J., and Litrico, X. (2013). “Real-time control of a small urban stormwater network.” *2013 10th IEEE International Conference on Networking, Sensing and Control (ICNSC)*, 526–531.

Dietz, M. E., and Clausen, J. C. (2008). “Stormwater runoff and export changes with development in a traditional and low impact subdivision.” *Journal of Environmental Management*, 87(4), 560–566.

Dirckx, G., Schütze, M., Kroll, S., Thoeye, C., De Gueldre, G., and Van De Steene, B. RTC versus static solutions to mitigate CSO’s impact. In Proceedings of the 12nd International Conference on Urban Drainage, Porto Alegre, Brazil, 10–15 September 2011.

Doblas-Reyes, F. J., García-Serrano, J., Lienert, F., Biescas, A. P., & Rodrigues, L. R. L. (2013). Seasonal climate predictability and forecasting: status and prospects. 4, 245-268. doi: 10.1002/wcc.217.

Dong, X., Huang, S., and Zeng, S. (2017). Design and evaluation of control strategies in urban drainage systems in Kunming city. *Front. Environ. Sci. Eng.*, 11(4), 13. doi:10.1007/s11783-017- 0968-9.

Dorato, P., Abdallah, C. T., Cerone, V., and Jacobson, D. H. (1995). *Linear-quadratic control: An introduction*. Englewood Cliffs, NJ: Prentice Hall

Duchesne, S., Mailhot, A., Dequidt, E., and Villeneuve, J.P. (2001). Mathematical modeling of sewers under surcharge for real time control of combined sewer overflows. *Urban Water*, 3, 241–252. doi:10.1016/S1462-0758(01)00037-1.

Duchesne, S., Mailhot, A., and Villeneuve, J.-P. (2003). Predictive real time control of surcharged interceptors: Impact of several control parameters. *J. Am. Water Resour. Assoc.*, 39, 125–135. doi:10.1111/j.1752-1688.2003.tb01566.x

DWA. (2013). *National Water Resource Strategy 2: Water for an equitable and sustainable future. June 2013*. Department of Water Affairs. Pretoria, South Africa.

El Fahem, T. (2008). Hydrogeological conceptualisation of a tropical river catchment in a crystalline basement area and transfer into a numerical groundwater flow model. Case study for the upper Ouémé catchment in Benin. Dissertation, University of Bonn. Available at http://hss. ulb.uni-bonn.de/diss_online/math_nat_fak/2008/el-fahem_tobias/1509.pdf. Accessed 12 January 2010

Emerson, C. H., Welty, C., & Traver, R. G. (2005). Watershed-scale evaluation of a system of storm water detention basins. *Journal of Hydrologic Engineering*, 10(3), 237–242. https://doi.org/10.1061/(ASCE)1084-0699(2005)10:3(237)

ESRI. (2016a). How Watershed works. ArcGIS. Retrieved October 15, 2022, from http://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/how-watershed-works.htm

Erbe, V., Schütze, M., and Haas, U. (2007). Application of A Guideline Document for Sewer System Real Time Control. *Novatech*, Lyon, France.

Faß, T. (2004). Hydrogeologie im Aguima Einzugsgebiet in Benin/Westafrika. Dissertation, University of Bonn. Available at http://hss.ulb.uni-bonn.de/diss_online/math_nat_fak/2004/fass_thorsten/ 0384.pdf. Accessed 12 January 2010

Falkenmark M., Rockström, J. (2004). Balancing water for humans and nature: the new approach in ecohydrology. Earthscan, London, Sterling

Fewkes, A., & Butler, D. (2000). Simulating the performance of rainwater collection and reuse systems using behavioural model. Building Services Engineering Research and Technology, 2(21), 99–106.

Fiorelli, D., and Schutz, G. (2009). Real-time control of a sewer network using a multi-goal objective function. *In 17th Mediterranean Conference on Control and Automation*, Makedonia Palace, Thessaloniki, Greece, 676–681.

Fisher-Jeffes, L. (2015). The viability of rainwater and stormwater harvesting in the residential areas of the Liesbeek River Catchment, Cape Town. University of Cape Town.

Fisher-Jeffes, L., Carden, K., Armitage, N., Spiegel, A., Winter, K., & Ashley, R. (2012). Challenges Facing Implementation of Water Sensitive Urban Design in South Africa. In *7th Conference on Water Sensitive Urban Design* (pp. 1–8). Engineers Australia. Melbourne, Australia, Australia. Retrieved from http://search.informit.com.au/ documentSummary;dn=829249994614282;res=IELENG.

Fitzgerald, S., Stanford, B., and Khan, S. (2014). Lessons from a decade of extreme weather events for Australian drinking water suppliers. *Water: Journal of the Australian Water Association*. 42(2):144.

Francis, B. A., & Wonham, W. M. (1976). The internal model principle of control theory. *Automatica*, 12(5), 457–465

Fuchs, L., Günther, H., & Lindenberg, M. (2004). Minimizing the Water Pollution Load by means of Real-Time Control – The Dresden Example. *Proceedings of the 6th International Conference on Urban Drainage Modelling*, (September 2004).

Gaborit, E´., Anctil, F., Fortin, V., and Pelletier, G., In press. On the reliability of spatially disaggregated global ensemble rainfall forecasts. *Hydrological Processes*. Doi: 10.1002/ hyp.9509. Available from http://onlinelibrary.wiley.com/ doi/10.1002/hyp.9509/full [Accessed 27 September 2012].

Gaborit, E., Muschalla, D., Vallet, B., Vanrolleghem, P. A., and Anctil, F. (2013). “Improving the performance of stormwater detention basins by real-time control using rainfall forecasts.” *Urban Water Journal*, 10(4), 230–246.

Gaborit, E., Anctil, F., Pelletier, G., and Vanrolleghem, P. A. (2016). “Exploring forecastbased management strategies for stormwater detention ponds.” Urban Water Journal, 13(8), 841–851.

Gagrani, V., Diemer, J. A., Karl, J. J., and Allan. C. J. (2013). Assessing the Hydrologic and Water Quality Benefits of a Network of Stormwater Control Measures in a SE U.S. Piedmont Watershed. *Journal of the American Water Resources Association (JAWRA)* 50(1): 128-142. DOI: 10.1111/jawr.12121

Garofalo, G., Giordano, A., Piro, P., Spezzano, G., and Vinci, A. (2017). A distributed real-time approach for mitigating CSO and flooding in urban drainage systems. *J. Netw. Comput. Appl.,* 2017, 78, 30–42.

García, L., Barreiro-Gomez, J., Escobar, E., Téllez, D., Quijano, N., and OcampoMartinez, C. (2015). "Modeling and real-time control of urban drainage systems: A review." *Advances in Water Resources,* 85, 120–132.

Gelormino, M.S., and Ricker, N. L. (1994). Model-predictive control of a combined sewer system. *Int. J. Control*, 59, 793–816. https://doi.org/10.1080/00207179408923105

Giertz, S., Diekkrüger, B., Jaeger, A., et al. (2006) An interdisciplinary scenario analysis to assess the water availability and water consumption in the Upper Ouémé catchment in Benin. ADGEO 9:3–13.

Giertz, S., Hiepe, C., Höllermann, B., and Diekkrüger, B. (2010a) Impacts of global change on water resources and soil degradation in Benin. In: Speth P, Christoph M, Diekkrüger B (eds) Impacts of global change on the hydrological cycle in West and Northwest Africa. Springer, Berlin (accepted for publication).

Giertz, S., Hiepe, C., Steup, G., Sintondji, L., and Diekkrüger, B. (2010b) Hydrological processes and soil degradation in Benin. In: Speth P, Christoph M, Diekkrüger B (eds) Impacts of global change on the hydrological cycle in West and Northwest Africa. Springer, Berlin (accepted for publication)

Gill, M. A. (1978). Flood routing by the Muskingum method. *Journal of Hydrology*, 36(3–4), 353–363. https://doi.org/10.1016/0022- 1694(78)90153-1

Giraldo, J.M., Leirens, S., Diaz-Granados, M.A., and Rodriguez, J.P. (2010). non-linear optimization for improving the operation of sewer systems: the Bogota Case Study. *In International Congress on Environmental Modelling and Software*, Ottawa, Canada, 1–8.

Gironás, J., Roesner, L. A., Davis, J., Rossman, L. A., & Supply, W. (2009). Storm water management model applications manual. National Risk Management Research Laboratory, Office of Research and Development, US Environmental Protection Agency Cincinnati, OH.

Gironás, J., Roesner, L. A., Rossman, L. A., & Davis, J. (2010). A new applications manual for the storm water management model (SWMM). *Environmental Modelling and Software*, 25(6), 813–814.

Golding, B. (1998). Nimrod: a system for generating automated very short range forecasts. *Meteorological Applications*, 5: 1–16

Goldsmith, R., D.J. Milton, and J.W. Horton, Jr., 1988. Geologic Map of the Charlotte 1°x2° Quadrangle, North Carolina and South Carolina: United States Geological Survey, Miscellaneous Investigations Series, Map I-1252-E.

Goodman, J. A., and Quigley, M. (2015). “Active hydromodification control.” *ASCE International Low Impact Development Conference 2015*, 1–10.

Grigg, N. S. (2012). *Water, wastewater, and stormwater infrastructure management*. Boca Raton, FL: CRC Press

Grondin, F., Grondin, M., Pleau, M., Colas, H., Lavallée, P. (2003). Csoft - a new software for the design and real-time operation of sewer networks. In CD-ROM Proceedings of the WEAO, 32nd Annual Symposium, Toronto

Gruber, I. (2008) The impact of socio-economic development and climate change on livestock management in Benin. Dissertation, University of Bonn. Available at http://hss.ulb.uni-bonn.de/diss_ online/landw_fak/2008/gruber_ina/1388.pdf. Accessed 12 January 2010

Gruber I, Kloos JR, Schopp M (2009) Seasonal water demand in Benin’s agriculture. J Environ Manag 90:196–205

Grum, M., Thornberg, D., Christensen, M. L., Shididi, S. A., and Thirsing, C. (2011). Full-Scale Real Time Control Demonstration Project in Copenhagen’s Largest Urban Drainage Catchments. *12th International Conference on Urban Drainage*, Porto Alegre/Brazil, 11-16 September 2011

Guo, J. C. Y. (2002). Overflow risk analysis for stormwater quality control basins. *Journal of Hydrologic Engineering*, 7 (6), 428– 434, doi:10.1061/(ASCE)1084-0699(2002)7:6(428).

GWP (2007) Global Water Partnership West Africa. Available at http://www.gwpforum.org/gwp/ library/Regprof_2008_West_Africa.pdf. Accessed 12 January 2010

Hashimoto, T., Stedinger, J., & Loucks, D. (1982). Reliability, resilience and vulnerability criteria performance evaluation. Water Research Resources, 18(1), 14–20.

He, S., Raghavan, S, V., Nguyen, N, S., & Liong, S. Y. (2013). “Ensemble rainfall forecasting with numerical weather prediction and radar-based nowcasting models.” *Hydrological Processes*,27, 1560 – 1571. DOI: 10.1002/hyp.9254

Heusch, S., and Ostrowski, M. (2011). Model Predictive Control with SWMM. *Journal of Water Management Modelling*, 19, 237 – 247. https://doi.org/10.14796/JWMM.R241-14

Höllermann, B., Giertz, S., and Diekkrüger, B. (2010). Benin 2025—Balancing Future Water Availability and Demand Using the WEAP ‘Water Evaluation and Planning’ System. *Water Resource Manage*, 24:3591–3613. DOI 10.1007/s11269-010-9622-z

HomeFinance. (2016). Historic inflation South Africa - CPI inflation. *Worldwide inflation data*. Retrieved July 25, 2016, from http://www.inflation.eu/inflation-rates/south-africa/historicinflation/cpi-inflation-south-africa.aspx

Hooke, R. and Jeeves, T.A. (1961). Direct Search Solution of Numerical and Statistical Problems. *Journal of the ACM*, Vol. 8, Issue 2.

HRWC (2013). Malletts creekshed report. Retrieved from https://www.hrwc.org/wp-content/uploads/Malletts_8x11.5.pdf

Hudson, D., Alves, O., Hendon, H. H., & Marshall, A. G. (2011). Bridging the gap between weather and seasonal forecasting: intraseasonal forecasting for Australia. *Q. J. R. Meteorol. Soc.*, 137: 673–689.

Iseh, A. J., & Woma, T. Y. (2013). Weather Forecasting Models, Methods and Applications. *International Journal of Engineering Research & Technology (IJERT)*. 2, 1945-1956.

Investing. (2016). South Africa 10-year bond yeild. *Investing*. Retrieved July 25, 2016, from http://za.investing.com/rates-bonds/south-africa-10-year-bond-yield-historical-data

Jackson, C. R., and Booth, D. B. (1997). “Urbanization of aquatic systems: degradation thresholds, stormwater detection, and the limits of mitigation.” *Journal of the American Water Resources Association*, 33(5), 1077–1090.

Jacopin, C., Lucas, E., Desbordes, M., and Bourgogne, P. (2001). “Optimisation of operational management practices for the detention basins.” *Water Science and Technology*, 44(2–3), 277–285.

Jafari, F., Mousavi, J., Yadzi, J., and Kim, J. H. (2019).” Investigating the Role of Gate Operation in Real-Time Flood Control of Urban Drainage Systems.” *Harmony Search and Nature Inspired Optimization Algorithms*, 1-10, https://doi.org/10.1007/978-981-13-0761-4_4

James, W. (2005). Rules for Responsible Modeling. ISBN: 0-9683681-5-8.

James, W., Rossman, L. E., and James, R. C. (2010). User guide to SWMM5 (13th Editi.). CHI, Guelph, Ontario, Canada. ISBN: 9780980885330.

Johnston P. A., Archer E. R. M., Vogel C. H., Bezuidenhout, C. N., Tennant W. J. & Kuschke, R. (2004). Review of seasonal forecasting in South Africa: producer to end user. *Clim Res*, 28, 67– 82.

Joksimovic, D., and Sander, M. (2016). “Performance modelling of actively controlled green infrastructure options in a mixed use neighborhood retrofit.” *World Environmental and Water Resources Congress*, 96–105.

Kändler, N., Annus, I., Vassiljev, A., and Puust, R. (2020) Real time controlled sustainable urban drainage systems in dense urban areas. *J. Water Supply Res. Technol.*, 69, 238–247.

Kerber, D. (2009). Entwicklung eines multi-kriteriellen, hybriden Optimierungsalgorithmus für den Einsatz in der Kanalnetzsteuerung. Diploma thesis, Technische Universität Darmstadt.

Kerkez, B., Gruden, C., Lewis, M., Montestruque, L., Quigley, M., Wong, B., Bedig, A., Kertesz, R., Braun, T., Cadwalader, O., Poresky, A., and Pak, C. (2016). “Smarter stormwater systems.” *Environmental Science and Technology*, 50(14), 7267–7273.

Kessler, R. (2011). Stormwater strategies: Cities prepare aging infrastructure for climate change. *Environmental Health Perspectives*, 119(12), A514–A519. https://doi.org/10.1289/ehp.119-a514

Kgakatsi, I. B., & Rautenbach, C. J. deW. (2014). The contribution of seasonal climate forecasts to the management of agricultural disaster-risk in South Africa. *International Journal of Disaster Risk Reduction*, 8, 100-113. https://doi.org/10.1016/j.ijdrr.2014.01.002

Kim, Y., Ratnam, J.V., Doi, T., Morioka, Y., Behera, S., Tsuzuki, A., Minakawa, N., Sweijd, N., Kruger, P., Maharaj, R., Imai, C. C., Sheng Ng, C. F., Chung, Y., & Hashizume, M. (2019). Malaria predictions based on seasonal climate forecasts in South Africa: A time series distributed lag nonlinear model. *Sci Rep*, 9(17882), 1-10. https://doi.org/10.1038/s41598-019-53838-3

Klopper, E., Vogel, C. H. & Landman, W. A. (2006). Seasonal Climate Forecasts - Potential Agricultural-Risk Management Tools? *Climatic Change*, 76(1), 73-90. DOI: 10.1007/s10584- 005-9019-9

Knight R.L., et al., (2003). Strategies for effective mosquito control in constructed treatment wetlands. *Ecological Engineering*, 21, 211–232.

Kok, P., & Collinson, M. (2006). *Migration and Urbanisation in South Africa - Report no. 03-04-02*. Statistics South Africa. Pretoria, South Africa. ISBN: 0621365092. Retrieved May 14, 2014 from http://beta2.statssa.gov.za/publications/Report-03-04-02/Report-03-04- 02.pdf.

Krishnamurthy, V. (2019). Predictability of weather and climate. *Earth and Space Science*, 6, 1043-1056. https://doi.org/10.1029/2019EA000586

Lampe, L., Andrews, H., Barrett, M. E., Woods-Ballard, B., Kellagher, R., Martin, P., Jefferies, C., & Hollon, M. (2005). *Performance and Whole Life Costs of Best Management Practices and Sustainable Urban Drainage Systems*. Water Environment Research Foundation / IWA Publishing. Alexandria, United States of America / London, United Kingdom. ISBN: 1843397439.

Landman, W. A., & Tennant, W. J. (2000). Statistical downscaling of monthly forecasts. *Int. J. Climatol.*, 20: 1521–1532.

Landman, W.A., Mason, S.J., Tyson, P., and Tennant W.J., 2001. Retroactive skill of multi-tiered forecasts of summer rainfall over southern Africa. Int J Climatol, 21(1), 1-19, https://doi.org/10.1002/joc.592

Landman, W. A. (2014). How the International Research Institute for Climate and Society has contributed towards seasonal climate forecast modelling and operations in South Africa. *Earth Perspectives*, 1(22), 1-13. http://www.earth-perspectives.com/1/1/22

Lawson, R., Riggs, E., Weiker, D. & Doubek, J. (2017). Total suspended solids reduction—Implementation plan for Malletts Creek: October 2011–September 2016. Retrieved from http://www.hrwc.org/wp-content/uploads/2011/11/MallettsCreek_BiotaTMDL_FINAL.pdf

Lee, J. H., & Bang, K. W. (2000). Characterization of urban stormwater runoff. Water Research, 34(6), 1773–1780. https://doi.org/10.1016/ S0043-1354(99)00325-5

Lee, A. (2008). Methodologies to Maintain Pre-Urbanization Low Flow Characteristics in an Urbanized Cathment Using Water Sensitive Urban Design Measures; The University of South Australia: Adelaide, Australia

Lee, J. G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J. X., Shoemaker, L., & Lai, F. (2012). A watershed-scale design optimization model for stormwater best management practices. *Environmental Modelling & Software*, 37, 6–18. https://doi.org/10.1016/j.envsoft.2012.04.011

Lefkowitz, J. R., Sarmanian, A. K., and Quigley, M. (2016). "Continuous monitoring and adaptive control—the internet of things transforms stormwater management." *Journal of the New England Water Environment Association*, 50(1), 44–51.

Leirens, S., Giraldo, J.M., Negenborn, R.R., and De Schutter, B. (2010). A pattern search method for improving the operation of sewer systems. *In Proceedings of the 12th IFAC Symposium on Large Scale Systems: Theory and Applications*, Villeneuve d'Ascq, France: IFAC, 591–596.

Lemos, J. M., and Pinto, L. F. (2012). "Distributed linear-quadratic control of serially chained systems: Application to a water delivery canal." IEEE Control Systems, 32(6), 26–38.

Lévite, H., Sally, H., and Cour, J. (2003). Water demand management scenarios in a water-stressed basin in South Africa: application of the WEAP model. Phys Chem Earth 28:779–786

Leutnant, D., Döring, A., & Uhl, M. (2019). Swmmr - an R package to interface SWMM. Urban Water Journal, 16(1), 68–76. doi:10.1080/1573062X.2019.1611889

Li, J., Burian, S., & Oroza, C. (2019). Exploring the potential for simulating systemlevel controlled smart stormwater system. *In World Environmental and Water Resources Congress 2019: Water, Wastewater, and Stormwater; Urban Water Resources; and Municipal Water Infrastructure* (pp. 46–56). American Society of Civil Engineers Reston, VA. doi:10.1061/9780784482360.006

Li, N., Li, Y, & Yoa, N. (2018). Bias correction of the observed daily precipitation andre-division of climatic zones in China. *Int J Climatol*, 38, 3369-3387. https://doi.org/10.1002/joc.5506

Lin, C., Vasic, S., Kilambi, A., Turner, B., & Zawadzki, I. (2005). Precipitation forecast skill of numerical weather prediction models and radar nowcasts. *Geophysical Research Letters* 32(L14801): 1–4.

Lindsay, J. & Supski, S. (2017). Changing household water consumption practices after drought in three Australian cities. *Geoforum*. 84(June):51–58. DOI: 10.1016/j.geoforum.2017.06.001.

Liong, S. Y., Chan, W. T., & Lum, L. H. (1991b). “Knowledge-based system for SWMM runoff component calibration.” *J. Water Resour. Plann. Manage*, 10.1061/(ASCE)0733-9496(1991)117:5(507), 507–524.

Litrico, X., & Fromion, V. (2009). *Modeling and control of hydrosystems*. Dordrecht, Heidelberg: Springer Science & Business Media. https://doi. org/10.1007/978-1-84882-624-3

Lowe, R., Vezzaro, L., Mikkelsen, P.S., Grum, M., and Madsen, H. (2016). Probabilistic runoff volume forecasting in risk-based optimization for RTC of urban drainage systems. *Environ. Model. Softw.*, 80, 143–158. doi:10.1016/j.envsoft.2016.02.027.

Lund, N. S. V., Falk, A. K. V., Borup, M., Madsen, H., and Steen Mikkelsen, P. (2018). “Model predictive control of urban drainage systems: A review and perspective towards smart real-time water management.” *Critical Reviews in Environmental Science and Technology*, Taylor & Francis, 48(3), 279–339.

Luo, L., & Wood, E. F. (2006). Assessing the idealized predictability of precipitation and temperature in the NCEP Climate Forecast System. *Geophys. Res. Lett.*, 33: L04708. https://doi.org/10.1029/2005GL025292.

Mackenzie, L.D. (2010). Water and wastewater engineering. Retrieved from http://www.wrc. org.za/Knowledge Hub Documents/Research Reports/TT 278-06

Macleod, A., (2008). MUSIC Calibration Based on Soil Conditions. In: Proceedings of Stormwater 2008, Stormwater Industry Assocation Regional Conference, Gold Coast, 2008

Maiolo, M., Palermo, S. A., Brusco, A. C., Pirouz, B., Turco, M., Vinci, A., Spezzano, G., and Piro, P. (2020). On the Use of a Real-Time Control Approach for Urban Stormwater Management. *Water*, 12, 2842, doi:10.3390/w12102842

Marcoon, K. B. and Guo, Q. (2004). Detention basin retrofit: optimization of water quality improvement and flood control. In: G. Sehlke, D.F. Hayes and D.K. *Stevens, eds. Critical Transitions in Water and Environmental Resources Management Proceedings of World Water and Environmental Resources Congress*. 27 June–1 July 2004. Salt Lake City, Utah, USA, 1–10. doi:http://dx.doi.org/10.1061/40737(2004)43

Macro, K., Matott, L. S., Rabideau, A., Ghodsi, S. H., & Zhu, Z. (2019). OSTRICH-SWMM: A New Multi-Objective Optimization Tool for Green Infrastructure Planning with SWMM. *Environmental Modelling & Software*, 113, 42–47. doi:10.1016/j.envsoft.2018.12.004

Maciejowksi, J.M. (2002). Predictive control with constraints. Essex, England: Pearson.

Malaterre, P. O., and Baume, J. P. (1998). Modeling and regulation of irrigation canals: Existing applications and ongoing researches. Paper presented at the Systems, Man, and Cybernetics, 1998.1998 {IEEE} International Conference On, 4 3850–3855 o.4.

Mandal, V., Utpal, K.D., & Biplab, K. B. (2007). Precipitation forecast verification of the Indian summer monsoon with intercomparison of three diverse regions. *Weather Forecast*, 22: 428–443.

Marinaki, M., and Papageorgiou, M. (1998). non-linear optimal flow control for sewer networks. *In Proceedings of the American Control Conference*, Philadelphia, Pennsylvania, 1289–1293.

Marinaki, M., and Papageorgiou, M. (1999). A non-linear optimal control approach to central sewer network flow control. *Int. J. Control* ,72, 418–429. doi:10.1080/002071799221055.

Marinaki, M., and Papageorgiou, M. (2001). Rolling-horizon optimal control of sewer networks. *In Proceedings of the 2001 IEEE International Conference on Control Applications*, Mexico City, Mexico, 594–599.

Marinaki, M., and Papageorgiou, M. (2003). "Linear-quadratic regulators applied to sewer network flow Control." *European Control Conference (ECC)*, 2407–2412.

Mason, S. J. (2008). Understanding forecast verification statistics. *Meteorol. Appl.*, 15: 31–40.

Marsalek, J. (2005). *Evolution of urban drainage: from cloaca maxima to environmental sustainability*, Paper presented at Acqua e Citta', I Convegno Nazionale di Idraulica Urbana, Cent. Stud. Idraul. Urbana, Sant'Agnello di Sorrento, Italy, 28 – 30 September 2005.

Marsden Jacobs Associates. (2006). Securing Australia's Urban Water Supplies: Opportunities and Impediments - Prepared for the Department of the Prime Minister and Cabinet. In: Philp, M., Mcmahon, J., Heyenga, S., Marinoni, O., Jenkins, G., Maheepala, S., & Greenway, M. (2008). Review of Stormwater Harvesting Practices Urban Water Security Research Alliance Technical Report No . 9. Camberwell, Victoria, Australia.

Martínez-Solano, F., Iglesias-Rey, P., Saldarriaga, J., & Vallejo, D. (2016). Creation of an SWMM toolkit for its application in urban drainage networks optimization. *Water*, 8(6), 259. doi:10.3390/w8060259

McCarthy. (1994). "Stormwater control system." US Patent 5342144.

McDonnell, B. E., Westover, J., Peña-Castellanos, G., Roberts, S., Mullapudi, A., Ratliff, K., and Kertesz, R. (2016). "PySWMM: Python wrapper for Stormwater Management Model (SWMM5)."

McDonnell, B. E., Ratliff, K., Tryby, M. E., Wu, J. J. X., and Mullapudi, A. (2020). " PySWMM: The Python Interface to Stormwater Management Model (SWMM)." *The Journal of Open Source Software*, 5(52), 2922. DOI: 10.21105/joss.02292

McGrane, S. J. (2016). “Impacts of urbanisation on hydrological and water quality dynamics, and urban water management: a review.” *Hydrological Sciences Journal,* Taylor & Francis, 61(13), 2295–2311.

McMahon, T.A., Adeloye, A.J. (2005). Water Resources Yield. Water Resources Publications, Denver.

McMahon, T. A., Adeloye, A. J., & Zhou, S.-L. (2006). Understanding performance measures of reservoirs. Journal of Hydrology, 324(1-4), 359–382. ISBN: 0022-1694. ISSN:00221694.

Meseguer, J., and Quevedo, J. (2017). Real-time monitoring and control in water systems. In V. Puig, C. Ocampo-Martinez, R. Perez, G. Cembrano, J. Quevedo, and T. Escobet (Eds.), *Realtime monitoring and operational control of drinking-water systems* (Chapter 1, pp. 1–19). Cham, Switzerland: Springer

MGCE. (20111a). Tehran Stormwater Management Master Plan, Vol. 4: Existing Main Drainage Network, Part 2: Hydraulic Modeling and Capacity Assessment, December 2011, MG Consultant Engineers, Technical and development deputy of Tehran municipality, Tehran, Iran.

Middleton, J. R., and Barrett, M. E. (2008). “Water quality performance of a batch-type stormwater detention basin.” *Water Environment Research,* 80(2), 172–178.

Millington, N. (2018). Producing water scarcity in São Paulo, Brazil: The 2014-2015 water crisis and the binding politics of infrastructure. *Political Geography*. 65(April):26–34. DOI: 10.1016/j.polgeo.2018.04.007.

Mitchell, V. G., Deletic, A., Fletcher, T. D., Hatt, B. E., & McCarthy, D. T. (2007). Achieving multiples benefits from stormwater harvesting. Water Science and Technology, 55(4), 135– 144.

Mitchell, V.G., McCarthy, D. T., Deletic, A., & Fletcher, T. (2008). Urban stormwater harvesting - sensitivity of a storage behaviour model. *Environmental Modelling and Software,* 23(6), 782–793. doi:10.1016/j.envsoft.2007.09.006. ISBN: 1364-8152. ISSN:13648152.

Montestruque, L., and Lemmon, M. D. (2015). “Globally coordinated distributed storm water management system.” *Proceedings of the 1st ACM International Workshop on Cyber-Physical Systems for Smart Water Networks.*

Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in WatershedMoriasi, D.N., Arnold, J.G., Liew, M.W. Van, Bingner, R.L., Harmel, R.D. & Veith, T.L. 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watersh. American Society of Agricultural and Biological Engineers, St. Joseph, Michigan, 50(3), 885–900. doi:10.13031/2013.23153)

Muleta, M. K., and Boulos, P. F. (2007). “Multiobjective optimization for optimal design of urban drainage systems.” World Environmental and Water Resources Congress, 1– 10.

Mullapudi, A., Wong, B. P., and Kerkez, B. (2017). Emerging investigators series: Building a theory for smart stormwater systems. *Environmental Science: Water Research & Technology*, 3(1), 66–77

Mullapudi, A., Bartos, M., Wong, B., and Kerkez, B. (2018). "Shaping streamflow using a real-time stormwater control network." Sensors, 18(7), 2259.

Muschalla, D. (2006). Evolutionäre multikriterielle Optimierung komplexer wasserwirtschaftlicher Systeme. PhD thesis, Technische Universität Darmstadt.

Muschalla, D. (2008). "Optimization of integrated urban wastewater systems using multiobjective evolution strategies." Urban Water Journal, 5(1), 59–67.

Muschalla, D., Fröhlich, F., Heusch, S., Hübner, C., Kerber, D., Reußner, F., and Ostrowski, M. (2009). BlueM.Opt - a generic framework for simulation based optimization, 18th Conference on Stormwater and Urban Water Systems Modeling, Toronto, 19.2 - 20.2.

Muschalla, D., Vallet, B., Anctil, F., Lessard, P., Pelletier, G., & Vanrolleghem, P. A. (2014). Ecohydraulic-driven real-time control of stormwater basins. *Journal of Hydrology*, 511, 82–91. doi:10.1016/j.jhydrol.2014.01.002. ISBN: 0022-1694. ISSN:00221694.

Nashville and Davidson County. (2009). "Stormwater wet ponds." *Nashville Stormwater Management Manual*, PTP-01 1-25.

National Treasury. (2004). National Treasury PPP Manual Module 4 : PPP Feasibility Study National Treasury PPP Practice Note.

NCDENR, (2003). Basinwide Assessment Report, Catawba River Basin. North Carolina Department of Environment and Natural Resources (NCDENR), Raleigh, North Carolina

Nganro, S., Trisutumo, S., Barkey, R. A., and Ali, M. (2020). Rainfall Analysis of the Makassar City using Thiessen Polygon Method Based on GIS. *Journal of Engineering and Applied Sciences*, 15 (6): 1426-1430. ISSN: 1816-949X

Niazi, M., Nietch, C., Maghrebi, M., Jackson, N., Bennett, B. R., Tryby, M., & Massoudieh, A. (2017). Storm Water Management Model: Performance Review and Gap Analysis. *Journal of Sustainable Water in the Built Environment*, 3(2), 04017002. doi:10.1061/JSWBAY.0000817

Nielsen, N. H., Ravn, C., and Mølbye, N. (2010). "Implementation and design of a RTC strategy in the sewage system in Kolding , Denmark." *NOVATECH*, 1–10.

NRMMC, EPHC, & NHMRC. (2009a). *Australian Guidelines for Water Recycling Stormwater Harvesting and Reuse*. (Biotext, Ed.). Natural Resource Management Ministerial Counci, Environment Protection and Heritage Council, and the Australian Health Ministers' Conference. Canberra, Australia. ISBN: 1921173459.

Ocampo-Martinez, C., Ingimundarson, A., Puig, V., and Quevedo, J. (2008). Objective prioritization using lexicographic minimizers for MPC of sewer networks. *IEEE Trans. Control Syst. Technol.*, 16, 113–121. doi:10.1109/TCST.2007.899741.

Ocampo-Martinez, C., and Puig, V. (2009a). Modelling Approaches for Predictive Control of Large-Scale Sewage Systems. Barcelona, Spain.

Ocampo-Martinez, C., and Puig, V. (2010). Piece-wise linear functions-based model predictive control of large-scale sewage systems. *IET Control Theory Appl.*, 4, 1581–1593. doi:10.1049/ iet-cta.2009.0206.

Ocampo-Martinez, C., Puig, V., Cembrano, G., and Quevedo, J. (2013). “Application of predictive control strategies to the management of complex networks in the urban water cycle.” *IEEE Control Systems,* 33(1), 15–41.

O’Connor, G. A., Elliott, H. A., & Bastian, R. K. (2007). Degraded water reuse: an overview. *Journal of Environmental Quality*, 37(5 Suppl), S157–S168. doi:10.2134/jeq2007.0459. ISSN:0047-2425. Retrieved August 2, 2011 from http://www.ncbi.nlm.nih.gov/ pubmed/18765762.

ODOT (Oregon Department of Transportation). (2014). “Chapter 14 Appendix E: Stormwater Treatment Facility Components.” *Hydraulics Design Manual*, 4–8.

Okedi, J. (2019). *The prospects for stormwater harvesting in Cape Town, South Africa using the Zeekoe Catchment as a case study*. Ph.D Thesis. University of Cape Town.

O’Malley, P.G. (2007), Stormwater Harvesting: A Project Survey, *Water Efficiency*, March/April 2007.

Opti RTC, and Geosyntec Consultants Inc. (2017). Water Quality Summary Report.

van Overloop, P.-J., Weijs, S., and Dijkstra, S. (2008). Multiple model predictive control on a drainage canal system. *Control Eng. Pract.*, 16, 531–540. doi:10.1016/j. conengprac.2007.06.002.

Palhegyi, G. E. (2010). “Designing storm-water controls to promote sustainable ecosystems: Science and application.” *Journal of Hydrologic Engineering*, 15(6), 504–511.

Palla, A., Gnecco, I., & Lanza, L. G. (2011). Non-dimensional design parameters and performance assessment of rainwater harvesting systems. Journal of Hydrology, 401(1-2), 65–76. doi:10.1016/j.jhydrol.2011.02.009. ISBN: 0022-1694. ISSN:00221694. Retrieved from http://dx.doi.org/10.1016/j.jhydrol.2011.02.009

Palmer, T. N., Brankovic, C., Buizza, R., Chessa, P., Ferranti, L., Hoskins, B. J., & Simmons A. J. (2000). A review of predictability and ECMWF forecast performance, with emphasis on Europe. ECMWF Research Department Technical Memorandum n. 326, ECMWF, Shinfield Park, Reading RG2-9AX, UK

Pathirana, A. (2014). SWMM5-EA – A Tool for Learning Optimization of Urban Drainage and Sewerage Systems with Genetic Algorithms.

Papa, F., Adams, B., and Guo, Y. (1999). Detention time selection for stormwater quality control ponds. *Canadian Journal of Civil Engineering*, 26 (1), 72 – 82, doi:10.1139/l98-046.

Papageorgiou, M. (1983). Automatic control strategies for combined sewer systems. *J. Environ. Eng.*, 109, 1385–1402. doi:10.1061/(ASCE)0733-9372(1983)109:6(1385).

Papageorgiou, M. (1988). Certainty equivalent open-loop feedback control applied to multireservoir networks. *IEEE Trans. Automat. Contr.*, 33, 392–399. doi:10.1109/9.192199.

Perica, S. and Foufoula-Georgiou, E., (1996). Model for multiscale disaggregation of spatial rainfall based on coupling meteorological and scaling descriptions. *Journal of Geophysical Research,* 101 (D21), 26347–26361.

Phakula, S., Landman, W. A., & Beraki, A. F. (2018)." Forecasting seasonal rainfall characteristics and onset months over South Africa." *International Journal of Climatology*, 889 – 900. DOI: 10.1002/joc.5417

Philp, M., Mcmahon, J., Heyenga, S., Marinoni, O., Jenkins, G., Maheepala, S., & Greenway, M. (2008). Review of Stormwater Harvesting Practices Urban Water Security Research Alliance Technical Report No. 9, (9). ISSN:1836-5566.

Pierce, C.E., et al., (2004). The nowcasting of precipitation during Sydney 2000: An appraisal of the QPF algorithms. *Weather Forecasting*, 19, 7–21.

Pleau, M., Colas, H., Lebrun, A., and Methot, F. (1996). Minimizing combined sewer overflows in real-time control applications. *Water Qual. Res. J.* Canada 31, 775–786.

Pleau, M., Colas, H., Lavallee, P., Pelletier, G., and Bonin, R. (2005). Global optimal real-time control of the Quebec urban drainage system. *Environ. Model. Softw.*, 20, 401–413. doi:10.1016/j.envsoft.2004.02.009.

Pratt, E. N. (2016). Rules and guidelines—Procedures and design criteria for stormwater.

Puig, V., Cembrano, G., Romera, J., Quevedo, J., Aznar, B., Ramon, G., and Cabot, J. (2009). Predictive optimal control of sewer networks using CORAL tool: Application to Riera Blanca catchment in Barcelona. *Water Sci. Technol.*, 60, 869–878. doi:10.2166/wst.2009.424.

Qin, S.J., and Badgwell, T.A. (2003). A survey of industrial model predictive control technology. Control Eng. Pract., 11, 733–764. doi:10.1016/S0967-0661(02)00186-7

Ratliff, K. M., McDonnell, B., Tryby, M., & Mikelonis, A. (2018). Expanding the EPA Storm Water Management Model (SWMM5) API for Tracking Contamination in Urban Environments. *In AGU Fall Meeting Abstracts*.

Rauch, W., and Harremoes, P. (1998). Correlation of combined sewer overflow reduction due to real-time control and resulting effect on the oxygen concentration in the river. *Water Sci. Technol.*, 37, 69–76.

Rauch, W., and Harremoes, P. (1999). Genetic algorithms in real time control applied to minimize transient pollution from urban wastewater systems. *Water Res*., 33, 1265–1277. doi:10.1016/S0043-1354(98)00304-2.

Rauch, W., Bertrand-Krajewski, J.-L., Krebs, P., Mark, O., Schilling, W., Schütze, M., and Vanrolleghem, P.A. (2002). Deterministic modelling of integrated urban drainage systems. *Water Sci. Technol.*, 45, 81–94.

Rawls, W. J., Brakensiek, D. L., & Miller, N. (1983). Green-ampt infiltration parameters from soils data. *Journal of Hydraulic Engineering*, 109(1), 62–70. https://doi.org/10.1061/(ASCE)0733-9429(1983)109:1(62)

Riaño-Briceño, G., Barreiro-Gomez, J., Ramirez-Jaime, A., Quijano, N., and Ocampo-Martinez, C. (2016). MatSWMM – An open-source toolbox for designing real-time control of urban drainage systems. *Environmental Modelling & Software*, 83, 143–154. doi:10.1016/j. envsoft.2016.05.009

Rohrer, A. R., & Armitage, N. P. (2017). Improving the viability of stormwater harvesting through rudimentary real time control. Water (Switzerland), 9(6). doi:10.3390/w9060371. ISSN:20734441.

Roman, D., Braga, A., Shetty, N., and Culligan, P. (2017). "Design and modeling of an adaptively controlled rainwater harvesting system." *Water*, 9(12), 974.

Rossman, L.A. (2006*). Storm Water Management Model, Quality Assurance Report: Dynamic Wave Flow Routing*. US Environmental Protection Agency, Office of Research and Development, National Risk Management Research Laboratory, Cincinnati, OH, USA.

Rossman, A. L. (2010). Stormwater Management Model. Stormwater Management Model Version 5. Roy, S. B., Chen, L

Rossman, L. A. (2015). "Storm Water Management Model user's manual version 5.1." *US EPA Office of Research and Development*, 353.

RSA. (2011a). National Climate Change Response: White Paper. Government Printer. Pretoria, South Africa. Retrieved from http://www.climateresponse.co.za/.

RSA. (2011b). National Development Plan: Our Future - make it work. National Planning Commission. Pretoria, South Africa. ISBN: 9780621411805. Retrieved from http://www.gov.za/issues/national-development-plan/.

Sadler, J. M., Goodall, J. L., Behl, M., and Morsy, M. M. (2019). " Leveraging Open Source Software and Parallel Computing for Model Predictive Control Simulation of Urban Drainage Systems Using EPA-SWMM5 and Python." : UDM 2018, GREEN, pp. 988–992, 2019. https://doi.org/10.1007/978-3-319-99867-1_170

Sadler, J. M., Goodall, J. L., Behl, M., Morsy, M. M., Culver, T. B., & Bowes, B. D. (2019). Leveraging open source software and parallel computing for model predictive control of urban drainage systems using EPA-SWMM5. *Environmental Modelling & Software*, 120, 104484. doi:10.1016/j.envsoft.2019.07.009

Sangal, S. K., Ph, D., Bonema, S. R., & Arbor, A. (1994). A Methodology for Calibrating SWMM Models. In Current Practices in Modelling the Mangagement of Stormwater Impact (First., pp. 375–388). CRC Press. doi:10.14796/JWMM.Rl76-24. ISBN: 1566700523.

Santana, F.J., et al., (1994). *Control of mosquito breeding in permitted stormwater systems*. Brooksville, FL: Sarasota County Mosquito Control and Southwest Florida Water Management District.

SAWS., 2016. Annual Report 2015/16. Creating a weather smart nation "innovating, adapting and facing the future together".

Shammaa, Y., Zhu, D. Z., Gyu¨re´k, L. L., and Labatiuk, C. W. (2002). Effectiveness of dry ponds for stormwater total suspended solids removal. *Canadian Journal of Civil Engineering,* 29 (2), 316– 324, doi:10.1139/l02-008.

Shongwe, M. E., Van Oldenborgh, G. J., Van Den Hurk, B. J. J. M., De Boer, B., Coelho, C. A. S., & Van Aalst, M. K. (2009). Projected changes in mean and extreme precipitation in Africa under global warming: part I: southern Africa. *J. Clim*. 22: 3819–3837

Schilling, W., Andersson, B., Nyberg, U., Aspegren, H., Rauch, W., and Harremoës, P. (1994). Real time control of wastewater systems. *J. Hydraul. Res*., 34, 785–797

Schmit, Z. K., Hodges, C. C., and Dymond, R. L. (2020). "Simulation and assessment of long-term stormwater basin performance under real-time control retrofits." Urban Water Journal, 17(5), 467-480, https://doi.org/10.1080/1573062X.2020.1764062

Schopp, M. (2004) Wasserversorgung in Benin unter Berücksichtigung sozioökonomischer und soziodemograpischer Strukturen—Analyse der Wassernachfrage an ausgewählten Standorten des Haute Ouémé. Dissertation, University of Bonn. Available at http://hss.ulb.uni-bonn.de/ diss_online/landw_fak/2005/schopp_marion/0526.pdf. Accessed 12 January 2010

Schutze, M., Campisano, A., Colas, H., Vanrolleghem, P., and Schilling, W. (2003). Real-time control of urban water systems. *In Proceedings of the International Conference on Pumps, Electromechanical Devices and Systems Applied to Urban Water Management*, Valencia, Spain, 1–19.

Schutze, M., Campisano, A., Colas, H., Schilling, W., & Vanrolleghem, P. A. (2004). Real time control of urban wastewater systems - Where do we stand today? *Journal of Hydrology*, 299(3–4), 335–348. doi:10.1016/j.jhydrol.2004.08.010. ISBN: 0022-1694. ISSN:00221 694.

Schuurmans, J., Bosgra, O., & Brouwer, R. (1995). Open-channel flow model approximation for controller design. *Applied Mathematical Modelling*, 19(9), 525–530. https://doi.org/10.1016/0307-904X(95)00053-M

Seggelke, K., Löwe, R., Beeneken, T., and Fuchs, L. (2013). "Implementation of an integrated real-time control system of sewer system and waste water treatment plant in the city of Wilhelmshaven." *Urban Water Journal*, 10(5), 330–341.

SEI (2006) Deliverable D28: adapted model for water demand and economic aspects in the Ouémé basin. Available at http://www.rivertwin.de/assets/publications/D28_Water%20demand%20model%20Oueme%20FINAL.pdf. Accessed 12 January 2010

Shukla, S. and Jaber, F.H. (2006), Stormwater as an Alternative Source of Water Supply: Feasibility and Implications for Watershed Management, Circular 1493, Institute of Food and Agricultural Sciences, University of Florida, Gainesville.

Singhofen, P. (2001). Calibration ad verification of stormwater model. In Florida Association of Stormwater Utilities (pp. 1–18).

Slingo, J., & Palmer, T. (2011). Uncertainty in weather and climate prediction. *Phil. Trans. R. Soc*. A, 369, 4751-4767 https://doi.org/10.1098/rsta.2011.0161

Smith, K. T., & Austin, G. L. (2000). Nowcasting precipitation — a proposal for a way forward. *Journal of Hydrology*, 239: 34–45.

StatsSA. (2022). P0141 - Consumer Price Index (CPI). Retrieved November 08, 2022, from http://beta2.statssa.gov.za/?page_id=1854&PPN=P0141&SCH=5892.

Stinson, M. K., Field, R., Jacquet, G., and Villeneuve, E. (2000). "Optimized real-time control of combined sewerage systems: Two case studies." *Joint Conference on Water Resource Engineering and Water Resources Planning and Management*, 1–10.

Sun, N., Hall, M., Hong, B., and Zhang, L. (2014). Impact of swmm catchment discretization: Case study in Syracuse, New York. J. Hydrol. Eng, 19, 223–234

Swamee, P. K., & Sharma, A. K. (2008). Design of water supply pipe networks (Tenth.). John Wiley & Sons, Inc. New Jersey. ISBN: 9780470178522.

Swyngedouw, E., Kaïka, M. & Castro, E. (2002). Urban water: A political-ecology perspective. *Built Environment*. 28(2):124–137.

Tadross, M. A., Hewitson, B. C., & Usman, M. T., (2005). The international variability of the onset of the maize growing season over South Africa and Zimbabwe. *J. Clim*., 18: 3356–3372.

Tebaldi, C., & Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. *Phil. Trans. R. Soc*. A, 365, 2053-2075. doi:10.1098/rsta.2007.2076

Thorndahl, S., Rasmussen, M. R., Grum, M., Neve, S. L. (2009): Radar based flow and water level forecasting in sewer systems – a Danish case study, Proceedings of the 8th International workshop on precipitation in urban areas, 10-13 December, 2009, St. Moritz, Switzerland.

Tillinghast, E. D., Hunt, W. F., and Jennings, G. D. (2011). "Stormwater control measure (SCM) design standards to limit stream erosion for Piedmont North Carolina." *Journal of Hydrology,* Elsevier B.V., 411(3–4), 185–196.

Tolson, B.A. and Shoemaker, C.A. (2007). Dynamically dimensioned search algorithm for computationally efficient watershed model calibration. Water Resources Research, Vol. 43.

Toz, G., & Erdogan, M. (2008). Dem (Digital Elevation Model) Production and Accuracy Modelling of Dem from 1:35.000 Scalable Aerial Photographs. The International

Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B1. Beijing.

Trading Economics. (2022). South Africa Government Bond 10. Retrieved November 08, 2022, from http://www.tradingeconomics.com/.

Tsihrintzis, V. A., & Hamid, R. (1998). “Runoff quality prediction from small urban catchments using SWMM.” *Hydrol. Process*, 12(2), 311–329.

Turton, A. R. (2008). Three strategic water quality challenges that decision-makers need to know about and how the CSIR should respond. South Africa.

UNEP. (2010). AFRICA - Water Atlas. Division of Early Warning and Assessment (DEWA), United Nations Environment Programme (UNEP). Nairobi, Kenya. ISBN: 9789280731101.

UNDP, UNEP, World Bank, & World Resources Institute. (2000). A Guide to World Resources 2000 –2001.

Untch, A., Miller, M., Hortal, M., Buizza, R., & Janssen, P. (2006). Towards a global meso-scale model: the high-resolution system TL799L91&TL399L62 EPS. Newsletter n. 108, ECMWF, Shinfield Park, Reading RG2-9A, UK

USDA-NRCS (U.S. Department of Agriculture-Natural Resources Conservation Service), (2010). Mecklenburg County Soil Survey Report. USDA-NRCS, Washington, D.C

US EPA. (2004). *Guidelines for Water Reuse. United States Environmental Protection Agency* (Vol. 26). Washington, D.C. ISBN: EPA 625/R-92/004.

USEPA. (2006). *Real Time Control of Urban Drainage Networks*. Washington, D.C. ISBN: EPA/600/R-06/120. Retrieved from http://nepis.epa.gov/Adobe/PDF/P1008A1S.pdf

USEPA. (2009). “Stormwater wet pond and wetland management guidebook.” *Center For Watershed Protection*.

USEPA. (2016). “Summary of state stormwater standards.” US Environmental Protection Agency Office of Water, 148.

Vallabhaneni, S., & Speer, E. (2011). Real-Time Control to reduce combined sewer overflows. *Water World*, 27(2), 1.

Vallet, B., (2011). *Mode´lisation d’un bassin d’orage en vue de l’ame´lioration de la qualite´ des rivie`res par la gestion en temps re´el* (Modelling a stormwater basin in view of improving river water quality by real-time control). Thesis (PhD). De´partement de ge´nie civil et de ge´nie des eaux, Universite´ Laval, Que´bec, QC, Canada.

Vergeynst, L., Vallet, B., and Vanrolleghem, P.A. (2012). Modeling pathogen fate in stormwaters by a particlepathogen interaction model using population balances. *Water Science and Technology*, 65 (5), 823– 832.

Vezzaro, L., and Grum, M. (2014). “A generalised Dynamic Overflow Risk Assessment (DORA) for Real Time Control of urban drainage systems.” *Journal of Hydrology*, 515, 292–303.

Vezzaro, L., Christensen, M. L., Thirsing, C., Grum, M., & Mikkelsen, P. S. (2014). Water quality-based real time control of integrated urban drainage systems: A preliminary study from Copenhagen, Denmark. *Procedia Engineering,* 70, 1707–1716. doi:10.1016/j.proeng.2014.02.188. ISBN: 1877-7058. ISSN:18777058. Retrieved from http://dx.doi.org/10.1016/j.proeng.2014.02.188

Vietz, G. J., Walsh, C. J., and Fletcher, T. D. (2015). "Urban hydrogeomorphology and the urban stream syndrome: Treating the symptoms and causes of geomorphic change." *Progress in Physical Geography,* 40(3), 480–492.

Vitasovic, Z. C. (2006). "Real time control of urban drainage networks.*" US Environmental Protection Agency Office of Research and Development*, 96.

Villarreal, E.L. and Dixon, A. (2005), Analysis of a rainwater collection system for domestic water supply in Ringdansen, Norrköping, Sweden, *Building and Environment*, 40 (9), pp 1174-1184.

Vollmert, P., Fink, A. H., and Besler, H. (2003). "Ghana Dry Zone" und "Dahomey Gap": Ursachen für eine Niederschlagsanomalie im tropischen Westafrika. Erde 134:375–393

Wanielista, M.P. (2006), Stormwater Reuse: A Summary, University of Central Florida, Orlando, Florida.

Wasimi, S. A., and Kitanidis, P. K. (1983). "Real- time forecasting and daily operation of a multireservoir system during floods by linear quadratic Gaussian control." Water Resources Research, 19(6), 1511–1522.

Wella-Hewage, S. (2013). Methodologies to Assess the Performance of Water Sensitive Urban Design Systems in Greenfield Catchment Development; Univeristy of South Australia: Adelaide, Australia

Werndl, C. (2017). Initial conditions dependence and initial conditions uncertainty in climate science. *The British Journal for the Philosophy of Science*, 70(4), 953-976. https://doi.org/10.1093/bjps/axy021

WERF. (2011). Overview: What is life cycle costing? *Water Environment & Reuse Foundation*. Retrieved August 12, 2016, from https://www.werf.org/_ad/SearchResults.aspx?q=lifecycle

Winsenius, H. C., Durta, E., Engelbrecht, F. A., van Gardesen, E. A., Wetterhall, F., Pappenberger, F., & Werner, M. G. F. (2014). The potential value of seasonal forecasts in a changing climate in southern Africa. *Hydrol. Earth Syst,* 18(4), 1525-1538. https://doi.org/10.5194/hess-18-1525- 2014.

Wong, T. H. F., (2000). Improving Urban Stormwater Quality – From Theory to Implementation. Journal of the Australian Water Association 27(6):28–31.

Wong, T. H. F., Fletcher, T. D., Duncan, H. P., and Jenkins, G. A. (2006). Modelling Urban Stormwater Treatment – A Unified Approach. *Ecological Engineering* 27(1):58-70, doi: 10.1016/j.ecoleng.2005. 10.014

Wong, B. P., & Kerkez, B. (2014). Adaptive, decentralized, and real-time sampling strategies for resource constrained hydraulic and hydrologic sensor networks. Paper presented at the HIC 2014 – 11th International Conference on Hydroinformatics, New York, USA. 1 Retrieved from http://academicworks.cuny.edu/cc_conf_hic/235/

Wong, B. P., & Kerkez, B. (2016a). Wong Brandon Preclaro and Kerkez Branko. GitHub Repository. Retrieved from https://github.com/klabum/ iot

Wong, B. P., and Kerkez, B. (2018). "Real-time control of urban headwater catchments through linear feedback: Performance, analysis, and site selection." *Water Resources Research*, 54(10), 7309–7330.

Woods-Ballard, B., Kellagher, R., Martin, P., Jefferies, C., Bray, R., & Shaffer, P. (2007). *The SUDS manual (C697)*. doi:London C697. ISBN: 9780860176978. Retrieved from http://hdl.handle.net/10373/994

Wright, J., and Marchese, D. (2018). "Briefing: Continuous monitoring and adaptive control: the 'smart'storm water management solution." *Proceedings of the Institution of Civil Engineers – Smart Infrastructure and Construction*, 170(4), 86– 89.

WWO. (2012). Cape Town Monthly Climate Average, South Africa. World Weather Online

Xu, C., & Singh, V. P. (2001). Evaluation and generalization of temperature-based methods for calculating evaporation. Hydrological Processes, 319(August 1999), 305–319.

Xu, M., Van Overloop, P., & Van De Giesen, N. (2011). On the study of control effectiveness and computational efficiency of reduced SaintVenant model in model predictive control of open channel flow. *Advances in Water Resources*, 34(2), 282–290. https://doi.org/10.1016/j. advwatres.2010.11.009

Xu, W., Fletcher, T., Duncan, H., Bergmann, D., Breman, J., & Burns M. (2018). Improving the multi-objective performance of rainwater harvesting systems using real-time control technology. Water, 10(2), 147; https://doi.org/10.3390/w10020147

Xuan, Y., Cluckie, I. D., Han, D. (2004). Rainfall Forecasts from a Local Area Mesoscale Model (MM5) and a Quantitative Weather Radar System. *Proceedings of International Symposium on Flood Forecasting and Management with GIS and Remote Sensing (FM2S)*, Guangzhou, China

Yates, D., Sieber, J., and Purkey, D., et al. (2005). WEAP 21—a demand-, priority-, and preference-driven water planning model. Part 1: model characteristics. Water Int 30:487–500

Yu, H., Huang, G., and Wu, C. (2014). Application of the stormwater management model to a piedmont city: A case study of Jinan city, China. *Water Science Technology*, 70, 858–864

Zaghloul, N. A. (1983). "Sensitivity analysis of the SWMM runoff-transport parameters and the effects of catchment discretisation." *Adv. Water Resour*, 6(4), 214–223.

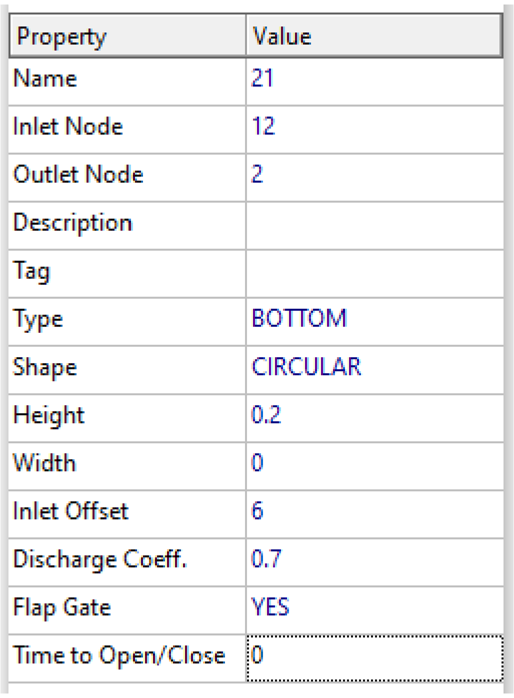
Zhen, X., Yu, S. L., & Lin, J. (2004). Optimal location and sizing of stormwater basins at watershed scale. *Journal of Water Resources Planning and Management*, 130(4), 339–347. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:4(339)

Zutari. (2020). Uct Sustainable Water Management Strategy

7 Appendix

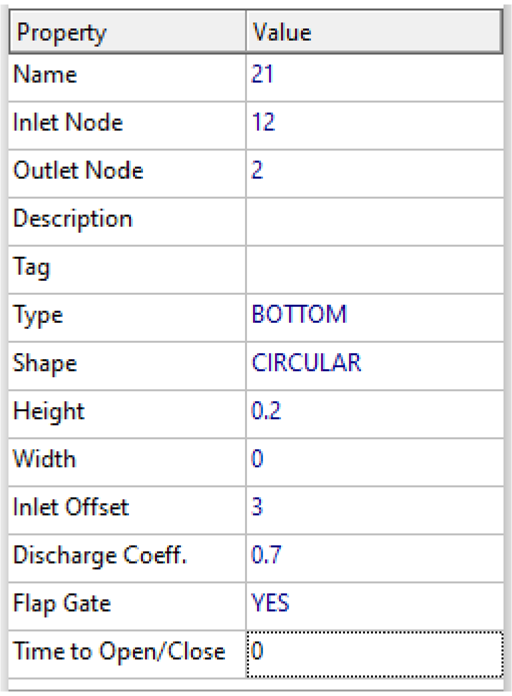
7.1 Appendix 1: UCT Dam Details

7.1.1 Appendix 1a: Outlet structure



Property	Value
Name	21
Inlet Node	12
Outlet Node	2
Description	
Tag	
Type	BOTTOM
Shape	CIRCULAR
Height	0.2
Width	0
Inlet Offset	6
Discharge Coeff.	0.7
Flap Gate	YES
Time to Open/Close	0

Figure A-1a: Outlet structure for SC1 (unit = metre)



Property	Value
Name	21
Inlet Node	12
Outlet Node	2
Description	
Tag	
Type	BOTTOM
Shape	CIRCULAR
Height	0.2
Width	0
Inlet Offset	3
Discharge Coeff.	0.7
Flap Gate	YES
Time to Open/Close	0

Figure A-1b: Outlet structure for SC2 (unit = metre)

7.2 Appendix 2: Static control configurations

The following appendix presents the actual Real Time Control (RTC) rules that were used to govern the two storage configurations. It should be noted that the depths listed are in meters. The orifice setting reflects the open/close status of the pond outlet; where: 0 = outlet is closed, 0.5 = outlet is half-open, and 1 = outlet is fully open.

7.2.1 Appendix 2a: SC1 control rules

RULE 1a

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH <= 12.5

AND NODE 12 DEPTH >= 12

THEN ORIFICE 21 SETTING = 0.08

RULE 1b

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 12

AND NODE 12 DEPTH >= 11.5

THEN ORIFICE 21 SETTING = 0.08

RULE 1c

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 11.5

AND NODE 12 DEPTH >= 11

THEN ORIFICE 21 SETTING = 0.08

RULE 1d

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 11

AND NODE 12 DEPTH >= 10.5

THEN ORIFICE 21 SETTING = 0.08

RULE 1e

```
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 10.5
AND NODE 12 DEPTH >= 10
THEN ORIFICE 21 SETTING = 0.08
RULE 1f
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 10
AND NODE 12 DEPTH >= 9.5
THEN ORIFICE 21 SETTING = 0.09
RULE 1g
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 9.5
AND NODE 12 DEPTH >= 9
THEN ORIFICE 21 SETTING = 0.09
RULE 1h
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 9
AND NODE 12 DEPTH = 8.5
THEN ORIFICE 21 SETTING = 0.09
RULE 1i
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 8.5
AND NODE 12 DEPTH >= 8
THEN ORIFICE 21 SETTING = 0.1
RULE 1j
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
```

AND NODE 12 DEPTH < 8

AND NODE 12 DEPTH >= 7.5

THEN ORIFICE 21 SETTING = 0.11

RULE 1k

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 7.5

AND NODE 12 DEPTH >= 7

THEN ORIFICE 21 SETTING = 0.12

RULE 1l

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 7

AND NODE 12 DEPTH >= 6.5

THEN ORIFICE 21 SETTING = 0.14

RULE 1m

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 6.5

AND NODE 12 DEPTH > 6

THEN ORIFICE 21 SETTING = 0.21

ELSE ORIFICE 21 SETTING = 0

7.2.2 Appendix 2b: SC2 control rules

RULE 1a

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

```
AND NODE 12 DEPTH <= 12.5
AND NODE 12 DEPTH >= 12
THEN ORIFICE 21 SETTING = 0.07
RULE 1b
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 12
AND NODE 12 DEPTH >= 11.5
THEN ORIFICE 21 SETTING = 0.07
RULE 1c
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 11.5
AND NODE 12 DEPTH >= 11
THEN ORIFICE 21 SETTING = 0.07
RULE 1d
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 11
AND NODE 12 DEPTH >= 10.5
THEN ORIFICE 21 SETTING = 0.07
RULE 1e
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 10.5
AND NODE 12 DEPTH >= 10
THEN ORIFICE 21 SETTING = 0.07
RULE 1f
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 10
AND NODE 12 DEPTH >= 9.5
```

THEN ORIFICE 21 SETTING = 0.07

RULE 1g

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 9.5

AND NODE 12 DEPTH >= 9

THEN ORIFICE 21 SETTING = 0.08

RULE 1h

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 9

AND NODE 12 DEPTH >= 8.5

THEN ORIFICE 21 SETTING = 0.08

RULE 1i

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 8.5

AND NODE 12 DEPTH >= 8

THEN ORIFICE 21 SETTING = 0.08

RULE 1j

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 8

AND NODE 12 DEPTH >= 7.5

THEN ORIFICE 21 SETTING = 0.08

RULE 1k

IF SIMULATION CLOCKTIME > 08:00:00

AND SIMULATION CLOCKTIME < 13:00:00

AND NODE 12 DEPTH < 7.5

AND NODE 12 DEPTH >= 7

THEN ORIFICE 21 SETTING = 0.08

RULE 1l

```
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 7
AND NODE 12 DEPTH >= 6.5
THEN ORIFICE 21 SETTING = 0.09
RULE 1m
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 6.5
AND NODE 12 DEPTH >= 6
THEN ORIFICE 21 SETTING = 0.09
RULE 1n
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 6
AND NODE 12 DEPTH >= 5.5
THEN ORIFICE 21 SETTING = 0.09
RULE 1o
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 5.5
AND NODE 12 DEPTH >= 5
THEN ORIFICE 21 SETTING = 0.1
RULE 1p
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 5
AND NODE 12 DEPTH >= 4.5
THEN ORIFICE 21 SETTING = 0.11
RULE 1q
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
```

```
AND NODE 12 DEPTH < 4.5
AND NODE 12 DEPTH >= 4
THEN ORIFICE 21 SETTING = 0.12
RULE 1r
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 4
AND NODE 12 DEPTH >= 3.5
THEN ORIFICE 21 SETTING = 0.14
RULE 1s
IF SIMULATION CLOCKTIME > 08:00:00
AND SIMULATION CLOCKTIME < 13:00:00
AND NODE 12 DEPTH < 3.5
AND NODE 12 DEPTH > 3
THEN ORIFICE 21 SETTING = 0.21
ELSE ORIFICE 21 SETTING = 0
```

7.3 Appendix 3: PySWMM Sample Code

7.3.1 Appendix 3a: PySWMM Script for RTC-1 and RTC-2

```
from pyswmm import Simulation, Links, Nodes, SystemStats
from datetime import datetime
with Simulation('C:/Users/Malesela/Downloads/CIV5000WProjectV1.inp') as sim: #SWMM file

    Or21_Uctdam = Links(sim)["21"] # initiate links
    Pond_Uctdam = Nodes(sim)["12"] # initiate nodes
    syst_stats = SystemStats(sim)

    sim.step_advance(300)

    for step in sim:
        RRF_Uctdam = syst_stats.runoff_stats["rainfall"] # System stats allow measurement of precipitation
        Vol_ro_Uctdam = PR*RRF_Uctdam*A   #PR = Runoff coefficient, A = Catchment area
        Vol_ex_Uctdam = Max volume - Pond_Uctdam.volume
        if Vol_ro_Uctdam > Vol_ex_Uctdam:
            Or21_Uctdam.target_setting = 1.0
        else:
            Or21_Uctdam.target_setting = 0
```

7.4 Appendix 4: Economic calculation module

7.4.1 Appendix 4a: LCCA Costing Module for SC1 & SC2

Table 4-1a: LCCA costing module in Rands

1 Year of Graphs	2 Discount factor	3 Capital costs	4 Maintenance & Operations	5 Sum 'Cash' Expenditure for year
0	1,000	1602400	0	1602400
1	0,972	0	158504	158504
2	0,944	0	158504	158504
3	0,918	0	158504	158504
4	0,892	0	158504	158504
5	0,867	0	158504	158504
6	0,842	0	158504	158504
7	0,819	0	158504	158504
8	0,796	0	158504	158504
9	0,773	0	158504	158504
10	0,751	0	158504	158504

Table 4-1a (continued)**: LCCA costing module in Rands**

6 PV of Capital costs	7 PV of Maintenance & Operations	8 PV of Year costs	9 Total Cash Expenditure	10 Sum Present Value Expenditure
1602400	0	1602400	1602400	1602400
0	154037	154037	1760904	1756437
0	149696	149696	1919408	1906133
0	145477	145477	2077912	2051610
0	141377	141377	2236416	2192987
0	137393	137393	2394920	2330379
0	133521	133521	2553424	2463900
0	129758	129758	2711928	2593657
0	126101	126101	2870432	2719758
0	122547	122547	3028936	2842305
0	119093	119093	3187440	2961398

7.4.2 Appendix 4b: LCCA Costing Module for RTC-1 & RTC-2

Table 4-1b: LCCA costing module in Rands

1	2	3	4	5
Year of Graphs	Discount factor	Capital costs	Maintenance & Operations	Sum 'Cash' Expenditure for year
0	1	1703890	0	1703890
1	0,972	0	242263	242263
2	0,944	0	242263	242263
3	0,918	0	242263	242263
4	0,892	0	242263	242263
5	0,867	0	242263	242263
6	0,842	0	242263	242263
7	0,819	0	242263	242263
8	0,796	0	242263	242263
9	0,773	0	242263	242263
10	0,751	0	242263	242263

Table 4-1b (continued)**: LCCA costing module in Rands**

6	7	8	9	10
PV of Capital costs	PV of Maintenance & Operations	PV of Year costs	Total Cash Expenditure	Sum Present Value Expenditure
1703890	0	1703890	1703890	1703890
0	235435	235435	1946153	1939325
0	228800	228800	2188416	2168126
0	222352	222352	2430679	2390478
0	216085	216085	2672942	2606563
0	209996	209996	2915205	2816559
0	204077	204077	3157468	3020636
0	198326	198326	3399731	3218962
0	192737	192737	3641994	3411698
0	187305	187305	3884257	3599003
0	182026	182026	4126520	3781029

7.5 Appendix 5: Borehole logs

7.5.1 Appendix 5a: New Engineering Building

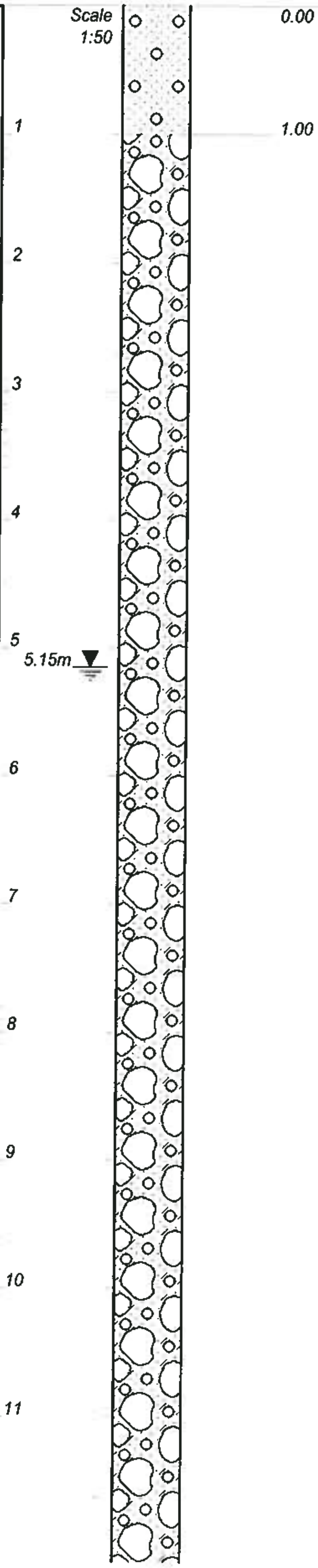
K&T
KANTEY & TEMPLER
CONSULTING ENGINEERS
ENGINEERING AFRICAN DEVELOPMENT

SUTHERLAND & ASSOCIATES
ENGINEERING COMPLEX, UCT.

HOLE No: BH1
Sheet 1 of 2

JOB NUMBER: 13282GG

DRILLING METHOD	*CORE REC.*	*ROD %*	*FRACT. PER m*	*TEST OR SAMPLE*	*VALUE "N"*
NWD4	10				
	32				
NX	N/W WASH BORE				
NWD4	100			SPT	
	90				
	25				
	24				
	66				
	58				
	94				



Yellowish orange, fine to medium grained (probably loose) SAND with scattered subangular ferruginous fine gravel: FILL.

Subrounded to subangular quartzitic sandstone GRAVEL and BOULDERS medium densely to densely packed in a matrix of brownish yellow blotched orange and red occasionally mottled light grey, variably clayey, medium grained sand: TRANSPORTED.

Gravel and boulders are completely to medium weathered and of very soft to hard rock consistency.

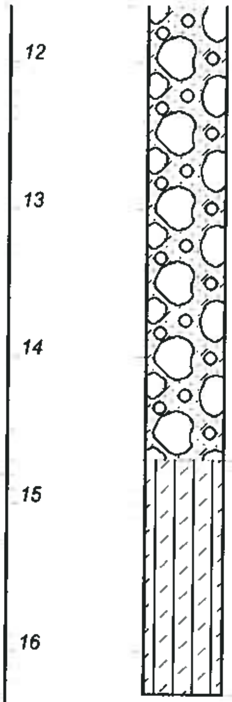
Profile stained dark brown to black between 13.30 - 13.80m depth indicating extensive ferruginisation, probably due to the abundant presence of groundwater.

SUTHERLAND & ASSOCIATES
ENGINEERING COMPLEX, UCT.

HOLE No: **BH1**
Sheet 2 of 2

JOB NUMBER: 13282GG

DRILLING METHOD	*CORE REC.*	*ROD %*	*FRACT. PER m*	*TEST OR SAMPLE*	*VALUE "N"*
	37				
	39				
	84			SPT	52
	67				



14.70

Brownish olive mottled dark yellow and light grey, very stiff intact slightly clayey SILT with remnant bedding structure tending to completely weathered very soft rock shale locally: RESIDUAL MALMESBURY.

16.30

NOTES

1) End of hole 16.30m.

2) SPT=Standard penetration test.

3) Water Table at 5.15m depth.

4) R=Refusal

CONTRACTOR : FAIRBROTHER
MACHINE : LH250
DRILLED BY : JAN NIEUWENHUIS
PROFILED BY : L.C.

TYPE SET BY : SHEILA
SETUP FILE : k&t-bore SET

INCLINATION : VERTICAL
DIAM :
DATE :
DATE : 23-08-2010

DATE : 29/09/10 07:55
TEXT : ..\DATA\B13282-1.TXT

ELEVATION : N/A
X-COORD : N/A
Y-COORD : N/A

HOLE No: **BH1**
Reinstrumentation

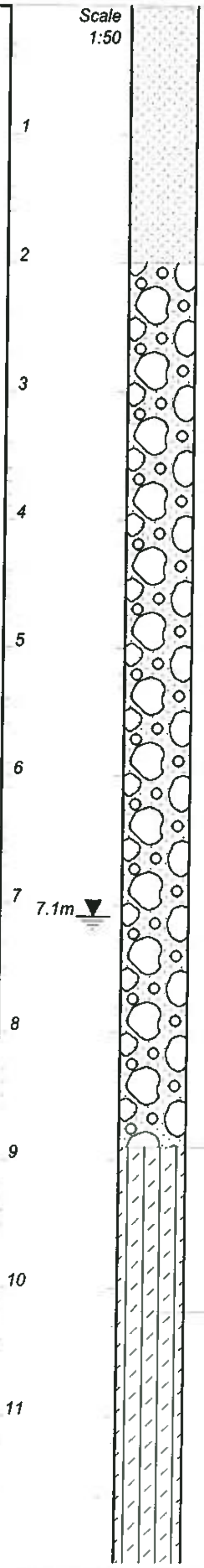
SUTHERLAND & ASSOCIATES
ENGINEERING COMPLEX, UCT.

HOLE No: BH2
Sheet 1 of 2

JOB NUMBER: 13282GG

DRILLING METHOD	*CORE REC.*	*ROD %*	*FRACT. PER m*	*TEST OR SAMPLE*	*VALUE "N"*
NWD4	N/A WASH SAMPLE				
	N/A WASH SAMPLE				
	17				
	36				
	23				
	62			SPT	R
	22				
	21				
	84			SPT	41
	0			SPT	R
	75				

Scale 1:50



0.00	Black continous graded hot mix ASPHALT: SURFACING.
0.02	Light greyish brown, fine to medium grained (probably loose) SAND: FILL. (Probably associated with retaining wall construction).
2.00	Subrounded to subangular quartzitic sandstone GRAVEL AND BOULDERS medium densely to densely packed in matrix of brownish yellow blotched orange and red occasionally mottled light grey, variably clayey, medium grained sand; TRANSPORTED. Gravel and boulders are completely to medium weathered and of very soft to <u>hard</u> rock consistency. Matrix material occurs as clay/sand and sandy clay locally. Boulders up to 0.35m in diameter.
8.90	Light reddish brown mottled dark yellow and occasionally light grey, speckled/stained dark brown, very stiff, fissured slightly clayey SILT with scattered ferruginous soft rock fragments: REWORKED RESIDUAL MALMESBURY.
10.17	Brownish olive mottled dark yellow and light grey, very stiff intact slightly clayey SILT with remnant bedding structure and zones of completely to highly weathered very soft rock shale: RESIDUAL MALMESBURY.

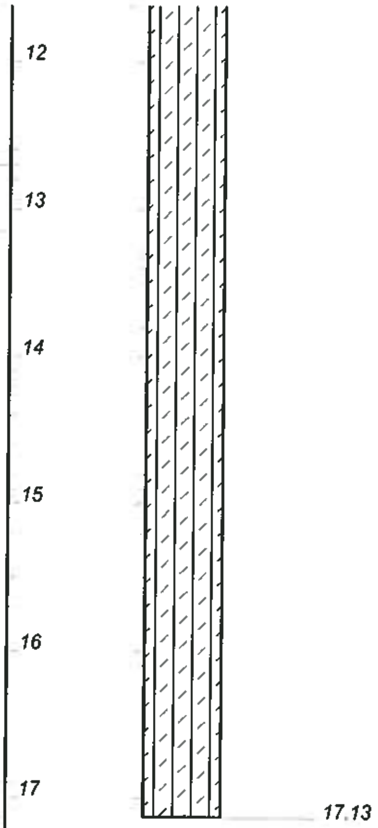
K&T
KANTEY & TEMPLER
CONSULTING ENGINEERS
ENGINEERING AFRICAN DEVELOPMENT

SUTHERLAND & ASSOCIATES
ENGINEERING COMPLEX, UCT.

HOLE No: BH2
Sheet 2 of 2

JOB NUMBER: 13282GG

DRILLING METHOD	CORE REC.	ROD %	FRACT. PER m	TEST OR SAMPLE	VALUE "N"
	62			SPT	52
	41				
	46				
	48				
	85			SPT	R



NOTES

1) End of hole 17.135m.

2) SPT=Standard penetration test.

3) Water Table at 7.1m depth.

4) R=Refusal

CONTRACTOR : FAIRBROTHER
MACHINE : LH250
DRILLED BY : JAN NIEUWENHUIS
PROFILED BY : L.C.

TYPE SET BY : SHEILA
SETUP FILE : k&t-bore.SET

INCLINATION : VERTICAL
DIAM :
DATE :
DATE : 23-08-2010

DATE : 29/09/10 07:56
TEXT : ..\DATA\B13282-2.TXT

ELEVATION : N/A
X-COORD : N/A
Y-COORD : N/A

HOLE No: BH2
Reinstrumentation

D016

dot.PLOT 4004 J&W

7.5.2 Appendix 5b: New Lecture Theatre

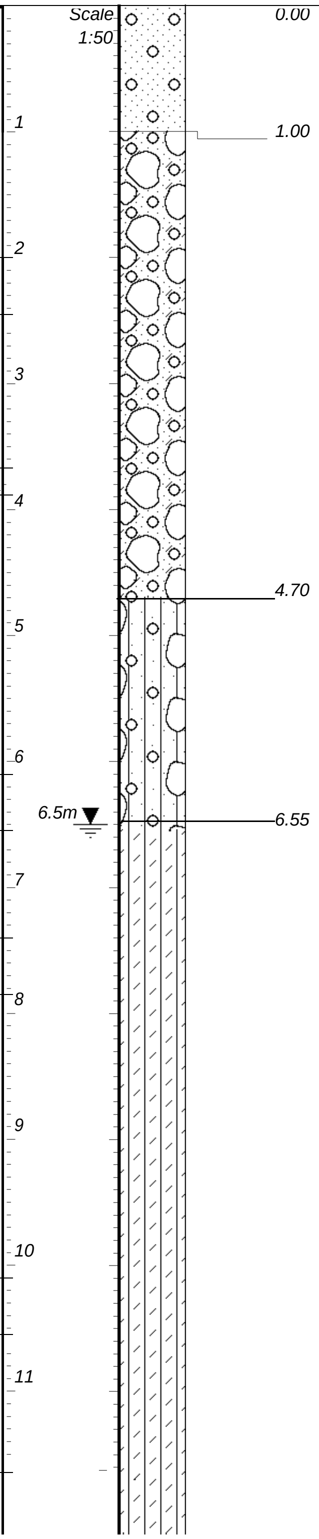
KANTEY & TEMPLER
CONSULTING ENGINEERS
Engineering African Development

HENRY FAGAN
NEW LECTURE THEATRE
UCT UPPER CAMPUS.

***HOLE No:* BH1**
Sheet 1 of 2

***JOB NUMBER:* 13852GG**

DRILLING METHOD	CORE REC.	ROD %	FRACT. PER m	TEST OR SAMPLE	VALUE "N"
NX	30				
	30				
NWD4	27				
	53			SPT	10
	35				
	67			SPT	R
	23				
	100				
	74			SPT	46
	34				
	74			SPT	37
	29				
	75			SPT	27
	31				



Yellowish orange fine to medium grained (probably medium dense) SAND with scattered subrounded to subangular sandstone gravel; TRANSPORTED (REWORKED).

Yellow to reddish orange and olive grey subrounded to subangular sandstone GRAVEL and BOULDERS densely packed in a matrix of slightly clayey medium to coarse grained gritty sand; TRANSPORTED.

Gravel and boulders are highly to medium weathered and of soft to hard rock consistency.

Dark reddish purple mottled olive and yellowish orange very stiff sandy SILT with occasional to scattered sandstone gravel and boulders; TRANSPORTED.

Gravel and boulders are highly to medium weathered and of soft to hard consistency.

Light olive and yellow mottled orange and brownish olive very stiff intact slightly clayey SILT; RESIDUAL MALMESBURY.

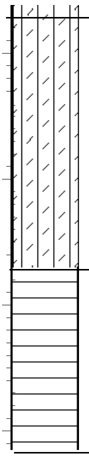
KANTEY & TEMPLER
CONSULTING ENGINEERS
Engineering African Development

HENRY FAGAN
NEW LECTURE THEATRE
UCT UPPER CAMPUS.

***HOLE No:* BH1**
Sheet 2 of 2

***JOB NUMBER:* 13852GG**

DRILLING METHOD	CORE REC.	ROD %	FRACT. PER m	TEST OR SAMPLE	VALUE "N"	
NWD4	75			SPT	26	12
	44					13
	67			SPT	R	14
						15



11.70

Olive brown mottled orange and purple verystiff intact slightly clayey SILT with remnant bedding structure; RESIDUAL MALMESBURY.

13.70

Olive brown mottled orange and purple to yellow completely weathered highly fractured very soft rock SHALE; MALMESBURY GROUP.

15.15

NOTES

1) End of hole 14.15m.

2) SPT=Standard penetration test.

3) R=Refusal

4) Water table at 6.5m two days after completion of drilling.

CONTRACTOR : FAIRBROTHER
MACHINE : SECA
DRILLED BY : J. NIEWENHUIS
PROFILED BY : L.C.

INCLINATION : VERTICAL
DIAM :
DATE :
DATE : 31-07-2012

ELEVATION : +107m AMSL
X-COORD : N/A
Y-COORD : N/A

TYPE SET BY : SHEILA
SETUP FILE : k&t-bore.SET

DATE : 29/08/14 14:00
TEXT : ..DATA\B13852-1.TXT

***HOLE No:* BH1**
Reinstrumentation

KANTEY & TEMPLER
CONSULTING ENGINEERS
Engineering African Development

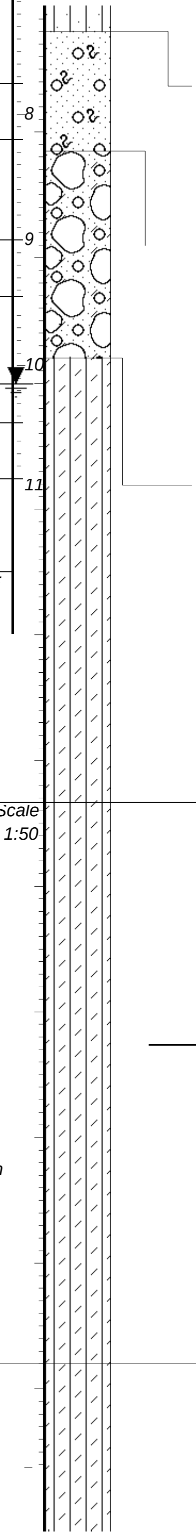
HOLE No: BH2
Sheet 1 of 2

JOB NUMBER: 13852GG

HENRY FAGAN NEW LECTURE THEATRE UPPER CAMPUS.

DRILLING METHOD	CORE REC.	ROD %	FRACT. PER m	TEST OR SAMPLE	VALUE "N"
	24			SPT	34
	23				
NWD4	89			SPT	12
	61				
	100			SPT	34
	38				
	100			SPT	27
	90				
	89			SPT	22
	100				

Depth: 5, 6, 7, 8, 9, 10, 11



HAND EXCA-VATION	60				
	N/A				
NX	WASH SAMPLE				
	33			SPT	R
	86				
	100			SPT	28
	94				
	84			SPT	26
	39				

Depth: 1, 2, 3 +3.0m, 4

Scale 1:50

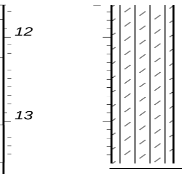
0.00	Dark brown very loose highly organic sandy SILT; FILL.
0.20	Yellowish orange fine to medium grained (posibably medium dense) SAND with scattered subrounded to subangular sandstone gravel and occasional fine roots; TRANSPORTED (REWORKED).
1.15	Yellow to reddish orange and olive grey subrounded to subangular sandstone GRAVEL and BOULDERS densely packed in a matrix of slightly clayey medium to coarse grained gritty sand; TRANSPORTED. Gravel and boulders are highly to medium weathered and of soft to hard rock consistency.
2.80	Light yellow mottled reddish orange becoming brownish purple mottled orange with depth slightly clayey SILT with remnant bedding structure at depth; RESIDUAL MALMESB

HENRY FAGAN
NEW LECTURE THEATRE
UCT UPPER CAMPUS.

HOLE No: **BH2**
Sheet 2 of 2

JOB NUMBER: **13852GG**

DRILLING METHOD	*CORE REC.*	*ROD %*	*FRACT. PER m*	*TEST OR SAMPLE*	*VALUE "N"*
NWD4	100			SPT	32
	100				
	100			SPT	34



13.50

NOTES

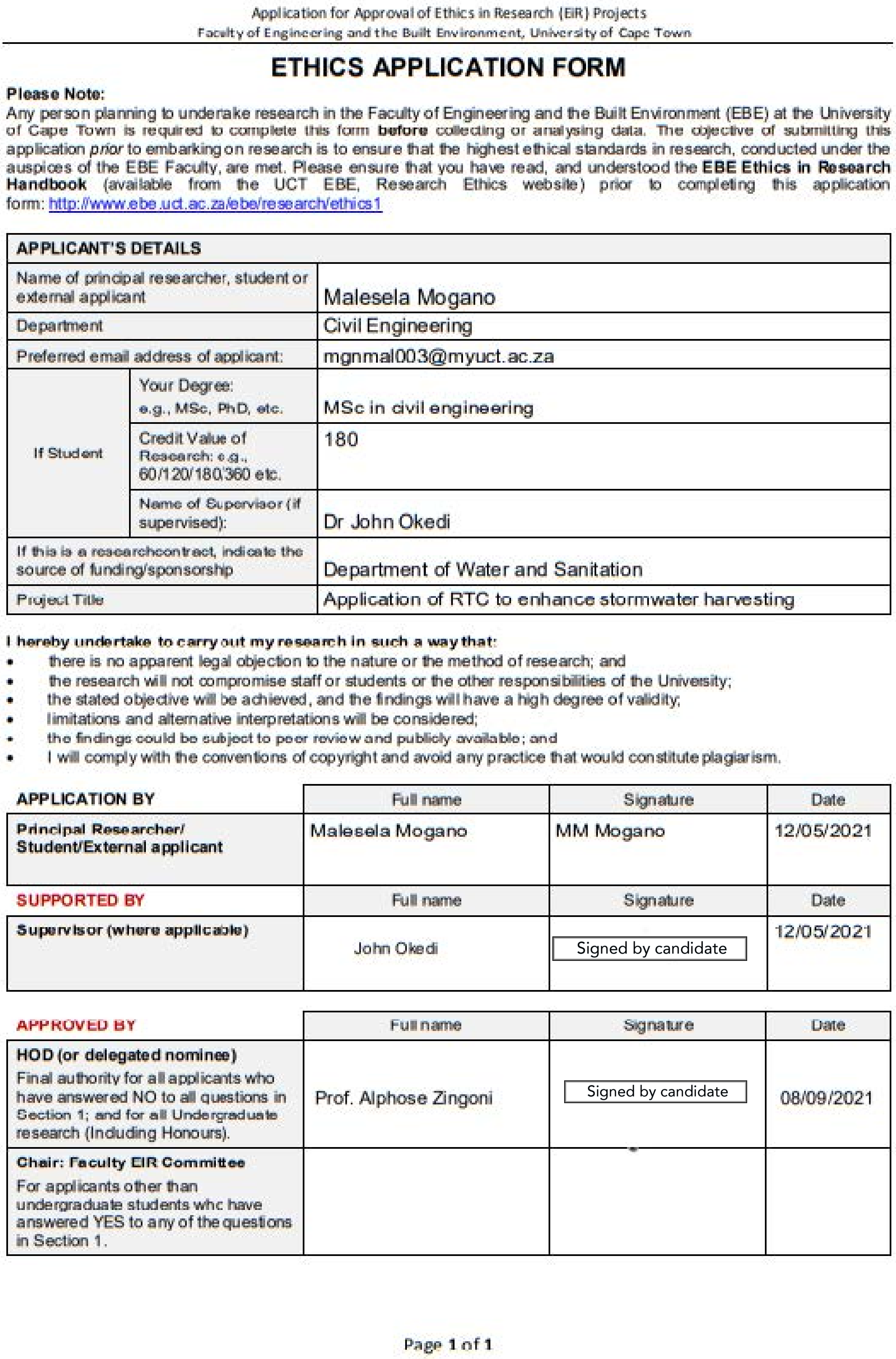
1) End of hole 13.50m.

2) SPT=Standard penetration test.

3) R=Refusal

4) Water table +3.0m two days after completion of drilling.

Appendix 6: Ethics clearance



Application for Approval of Ethics in Research (EiR) Projects
Faculty of Engineering and the Built Environment, University of Cape Town

ETHICS APPLICATION FORM

Please Note:
Any person planning to underake research in the Faculty of Engineering and the Built Environment (EBE) at the University of Cape Town is required to complete this form **before** collecting or analysing data. The objective of submitting this application *prior* to embarking on research is to ensure that the highest ethical standards in research, conducted under the auspices of the EBE Faculty, are met. Please ensure that you have read, and understood the **EBE Ethics in Research Handbook** (available from the UCT EBE, Research Ethics website) prior to completing this application form: http://www.ebe.uct.ac.za/ebe/research/ethics1

APPLICANT'S DETAILS		
Name of principal researcher, student or external applicant		Malesela Mogano
Department		Civil Engineering
Preferred email address of applicant:		mgnmal003@myuct.ac.za
If Student	Your Degree: e.g., MSc, PhD, etc.	MSc in civil engineering
	Credit Value of Research: e.g., 60/120/180/360 etc.	180
	Name of Supervisor (if supervised):	Dr John Okedi
If this is a researchcontract, indicate the source of funding/sponsorship		Department of Water and Sanitation
Project Title		Application of RTC to enhance stormwater harvesting

I hereby undertake to carry out my research in such a way that:

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

APPLICATION BY	Full name	Signature	Date
Principal Researcher/ Student/External applicant	Malesela Mogano	MM Mogano	12/05/2021
SUPPORTED BY	Full name	Signature	Date
Supervisor (where applicable)	John Okedi	Signed by candidate	12/05/2021

APPROVED BY	Full name	Signature	Date
HOD (or delegated nominee) Final authority for all applicants who have answered NO to all questions in Section 1; and for all Undergraduate research (Including Honours).	Prof. Alphose Zingoni	Signed by candidate	08/09/2021
Chair: Faculty EIR Committee For applicants other than undergraduate students whc have answered YES to any of the questions in Section 1.			

Page 1 of 1