Modelling for Rainwater Harvesting Structures Using Geospatial Techniques

BY

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SUPERVISOR

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A thesis submitted to the Faculty of Science, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Science (MSc) in Geographic Information Systems and Remote Sensing.

Declaration

I, Precious Nkhensani Makaringe, declare that this Dissertation entitled "*Modelling for Rooftop Rainwater Harvesting Structures Using Geospatial Techniques*." is my own, unaided work. It is being submitted for the Degree of Master of Science at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

Miss Precious Nkhensani Makaringe

Signed on……11 October 2024…….in Johannesburg, South Africa

Abstract

Climate change poses a significant threat, leading to droughts, floods, and hindering sustainable development. Water scarcity is a growing concern, particularly in developing countries like South Africa, where limited freshwater resources are further strained by climate variability. This research explores the potential of rainwater harvesting (RWH) as a strategy to address water scarcity in such regions.

This study aims to model potential rainwater harvesting sites in Lynwood Park, Pretoria, South Africa, utilising geospatial techniques. Object-Based Image Classification (OBIC) was employed to extract building footprints from high-resolution satellite imagery. Microsoft and Google building footprints were utilised to determine the suitable automated building footprints for Lynnwood Park. ArcGIS Pro software served as the primary platform for spatial data analysis and mapping potential RWH sites. Data integration included high-resolution satellite imagery, a Digital Elevation Model (DEM), building footprints, and rainfall data. Additionally, questionnaires were distributed to estimate population and water demand within the study area.

The research demonstrates the efficacy of geospatial tools in identifying suitable locations for RWH systems. Indicating that steeper slopes in the southern region of Lynnwood Park have limited collection from large rooftops, while the flatter north offered greater potential. Rainfall graphs and PRWH results suggest that over half of Lynwood Park's annual water demand could be met through rooftop rainwater collection. However, factors such as system losses due to evaporation, inefficiencies in collection and storage, and variability in rooftop sizes across different buildings would need to be incorporated into more detailed models, as well as water quality analysis for rooftop harvested water in future studies. This study highlights the potential of RWH as a viable water security strategy in water-scarce regions. The findings contribute to the development of geospatial approaches for RWH implementation, promoting water security and sustainability in a changing climate.

Keywords: Rainwater harvesting, water scarcity, climate change, geospatial techniques, spatial modeling

Dedication

This work is dedicated with profound gratitude and love to the guiding lights in my life, whose unwavering support and encouragement have been the cornerstone of my journey.

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Table of contents

List of Tables

List of Figures

List of Abbreviations

APRWH	Average Potential Rainwater Harvesting
CC	Climate Change
CoCT	City of Cape Town
COL	Cut-off low
DRHW	Domestic Rainwater Harvesting
XRWH	ex-Situ Rainwater Harvesting
GIS	Geographic Information Systems
iRWH	in-Situ Rainwater Harvesting
LULC	Land Use Land Cover
MDGs	Millennium Development Goals
NE	Northeast
NN	Natural Neighbor
NW	North-western
OBIC	Object-Based Image Classification
RWH	Rainwater Harvesting
RWHS	Rainwater Harvesting Systems
SAWS	South African Weather Services
SSA	Sub-Saharan Africa
UNISA	University of South Africa
UN	United Nations
WHO	World Health Organization

CHAPTER 1: INTRODUCTION

1.1. Introduction

Climate change (CC) stands as a prominent and unavoidable threat to humanity, manifesting through consequences like droughts and floods (Brown et al., 2012; Dube and Phiri, 2013). It transcends national borders, presenting a multifaceted global challenge that impacts ecological, environmental, socio-political, and socio-economic spheres (Abbass et al., 2022; Feliciano et al., 2022). A comprehensive understanding of CC necessitates examining not only average temperature and rainfall fluctuations but also long-term trends in atmospheric pressure and humidity that influence the broader environment (Abbass et al., 2022).

Climate change has emerged as a significant challenge to achieving sustainable development, continuously generating novel environmental and social challenges (Brown et al., 2012; Dube and Phiri, 2013). Sustainable development hinges on the balanced integration of three pillars: social, economic, and environmental factors (NEMA, 1998). This framework guides planning, implementation, and decision-making processes to ensure development meets the needs of both present and future generations without compromising the ability of future generations to meet their own needs (NEMA, 1998). The severity of CC is directly linked to the cumulative amount of greenhouse gases released into the atmosphere, although the impacts can vary considerably based on geographical location (Tripathi and Mishra, 2017).

The World Meteorological Organisation (WMO, 2021) highlights the significant impact of climate change on global environmental conditions, with South Africa experiencing similar effects (Ampitiyawatta and Guo, 2009). Precipitation patterns serve as a crucial long-term indicator for detecting climate-driven changes affecting water resources (Ampitiyawatta and Guo, 2009). Variations in precipitation pose a significant challenge for water resource managers responsible for planning and managing these vital resources (Ampitiyawatta and Guo, 2009). Global warming, a key aspect of climate change, drives extreme weather events such as intense precipitation events and droughts (Horton, 2020). These events can deplete or reduce water resources, jeopardising

ecosystems and their habitats (Horton, 2020). Climate change is expected to significantly impact water bodies, potentially altering annual rainfall patterns (Immerel et al., 2010).

Water serves as a cornerstone for human survival, underpinning our social, economic, and environmental needs (Alwan et al., 2018). However, a growing demand for water coincides with a decline in readily available freshwater resources (Immerzeel et al., 2010). These combined challenges necessitate the exploration of alternative water sources to mitigate the negative impacts of climate change and pollution in a cost-effective manner. Rainwater harvesting (RWH) emerges as a promising water conservation approach. This technique involves collecting and storing precipitation from various surfaces, such as rooftops, natural rock formations, open land areas, and even roadways (Ojwang et al., 2017).

Rooftop rainwater harvesting (RWH) offers a decentralised approach to water management by collecting and storing rainwater from rooftops (Gould and Nissen-Petersen, 1999). This system typically comprises a guttering system that channels runoff from the catchment area (rooftop) to a storage tank (Wallace et al., 2015). RWH implementation requires minimal expertise and can be adopted at the household level, fostering broad public acceptance (Domènech and Saurí, 2011). This versatile water supply solution can function as a primary water source in specific locations or supplement existing sources by reducing overall water demand (Ojwang et al., 2017).

Rainwater harvesting shows a rich history, with evidence of its use for potable and non-potable purposes dating back over 4,000 years (Londra et al., 2015). Water availability and local needs have shaped rainwater harvesting practices across various countries (Kisakye et al., 2018). Developed nations like Sweden, Australia, and the United States often utilise harvested rainwater for non-potable applications such as irrigation, laundry, and toilet flushing (Villarreal and Dixon, 2005; Rahman et al., 2012; Jones and Hunt, 2010). In contrast, developing countries, including South Africa, Namibia, and Uganda, frequently rely on harvested rainwater for both consumption and hygiene (Kahinda et al., 2007; Sturm et al., 2009; Kisakye et al., 2018).

The United Nations Agenda 2030 Sixth Sustainable Development Goal (SDG) on Clean Water and Sanitation, indicates that more 733 million people reside in countries that are characterised by

high water stress levels (United Nations, 2019). The world population is increasing, and it is expected that by 2050, 64% of the worlds population will be residing in cities (Kummu et al., 2016). As a result, this will lead to an increase in water demand (Kummu et al., 2016). Therefore, to meet the SDGs and improve climate reseilience, sustainable rainwater management emerges as a pivotal method to achieve this. The strategy includes the maintenance, restoration and management of the natural infrastructure, ensuring that there is universal alignment to clean water accessibility and sanitary facilities (Lepcha et al., 2024). Rainwater Harvesting signifies a positive correlation with several of the seventeen SDGs. The most important SDGs are SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action) and SDG 15 (Life on Land) (Relx, 2024).

Rainwater Harvesting aligns to SDG 6 as it contributes to the enhancement of water security through the provision of alternative, sustainable as well as local sources of freshwater (Relx, 2024). In addition, it reduces the detrimental impact of water scarcity, particularly in regions suffering from water stress challenges as a result of climate change or population growth. RWH also aligns with SDG 11, this is because the urban RWH systems can reduce pressure from municipal water supplies and reduce the risk of droughts and floods (Relx, 2024). In relation to SDG 12, RWH ensures climate resilience by securing water resources under changing climate events and patterns. Lastly, through effective implementation, RHW systems can support SDG15 (Relx, 2024). This can be achieved through the reduction of soil erosion and replenishment of ground water levels, thus contributing to the ecosystem's health (Relx, 2024). Therefore, RHW provides a systematic, cross-cutting and valuable strategy in the pursuit if alternative water sources and sustainable development (Relx, 2024).

Numerous studies have traditionally relied on historical rainfall data to design rainwater harvesting systems (Bashar et al., 2018; Montalto et al., 2010). However, the Intergovernmental Panel on Climate Change (IPCC) reports on rising global temperatures, raising concerns about the validity of solely relying on historical data (IPCC, 2021). This potential shift necessitates a re-evaluation of rainwater harvesting design. While previous research focused on historical data, anticipated climate change could negatively impact water storage and security in rainwater harvesting systems, particularly in developing countries facing water scarcity (Kisakye et al., 2018). This research

addresses this gap by exploring how climate change affects water availability and examines the potential of geospatial tools to leverage rainwater harvesting as a water scarcity mitigation strategy.

1.1. Background

Although water is the most abundant resource on earth, there is less than 1% of freshwater available for human use and consumption. About 90 000 km^3 of the worlds freshwater is physically accessible, however, thirty-five (35) million km^3 of the water is inaccessible because of the water being locked in ice cover of Arctic, Antartica or being locked in deep acquifers (Department of Water and Sanitation (DWS), 2023). South Africa shares four major rivers with neighbouring countries such as Botswana, Mozambique, Lesotho, Zimbabwe, Namibia and Swaziland. The Orange and Limpopo River basins account for the majority of South Africa's surface water potential in its major drainage systems (DWS, 2023). Therefore, over 60% of South Africa's River flow comes from 20% of the land area.

South Africa is characterised by an arid to semi-arid climate and an average rainfall of 465mm (half the world average) and produces a total annual runoff of approximately 49 000 million m^3/a (DWS, 2023). Currently, the dependable supply of surface water in South Africa is estimated to be around 10 200 million m^3/a per year. In addition, the total of accessible groundwater potential in South Africa is approximately 4 500 million m^3/a of which 2 000 and 3 000 million m^3/a of the accessible water is currently being utilised (DWS, 2023). There are approximately 5000 registered water dams of which 3832 are small dams (less than 12m) that currently serve farms and municipalities (DWS, 2023). These small dams play a crucial role in local water security and climate resilience as South Africa is still heavily reliant on surface water and where there is additional water available such as the uThukela, Mzimvubu and Pongola basins (DWS, 2023). Therefore, it is important for South Africa to explore alternative water sourcing methods to ensure continued water security (DWS, 2023).

This looming water crisis poses a serious threat to key economic sectors that rely heavily on water, such as agriculture, heavy industries, and mining (Bwapwa, 2017). Mitigating this risk requires

the development and implementation of innovative strategies and policies. These strategies should focus on promoting efficient water management practices within industries, encouraging rainwater harvesting at various scales, and exploring cost-effective methods for the reuse and recycling of domestic and industrial wastewater. By actively pursuing alternative water sources and implementing sustainable water management practices, South Africa can work towards maximising and ensuring water availability for its future.

1.2. Research Problem Statement

Despite Earth's surface being 71% water, only 3.5% is readily available freshwater (USGS, 2019). The vast majority of this freshwater is locked away in ice caps and glaciers (68.7%), with groundwater accounting for 30.1% and surface water constituting a mere 1.2% (USGS, 2019). This limited availability of surface freshwater highlights its critical status as a scarce resource (USGS, 2019).

Water scarcity is an escalating global concern, particularly in developing countries (Singh et al., 2009). The imbalance between the supply and demand of freshwater plays a key role in this problem (Lani et al., 2018; Vörösmarty et al., 2000). Population growth, rising living standards, shifting consumption patterns, and increased water demands from various industries all contribute to this growing demand (Ercin and Hoekstra, 2014; De Fraiture and Wichelns, 2010; Vörösmarty et al., 2000). Furthermore, challenges like water source contamination and climate change exacerbate the situation by further straining already limited freshwater resources (Bwapwa, 2018).

Geospatial techniques and the integration of big data is of paramount importance with the increase in demand and technological advancements. Significantly, when Geospatial and big data are combined, they provide powerful insights into a wide range of problems and offer real world solutions. Therefore, this research will apply geospatial techniques with deep learning methods to achieve the aim and objectives.

1.3. Aim and Objectives

1.3.1. Aim

The study aims to model the potential rainwater harvesting sites in Lynwood Park, Pretoria South Africa.

1.3.2. Objectives

The specific objectives of this research are:

- To apply the Object-Based Image Classification (OBIC) technique for semi-automated building footprints extraction using high resolution satellite imagery.
- To map potential RWH sites in the study area using geospatial techniques.
- To calculate per capita water demand in the Lynnwood Park, Pretoria.

1.4. Research Questions

1) How efficiently and accurately can building footprints be delineated using an Object-Based Image Classification (OBIC) method?
2) How well can remote sensing data be used to classify building footprints in a complicated urban environment?
3) What are the appropriate object-based parameters and rule sets for the delineation of the building footprint?
4) How can GIS and Remote Sensing technologies are used to generate potential rainwater harvesting maps?

1.5. Structure of the research report

This research report unfolds across six chapters. The introductory chapter (Chapter 1) lays the groundwork by providing background information, the research problem statement, clearly defined aims and objectives, and the specific questions the study seeks to answer. Chapter 2, the literature review, delves into relevant scholarly works on climate change, water demand and availability, rainwater harvesting in both domestic and rooftop settings, and the overall significance of this approach. Chapter 3, dedicated to methodology, outlines the research methods. It reiterates the study's aims and objectives before describing the chosen study area, the survey procedures and sampling framework used to select participants, the methods applied for data collection, and the chosen approach for data analysis. Chapter 4 focuses on the detailed analysis of the collected data, employing appropriate methods to explore and interpret the findings. Chapter 5 presents the key findings of the research, accompanied by a thorough discussion that interprets these findings in the context of existing knowledge and the research objectives. Finally, Chapter 6, the conclusion, provides a summary of the research findings, along with any key conclusions drawn. This chapter also outlines recommendations for future research and acknowledges any limitations encountered during the study.

CHAPTER 2: Literature Review

2.1. Introduction

The chapter is divided into six main sections. The chapter commences with an introductory section (Section 2.1), which provides an overview of chapter 2. Following this, Section 2.2 delves into the introduction of climate change, expanding upon its various dimensions and implications. Section 2.3 offers a review of water demand and availability, briefly explaining the critical factors impacting water supply and consumption in South Africa. Section 2.4 offers a detailed review of rainwater harvesting and is further subdivided into two distinct subsections. The first subsection, section 2.4.1 explores the different rainwater harvesting types. It dissects the diverse approaches and gives examples of the methods employed in the practice of rainwater harvesting, offering real life insights into the applicability of rainwater harvesting.

The subsequent subsection, Section 2.4.2, is dedicated to the distinct subcategory of rooftop rainwater harvesting, focuses on rooftop rainwater harvesting, its characteristics, advantages, considerations as well as practical examples. Following these subsections is, Section 2.5, which unpacks the significance of rainwater harvesting. It encapsulates the overarching importance and implications of rainwater harvesting within the broader context of water resource management and sustainability. It consolidates the insights gathered from the preceding sections and highlights the relevance of rainwater harvesting in addressing contemporary water-related challenges.

2.2. Climate Change

Climate change stands as a significant and undeniable global challenge, with projections indicating a decline in water accessibility in the coming years, placing immense pressure on water resources (Vilane and Simiso, 2017). In South Africa, the existing water stress challenges are further exacerbated by the effects of climate change, coupled with socio-economic pressures and management difficulties (Vilane and Simiso, 2017; Kahinda, 2007). This complex situation is characterised by low precipitation rates, high evaporation, soil loss, and extreme runoff events (Kahinda and Taigbenu, 2011). Socio-economic factors add another layer of complexity. The historical legacy of apartheid has resulted in the exclusion of certain groups from accessing water

resources. This segregation led to high water demand and population density within specific areas predominantly occupied by Black communities, contributing to the current water supply crisis.

Although the precise extent of climate change remains under investigation, its consequences for freshwater resources are undeniable (Arnell et al., 2001). These repercussions directly impact sustainable development and pose a significant threat to a nation's economic progress (Kahinda et al., 2010; Rutashobya, 2008). The ramifications extend even further, potentially hindering the effectiveness of poverty alleviation strategies and jeopardising food security. Ultimately, climate change poses a risk to the well-being of both society and ecological systems (Kahinda et al., 2010; Rutashobya, 2008).

South Africa's growing water demand necessitates exploring diverse water source alternatives. Rainwater harvesting emerges as a viable option to help the country achieve its Millennium Development Goals (MDGs) for improved access to safe drinking water and sanitation (Kahinda and Taigbenu, 2011). The established link between access to clean water, sanitation facilities, and overall health underscores the importance of addressing water scarcity (Kahinda and Taigbenu, 2011). By capturing and storing rainwater, rainwater harvesting systems offer a two-pronged approach. They can directly increase the available water quantity, and as the harvested rainwater is typically free from many contaminants, it can also improve water quality (Kahinda and Taigbenu, 2011). This, in turn, can lead to improved sanitation levels within communities. Therefore, rainwater harvesting presents a promising strategy for South Africa to address both water quantity and quality challenges.

Rising temperatures and erratic rainfall patterns are stark illustrations of the current impacts of climate change, with projections suggesting Southern Africa will be particularly vulnerable (Kahinda et al., 2010). Implementing suitable adaptation strategies is, therefore, critical to address these evolving challenges. Sub-Saharan Africa (SSA) has a long history of vulnerability to floods, with the eastern, southern, and central regions experiencing the highest prevalence of these disasters, followed by the western region (Osbahr et al., 2008). Studies by Urama et al., (2010) pinpoint several SSA nations particularly susceptible to flooding, including Burkina Faso, Chad, Ethiopia, Ghana, and others. These flood events often result in fatalities, displacement, and damage

to agricultural land, settlements, and ecosystems (Urama et al., 2010). Notably, floods accounted for 26% of all drought occurrences in Africa during 1971-2001, highlighting their detrimental effects (Ngoram, 2015).

Several historical flooding events illustrate the devastating consequences of floods in Southern Africa. The El Niño-related flood of 1997/1998 in Kenya exemplifies this, causing an estimated $1.8 billion in infrastructure and property damage (Ngoram, 2015). Similarly, the 2000 Mozambique flood resulted in a significant economic downturn, with the annual growth rate decreasing from 10% to 4% (Ngoram, 2015). This catastrophic event tragically claimed 800 lives and impacted nearly 2 million people. An estimated one million individuals required immediate food assistance, and approximately 329,000 were displaced (Ngoram, 2015).

Recently, in April 2022, the eastern coastline of South Africa experienced a significant episode of heavy rainfall due to the influence of mid-tropospheric cut-off low (COL) pressure systems (Mashao et al., 2023). This meteorological event resulted in widespread flooding, causing extensive damage to residential properties, electrical transmission lines, and road networks (Mashao et al., 2023). Tragically, this catastrophe resulted in the loss of 448 lives (Mashao et al., 2023).

Floods that occur after extended dry spells are beneficial due to their ability to replenish dried up water sources such as rivers and dams offering water (Payus et al., 2020). In contrast, longer-lasting floods harm the ecosystem by causing crop failure and livestock loss. Social droughts cause displacement of families, cars, homes, and health issues (Ngoram, 2015). Economically, this results in debt, a decline in GDP, infrastructural loss, and the inability of enterprises, particularly those in the agricultural sector, to operate normally during such occurrences (Ngoram, 2015).

Sub-Saharan Africa is also characterised by the recurrence of droughts, droughts refer to a deficiency in rainfall occurring over an extended duration, typically spanning a season or longer, leading to a scarcity of water and yielding adverse consequences for vegetation, wildlife, and/or human populations (Ngoram. 2015). Drought is a recurring, inherent component of climate change that manifests across a wide spectrum of climatic zones, ranging from those characterised by high

precipitation levels to those marked by aridity. South Africa, specifically Cape Town, has experienced drought.

Cape Town's 4 million residents face an uneven water challenge. While formal housing uses two-thirds of the city's water, 14% of residents living in informal settlements make do with only 4% (CoCT 2017; Ziervogel 2019). This housing crisis is further strained by a growing population, forcing more people into informal settlements. With nearly a third of the city unable to afford water, Cape Town allocates free monthly water to these households (CoCT 2017).

Cape Town' water policy focuses on cost recovery for water services, except for free basic water allocations funded by a national grant (CoCT, 2017). However, revenue generated often falls short of covering all expenses, particularly those related to maintaining and replacing aging infrastructure. This financial strain is further compounded by the city's climate. Cape Town boasts a Mediterranean climate with warm, dry summers and cool, wet winters. Rainfall is concentrated between May and October, with annual totals ranging from 400 mm on the west coast to 2,000 mm in the surrounding mountains (CoCT, 2017). The Western Cape province has grappled with recurring droughts since June 2015, posing significant challenges for water resource management (CoCT, 2017).

A group of scientists investigating the Cape Town droughts employed a risk-based, multi-method approach to assess the impact of climate change on these events (CoCT, 2017). Their findings, based on historical rainfall patterns and dam inflow data, suggest that human-induced climate change tripled the likelihood of the 2015-2017 droughts (Otto et al., 2018). Although pinpointing the exact causes of climate change remains a complex undertaking with varying degrees of certainty depending on the methodology used, one undeniable consequence is a shift in climate risks. This is particularly concerning for Cape Town, which relies heavily on a network of six rain-fed dams for over 95% of its water needs, serving both agricultural and urban areas (CoCT, 2017). The combined storage capacity of these dams is approximately 900 million cubic meters, which is sufficient for roughly one and a half years' worth of agricultural and urban water demand, accounting for evaporation (Ziervogel, 2019). However, Cape Town consumes a significant portion (58%) of the water allocated by the Western Cape Water Supply System (WCWSS).

Agriculture utilizes 26%, smaller towns account for 6%, and evaporation claims around 10% of the available water (Ziervogel, 2019).

The increasing frequency and intensity of floods and droughts, hallmarks of climate change, underscore the need for adaptation strategies within the water industry (Kahinda et al., 2010; Rutashobya, 2008). Rainwater harvesting emerges as a promising approach for water resource management in the face of a changing climate.

2.3. Water Demand and Availability

Water scarcity and availability pose a growing threat to the global population. Over 1.7 billion people reside in watersheds where water use exceeds natural recharge rates (Marques et al., 2022; United Nations, 2019). This challenge is particularly severe in developing regions, where water scarcity creates a vicious cycle of food insecurity, poor health outcomes, and poverty (Marques et al., 2022). Conversely, even nations with abundant water resources face increasing pressure due to rising freshwater demand and declining water quality. Population growth and economic development are key factors driving these trends (Marques et al., 2022; Oki and Kanae, 2006). Water demand, as defined by Durgasrilakshmi (2019), refers to the total water use within a system, calculated by multiplying per capita demand by population and duration. Climate change is expected to further exacerbate water demand pressures (Marques et al., 2022).

Rainwater harvesting emerges as a promising solution to address water demand and supply issues. It incentivises exploring alternative water sources. For instance, Bocanerga-Martinez et al., (2014) developed an optimization-based model for designing domestic rainwater harvesting systems (RWHS). This model considers the optimal placement of RWH equipment, pipes, and reservoirs to maximise rainwater capture, distribution, and storage (Bocanerga-Martinez et al., 2014). Additionally, it aims to meet household water demand while minimising total costs associated with water supply, pumping, maintenance, and treatment. A successful implementation in Morelia, Mexico, demonstrated the potential of this approach to meet a significant portion of water demand while reducing long-term operational costs (Bocanerga-Martinez et al., 2014).

2.4. Rainwater Harvesting

Rainwater harvesting (RWH) is a technique for collecting and storing runoff for various uses, including agriculture, domestic purposes, and environmental applications (Fentaw et al., 2002; Oweis and Hachum, 2006; Stott et al., 2001). Beyond irrigation, harvested rainwater can be used for domestic activities, human consumption, and even small-scale productive endeavourss (Kahinda and Taigbenu, 2011; Oweis et al., 2001).

There are three main classifications of RWH systems, which include In-situ Rainwater Harvesting (iRWH), a system that utilises designated areas within a field or plot as the catchment zone (Kahinda and Taigbenu, 2011). Ex-situ Rainwater Harvesting (xRWH), the harvesting system draws water from an uncultivated area dedicated as the catchment (Kahinda and Taigbenu, 2011) and Domestic Rainwater Harvesting, this is where the system collects rainwater from rooftops, courtyards, or treated surfaces, storing it in tanks for domestic use (Kahinda and Taigbenu, 2011).

Despite advocacy efforts by various organizations, the adoption rate of RWH structures remains slow in South Africa (Kahinda et al., 2008). Potential reasons include inadequate attention to social factors, insufficient verified data on practical applications, and a lack of research showcasing the feasibility of rainwater collection (Kahinda et al., 2008; Rockström, 2000; Mati et al., 2006). Notably, domestic rainwater harvesting is the least utilised source, with less than 2% of rural families relying on it as their primary water source (Kahinda et al., 2007). Conversely, in-situ harvesting is the most common household approach, while ex-situ harvesting is rarely implemented (Kahinda et al., 2007, 2008).

Historically, RWH played a vital role in pre-modern water supplies for schools, farms, and hospitals (Kahinda et al., 2010). In rural South Africa, rainwater collection for domestic uses like gardening has always been a crucial component of water management, evidenced by 96% of the reported 34,000 RWH tanks being located in rural areas (Kahinda et al., 2010). RWH becomes even more critical considering South Africa's challenges with water scarcity due to uneven temporal and spatial rainfall patterns (Kahinda et al., 2010).

Several studies highlight the potential of RWH systems. For example, Zuberi et al., (2013) explored the viability of rainwater collected from dormitory rooftops at METU-NCC to supply toilet water. Their RWH system achieved 93% reliability and could collect 2,831 m^3 annually, demonstrating the potential for water-scarce regions to optimise limited resources. Strand's (2013) field study in Colombo, Sri Lanka, examined how RWH systems can contribute to sustainable water management and generate positive economic and ecological impacts. Given Sri Lanka's annual rainfall variation (2,500-5,800 mm in the southwest and 1,250 mm elsewhere), the study concluded that RWH systems offer an environmentally friendly and long-lasting solution due to their economic and environmental benefits.

2.4.1. Domestic Rainwater Harvesting

Domestic rainwater harvesting (DRWH) utilises aboveground or underground storage tanks to collect rainwater channeled from rooftops, courtyards, or treated surfaces. This harvested water can then be directed towards various domestic uses and small-scale income-generating activities (Kahinda et al., 2010). There are two main catchment area categories, allowing for above or below ground storage depending on space and needs (Kahinda et al., 2010).

DRWH offers a multitude of benefits. The harvested water can be used for small-scale productive activities like brickmaking or brewing, potentially increasing household income (Kahinda et al., 2010). It can also improve sanitation, reduce time spent collecting water (especially in rural areas), and enhance food security by mitigating malnutrition in young children (Kahinda et al., 2010).
However, limitations exist. Implementing DRWH can be expensive, requiring construction expertise and ongoing maintenance (Kahinda et al., 2010). Additionally, water service providers might experience revenue loss due to decreased water demand. Despite these drawbacks, only 1% of rural South African households utilise rainwater harvesting tanks as their primary water source (Kahinda et al., 2010).

Rainwater harvesting systems offer a solution for water access, eliminating the need for long water collection trips often undertaken by women and children in developing countries (Kahinda et al.,

2010; Ojwang et al., 2017). It can also be seen as a climate change adaptation strategy for water supply systems (Ojwang et al., 2017).

Sub-Saharan Africa, with its distinct rainfall patterns, can benefit significantly from DRWH. Factors like rainfall frequency, intensity, and system design all influence its effectiveness (Ojwang et al., 2017). Roof material also plays a vital role in both the quantity and quality of collected water. Hard surfaces like metal, concrete, and tiles collect the most water due to high runoff coefficients (Ojwang et al., 2017). However, research by Lee et al., (2012) suggests galvanised steel roofs provide the cleanest rainwater, meeting WHO drinking water standards. The roof's slope also impacts the amount of runoff collected (Farreny, 2011).

Studies by Aladenola and Adeboye (2009) in Nigeria demonstrate the potential of DRWH to meet household water needs from November to February, covering toilet flushing and washing demands with an average annual rainfall of 1156 mm. Surplus collected during peak rainfall months can even cater to drier periods. Similarly, Kahinda et al., (2009, 2010) found rainwater harvesting for drinking water to be common in rural South Africa, particularly in Eastern Cape and KwaZulu-Natal, likely due to environmental and economic factors in those regions. However, research on rooftop rainwater harvesting in South African cities remains scarce.

2.4.2. Rooftop Rainwater Harvesting

RRWH is a popular method for collecting water from rooftops and storing it in tanks for various uses. A key benefit is that the water is captured before reaching the ground, minimising contamination (Vilane and Simiso, 2017). Untreated rainwater is suitable for non-potable uses like toilet flushing, car washing, and irrigation (Norman et al., 2019; Lani et al., 2018). However, for uses like drinking, showering, and laundry, some level of treatment may be necessary (Norman et al., 2019; Lani et al., 2018).

Despite its relative cleanliness, rooftop-harvested rainwater can still contain contaminants. Therefore, water quality assessment is crucial before using it for any purpose (Norman et al., 2019). These assessments should comply with relevant water quality standards (Norman et al.,

2019). Several factors can influence the quality of rooftop rainwater, as highlighted by various studies. These factors include roof design where steeper roofs tend to shed contaminants more efficiently, potentially leading to easier treatment (Farreny et al., 2011; Ugai, 2016). Conversely, larger catchment areas might collect more pollutants (Farreny et al., 2011; Ugai, 2016). Roof Material where concrete, asphalt, and ceramic tiles can negatively impact water quality (Zhang et al., 2014). The age and condition of the roof surface also play a role, with older or weathered metal roofs potentially releasing higher levels of heavy metals (Clark et al., 2008; Gwenzi et al., 2015). Surrounding Environment where land use in the surrounding area can affect water quality. Industrial areas with air pollution and atmospheric deposition from traffic and factories can lead to poorer water quality (WHO, 2023).

Although, some studies have found that rooftop-harvested water meets water quality standards (Igbinosa and Aighewi, 2017; Vilane and Mtshali, 2015; Ghanayem, 2001), others highlight potential issues. For instance, a study by Abdulla and Al-Shareef (2009) in Jordan found that while rainwater met WHO standards for inorganic chemicals, it exceeded the fecal coliform limit, a crucial indicator of bacterial contamination.

2.4.3. The Significance of Rainwater Harvesting

Rainwater harvesting offers a compelling solution to water challenges. These systems can seamlessly integrate with existing water sources, acting as a reliable supplement during shortages (Vilane and Simiso, 2017). They provide a buffer in times of drought, emergencies, or public water system disruptions (Kahinda et al., 2010; Vilane and Simiso, 2017). Additionally, rainwater harvesting can alleviate urban flooding and storm drainage issues. Since harvested rainwater is a finite resource readily visible to users, it is likely to promote water conservation practices (Vilane and Simiso, 2017).

A recent study by Ertop et al., (2023) highlights several key benefits of rainwater harvesting. Harvested water serves as a valuable additional source during periods of scarcity. The system itself is self-sufficient and promotes responsible water resource management (Ertop et al., 2023). With proper purification, it can even provide safe drinking water. Beyond domestic uses, harvested

rainwater can be utilised for agricultural purposes like irrigation. This technique not only reduces surface water runoff but also lessens the demand for freshwater sources like rivers and groundwater (Ertop et al., 2023). A significant advantage is its adaptability – rainwater harvesting can be implemented in diverse landscapes, regardless of geological features or existing infrastructure (Ertop et al., 2023).

The harvested water can be delivered directly to homes or nearby locations, saving time and energy by eliminating the need for long-distance transportation (Ertop et al., 2023; United Nations Environment Programme (UNEP), 2022 and World Resources Institute (WRI), 2023). It also contributes to effective stormwater management by transforming rainwater into a valuable resource. This mitigates problems associated with inadequate drainage infrastructure and urban flooding during heavy rainfall events (Ertop et al., 2023; UNEP, 2022 and WRI, 2023). Furthermore, rainwater harvesting aids in flood control by minimising urban surface water runoff and protecting surface water sources from pollutants like fertilisers, pesticides, and sediment (Ertop et al., 2023; UNEP, 2022 and WRI 2023). As a cost-effective and environmentally friendly solution, rainwater harvesting offers excellent water quality. Any surplus rainwater can even be redirected to replenish groundwater supplies (Ertop et al., 2023; UNEP, 2022 and WRI 2023).

2.5. Rainwater Harvesting Site Selection Techniques and Associated Problems

An effective site selection for RWH is essential to maximise the potential for Rainwater collection and ensuring sustainability. Therefore, throughout the years, numerous site selection methods have been developed with each posing its different set of advantages and limitations. Previously, RWH site selection relied on traditional methods such as ground surveys, ground truthing and expert opinions introducing a limitation in scope (Kahinda et al., 2007). These traditional methods of RWH required high amounts of time and fieldwork which can be a challenge in large and remote areas (Mbilinyi et al., 2007). In addition, these traditional methods bypassed key spatial factors such as landuse, slope and soil type which were essential in determining optimal RWH sites according to the requirements of the studies conducted (Baguma et al., 2010).

The arrival of Geographic Information Systems (GIS) revoluntionalised RWH site selection by integrating a variety of spatial data layers such as topography, land cover, and hydrology. The integration of these layers allowed users to identify the suitable locations for RWH sites according to specified criteria's (Kahinda et al., 2008). However, despite the improvement from traditional methods, convectional GIS- based approaches rely on pixel-based classification methods which can be limited based on their spatial resolution and complexity of land cover types, specifically in heterogeneous landscapes (Zhang et al., 2014). The pixel-based approach also has challenges such as mixed-pixel problems, where different land cover types are incorrectly classified within a single pixel, leading to reduced accuracy in RWH site identification (Blaschke, 2010).

Object-Based Image Classification (OBIC) offers a more refined alternative for modeling potential RWH sites by addressing limitations of pixel-based methods. OBIC considers not only spectral information but also spatial, textural, and contextual information to classify homogeneous objects in an image (Blaschke, 2010). This method is particularly well-suited for complex and fragmented landscapes where traditional pixel-based approaches fail to accurately capture land cover heterogeneity (Blaschke, 2010). In addition, OBIC improves site selection through the integration of multiple datasets, such as satellite imagery and elevation models, to identify locations that meet optimal criteria for RWH sites, such as slope, land cover, and proximity to water bodies etc. The OBIC technique allows for more precise classification, reducing errors caused by mixed pixels and enhancing the accuracy of RWH site suitability modeling (Li et al., 2014). Therefore, considering the challenges of traditional and pixel-based geospatial methods, OBIC presents a more reliable, efficient and accurate tool for RWH site selection (Blaschke, 2010). By incorporating both spectral and contextual information, OBIC enhances the precision of land cover classification, which is essential for modeling RWH suitability, especially in regions with complex topography and land use patterns (Blaschke, 2010; Li et al., 2014) . The use of OBIC in this research addresses the need for higher accuracy in RWH site identification, particularly in developing countries where water scarcity is an increasingly pressing issue (Blaschke, 2010; Li et al., 2014).

CHAPTER THREE: Materials and Methods

3.1. Introduction

This chapter discusses the methodology that was applied in this study. According to Kothari (2004) research methodology refers to a methodical approach for addressing the research problem. It can also be described as the systematic approach in science for conducting research involving the specific methods and reasoning employed by the researcher to explore the research problem (Kothari, 2004). According to Kumar (2008), the theoretical knowledge that constitutes research methodology is structured based on the practical stages constituting the research process for both quantitative and qualitative studies. This involves the methods employed by researchers to acquire information and to carry out the tasks involved in describing, explaining, and forecasting phenomena (Rajasekar et al., 2006). In this study, we define methodology as encompassing the establishment of sample size, the selection of sampling techniques for determining the sample size, the instruments utilised for data collection, and the approach for organising and analysing the gathered data.

Chapter three delves into the research methodology, offering a comprehensive presentation and discussion. Within this chapter, Section 3.2 provides an in-depth description of the study area, whereas Section 3.3 extensively explores the survey procedures and the sampling framework. Section 3.3 is further subdivided into five segments, namely Object-Based Image Classification (3.3.1), Potential Harvested Rainwater (3.3.2), Runoff Coefficient (Cr) (3.3.3), Estimating Water Demand (3.3.4), Finally, Section 3.5 offers insights into the data analysis process.

3.2. Description of the Study Area

This study was conducted amongst household rooftops within the suburb of Lynwood Park. Lynwood Park is a tranquil residential district situated in Pretoria, South Africa. It is renowned for its serene suburban ambiance and is often favoured for its peaceful and family-friendly environment. The area typically comprises well-kept houses, tree-lined streets, and green spaces, creating an enjoyable residential setting. Situated within Gauteng province's Tshwane Metropolitan Municipality, Pretoria holds the distinction of being South Africa's administrative

capital. Jacaranda-lined streets grace this city, which encompasses an area of approximately 687.5 square kilometers. Pretoria experiences a humid subtropical climate with distinct seasons. Summers are warm, averaging 23.5°C, while winters are chilly with an average of 12°C. January marks the wettest month, while the city experiences short, dry, and clear winters.

3.3. Study Area Map

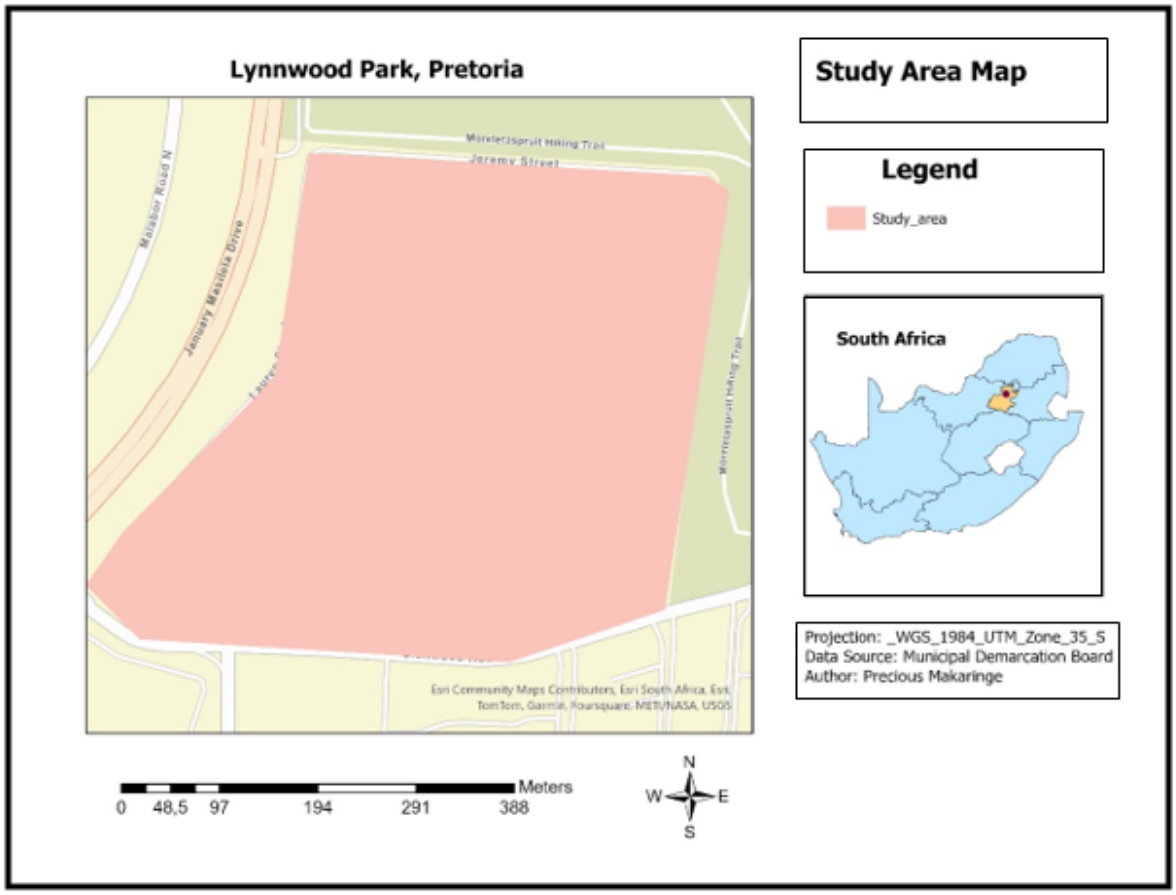

Figure 1: Study Area Map

3.4. Research Design

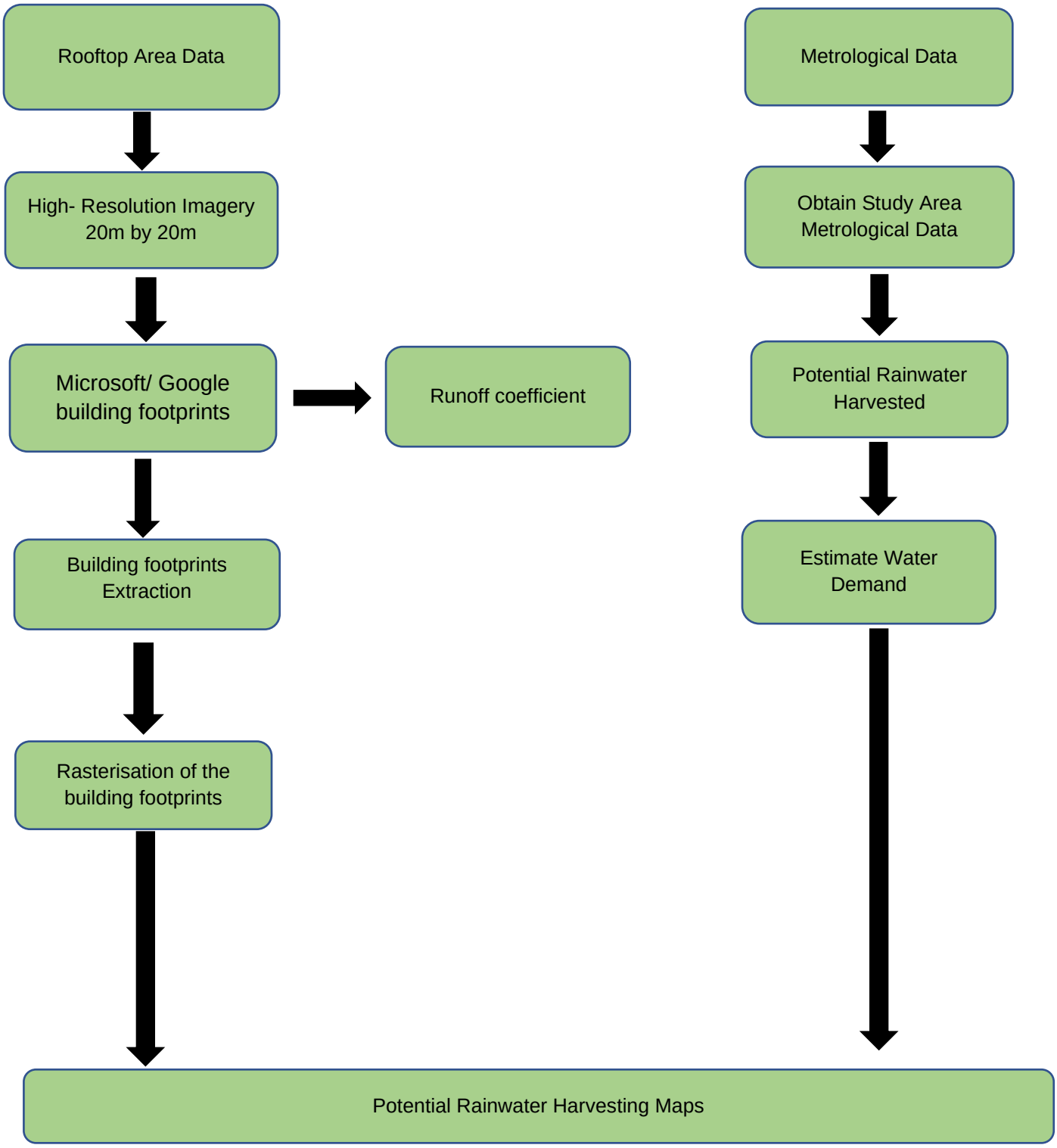

Figure 2: Methodological flow chart

3.4.1. Dataset Utilised

The study relied on two key datasets: high-resolution satellite imagery and meteorological data. The satellite imagery, acquired from Geospace International, provided detailed views of the study area. Additionally, historical meteorological data (2011-2021) was obtained from the South African Weather Service. This data included rainfall patterns and temperature information. The selection of these datasets reflects the importance of rooftops as the primary catchment surface for rainwater harvesting. Maximising rainwater collection necessitates an accurate understanding of rooftop area, which the high-resolution imagery facilitates. Table 1 provides a more detailed breakdown of the data characteristics.

Table 1:Data characteristics

Dataset	**Source**	**Spatial Resolution**	**Temporal Resolution**	**Format**
1. Atmospheric Data	South African Weather Service (SAWS)	N/A	N/A	Excel
2. Satellite Imagery	Geospace International	20m	20m	Tiff

3.5. Survey Procedures and Sampling Framework

This study aimed to model the potential rainwater harvesting sites in Lynwood Park, Pretoria South Africa. To achieve this aim, the first step was to apply the Microsoft and Google building footprints technique for semi-automated building footprint extraction using high resolution satellite imagery. The second step was to map potential RWH sites in the study area using geospatial techniques and the last step was to calculate per capita water demand in the study area. To achieve this aim ArcGIS Pro, the various tools and processes followed have been detailed within the specific sections; QGIS (pre-processing) and the various spatial analysis tools in ArcGIS Pro were utilised to effectively map the potential rainwater harvesting sites.

3.5.1. Building Footprint Extraction

Object-based image classification (OBIC) has become a popular technique for identifying and classifying features in remotely sensed imagery (Benz et al., 2004; Blaschke, 2003). Unlike traditional pixel-based approaches, OBIC groups pixels into objects based on characteristics like shape, size, texture, and spectral response. This allows for more accurate classification of features like land cover (Kressler and Steinnocher, 2008), buildings (Chen et al., 2006), and transportation infrastructure (Nobrega et al., 2008). In the OBIC workflow, pre-processed data undergoes segmentation, where the image is divided into objects based on their visual properties. These objects then have their attributes, such as size, shape, texture, and spatial context, analysed for classification**.**

While Object-Based Image Classification (OBIC) was previously a popular method for extracting building footprints, recent advancements favour pixel-based or patch-based approaches powered by deep learning (Huang et al., 2020). OBIC suffers from two main drawbacks. First, selecting parameters during the segmentation stage can be time-consuming (Huang et al., 2020). Second, the segmentation process may not always accurately represent the target objects, potentially compromising results (Huang et al., 2020). An additional limitation of OBIC is its incompatibility with deep learning techniques, which are generally considered more powerful and advanced than traditional machine learning methods used in OBIC (Hongjie et al., 2020; Shu 2014). While OBIC can be combined with traditional methods like surveying, these approaches can be labor-intensive and time-consuming, further hindering practicality (Hongjie, 2021). For these reasons, building footprint extraction techniques that leverage deep learning, such as those offered by Microsoft and Google, have gained popularity due to their superior efficiency and accuracy.

Although Microsoft and Google Building Footprints parameters are unknown, the parameters for Google's deep learning models include network architecture, learning rate, batch sizes, and data augmentation techniques (Google Open Buildings, 2024). The parameters for Microsoft's deep learning models include architectural configurations, optimization algorithms, regularization techniques, and hyperparameters such as learning rate and dropout probability (Microsoft, 2024). Google leverages on its broad repository of high-resolution satellite imagery and applies state of

the art deep learning architectures to generate their building footprints. Google applied the convolutional neural networks (CNNs), specifically the U-Net architecture for semantic segmentation of buildings from satellite imagery (Google Open Buildings, 2024). The U-Net architecture with its encoder-decoder structure, has demonstrated remarkable performance in various image segmentation tasks, making it suitable for extracting building footprints accurately (Google Open Buildings, 2024). In addition, Microsoft applies a similar deep learning approach for the generation of its building footprints, using its Bing Maps platform and proprietary aerial imagery datasets (Microsoft, 2024). Similarly, to Google footprints, Microsoft applies convolutional neural networks; however, it may use variations in architecture and training strategies tailored to their specific datasets and requirements (Microsoft 2024).

There are many data sources for characterising the built environment. However, building footprints have been regarded as the most useful for several purposes from services such as OpenStreetMap to other population modelling methods such as Worldpop as well as LandScan (Gonzalez, 2023; Boo et al, 2022 and Moehl 2021). At large scale, the building footprints are generated from satellite imagery through automated machine learning models such as Continental-Scale Building Detection from High Resolution Satellite Imagery, Convolutional Neural Network and Microsoft global ml footprints (Gonzalez, 2023). Alternatively, volunteers are used to manually digitize building footprints as in the case of OpenStreet (Gonzalez, 2023 and OpenStreet Map Contributors, 2023). In addition, Google and Microsoft have both released expansive datasets of building footprints, the datasets can be used by the public by various industry professionals such as researchers, analysts among others (Gonzalez, 2023). The Microsoft and Google building footprints contain massive datasets which cover multiple continents, seeking to expand its continent footprint availability (Gonzalez, 2023). In addition to Micorsofts' 1.2 billion building datasets covering, Europe, Americas, Africa as well as Asia, they have released several independent country-scale datasets including the 2018 dataset for the United States (Microsoft, 2024).

The Google Open Buildings dataset emerged with a near complete mapping buildings of Africa, later expanding to Asia and the Americas covering 1.8 billion buildings (Google Open Buildings 2024). Microsoft and Google building footprints both utilise the convolutional neural network-

based semantic segmentation models to identify buildings by classifying pixels in high-resolution satellite imagery (Gonzalez, 2023). The buildings are classified as building or non-building, after the classification, the building footprints polygons are generated from the positively classified pixels (Google Open Buildings, 2024; Microsoft, 2024 and Sirko et al., 2021). While both these datasets provide and efficient and excellent data resource for geospatial applications, they vary in quality, accuracy and completeness (Gonzalez, 2023). Sometimes requiring the use of both building footprints to determine which would be applicable for the study area. Therefore, for the purposes of extracting the building footprints of this study, both Microsoft and Google footprints were utilised. However, the google footprints were processed before they were analysed, the preprocessing step was done of QGIS.

3.5.2. Potential Harvested Rainwater

Annual average rainfall on a rooftop significantly influences the potential rainwater harvest (Gould and Nissen-Petersen, 1999). To estimate this potential, this study employed a modelling equation from Gould and Nissen-Petersen (1999).

$$S = R \; x \; A \; x \; Cr \qquad \textit{Equation 1}$$

Where:

S= Potential rooftop rainwater harvesting,

R= Average annual rainfall in mm,

A=Roof Area in square meters, and

Cr= runoff coefficient.

The rationale behind this specific equation is due to its simplicity and relevance to the study. The equation is straightforward and involves multiplying the average annual rainfall (R), roof area (A), and runoff coefficient (Cr). Its simplicity makes the equation easy to understand, calculate, and apply in various contexts and studies. In addition, the variables in the equation (R, A, Cr) are directly related to rainwater harvesting. Average annual rainfall is a crucial factor, as it determines the potential water supply. Roof area represents the collection surface, and the runoff coefficient accounts for the efficiency of water collection.

The sources of data for the variables can be obtained from distinct sources for examples, rainfall data can be obtained from meteorological agencies, weather stations, or historical records. The accuracy depends on the quality and precision of the data source. Weather stations and reliable historical records are generally considered accurate. In this instance, rainfall data was sourced from the South African Weather Services (SAWS), the agency offered data from two weather stations, one is stationed at the university of Pretoria and the other at the University of South Africa (UNISA). The rationale behind using data from two weather stations is while one station had not recorded rainfall data, the other station would have recorded it. Any errors or inaccuracies can be attributed to months or years where both weather stations have not recorded any atmospheric changes.

Roof area can be measured directly or obtained from architectural plans. The accuracy depends on the precision of the measurement or the reliability of the plans. In this study, the Roof Area was determined through ArcGIS Pro. Any errors or inaccuracies can be attributed to any to infrastructural changes or changes to the buildings. The Runoff coefficient represents the proportion of rainfall that becomes runoff. It can be determined through empirical methods or using coefficients for different types of surfaces. The accuracy depends on the appropriateness of the coefficient for the specific roof type and conditions. In this study the Runoff coefficient was determined through the most common rooftop type in the study area. The common rooftop type was determined through Google Earth Pro.

Potential sources of error in the equation include, assumptions, rooftop condition and climate change. The equation assumes a constant runoff coefficient, which might not be accurate if the roof characteristics change over time. Changes in roof condition, for example, dirt and debris can affect runoff coefficients and, consequently, the accuracy of the equation. Long-term shifts in climate patterns can impact rainfall data, affecting the accuracy of predictions based on historical records.

3.5.3. Runoff Coefficient (C_r)

The runoff coefficient, as defined by Biswas and Mandal (2014), represents the proportion of rainwater that flows off a surface compared to the total rainfall. A coefficient of 0.75 indicates that

75% of rainfall is collected. Studies by WMS Runoff Coefficient (2020) suggest that rooftops typically have a runoff coefficient between 0.75 and 0.95, signifying a high rainwater collection potential (Biswas and Mandal, 2014). Importantly, factors like roof material and slope can influence this coefficient (Biswas and Mandal, 2014).

Roof material plays a dual role, affecting both the amount and quality of harvested rainwater (Biswas and Mandal, 2014). While painted roofs are sometimes used for rainwater harvesting, it's essential to ensure the paint is non-toxic and doesn't contaminate the collected water (Biswas Mandal, 2014). Generally, impermeable roofs yield a higher volume of cleaner runoff, suitable for various domestic uses like drinking, cooking, and washing (Biswas and Mandal, 2014). This study will determine the appropriate runoff coefficient based on the dominant rooftop type in the study area. Table 2 shows the runoff coefficients for the different catchment types that will be used in the study area. Using Google earth and the high satellite resolution imagery, the study was able to determine the most frequent rooftop types in the study area. The building footprints were extracted using Google and Microsoft building footprints. The catchment types were obtained through google earth, and the runoff coefficient will be determined based on the most frequently used rooftop.

Table 2: Runoff Coefficients for Different kind of Catchments

Type	**Runoff coefficient**
Galvanised iron sheet	>0.9
Corrugated metal sheet	0.7–0.9
Tiles	0.8-0.9
Concrete	0.6–0.8
Brick pavement	0.5-0.6
Rocky natural catchment	0.2–0.5
Soil with slope	0.0–0.3
Green Area	0.05–0.1

3.5.2. Mapping potential RWH sites

To achieve the of modeling the potential rainwater harvesting sites in Lynwood Park, Pretoria South Africa, several datasets were applied on ArcGIS Pro. The datasets used for modelling the rooftop rainwater harvesting structures include, the high satellite imagery of Lynnwood Park, the Digital Elevation model (DEM), the building footprints and rainfall data. The building footprints were extracted on ArcGIS Pro using the Google and Microsoft Google footprints. The SAWS rainfall data was processed on QGIS and exported into ArcGIS Pro. As mentioned in section 3.6.1. the building footprints were generated using both Microsoft and Google building Footprints. However, for the purposes of this study the focus was on applying the Google footprints because they extract more buildings over the study area in comparison to Microsoft building footprints.

Acquiring the DEM was an important step in achieving the aim and objectives of the study area as it would determine the steep and gentle slopes to identify the areas of high infiltration and low infiltration. Some of the challenges encountered when mapping the rainwater harvesting sites pertained to the data acquisition. Downloading the DEM from USGS was a successful step, however, due to the size of the study area, the DEM would not show the variations of elevation over the study area. Therefore, alternatives were explored such as collecting the X and Y coordinates of the study area using Google Earth Pro, GPS visualiser was used to generate the Z coordinates. GPS Visualiser adds the heights as points and it extracts a Y, Z GPX output file. The next step was to generate a DEM from the GPX file by using ArcGIS Pro conversion tool, converting from GPX to features. Since the collected points represent discrete locations with elevation values, they don't inherently create a continuous elevation surface. Therefore, the spatial analyst tool was used to interpolate the data, this tool interpolated unknown elevation values for areas between the collected points based on the inverse distance weighted (IDW) method. The rule of interpolation is that points closer to a specific location have a greater influence on the interpolated elevation value for that area compared to distant points. The advantages of applying the IDW interpolation to the study area are that it created a more detailed DEM compared to the imagery that was downloaded on USGS and it estimated the elevation of unsampled areas. A limitation of this method would be that it assumes a smooth variation in elevation between points. Therefore, it would not be ideal for areas with abrupt changes in slopes however, this is not a

limitation in the study area. Through the application of the IDW interpolation the DEM was generated, and the contours were generated using the surface analysis tool in ArcGIS PRO and the steep and gentle slopes were determined a

In addition, to identify the rooftop areas based on the building footprints and elevation data, the building footprints were rasterised and overlayed with the DEM to extract the building footprints. Precipitation data was then incorporated to calculate the potential rainwater accumulation on each rooftop area based on its surface area, slope and rainfall data. Before the rainfall data could be clipped using the buildings footprints, the vector Microsoft building footprints were converted to raster format. The next step was to model surface water flow paths from rooftops to the designated collection points (potential sites), this process involved analysing the slope and direction of the terrain to determine the flow paths. These steps have been visualised in Figure 15.

3.5.4. Estimating Water Demand

The first step was to determine the population in Lynnwood Park. An Anonymous online questionnaire was administered, specifically targeting household heads. The questionnaire remained anonymous to maintain participant confidentiality and privacy of the information collected. The survey was conducted from July to August 2020 (this was before registration for my MSc). The respondents were selected through a random sampling procedure. According to Leedy and Ormrod (2015), a random sampling procedure is a probability sampling method which ensures that each unit of the study population stands an equal chance of being selected for the research (Leedy and Ormrod, 2015). Therefore, when a random sample is used, the researcher can assume that the sample characteristics are an approximate representation of the entire population (Leedy and Ormrod, 2015).

In total, 130 questionnaires were administered to household respondents during the data collection process. However, only 98 were successfully populated, thus yielding a response rate of 75%. The questionnaire was targeted at household heads, this was done to reduce redundancy of collected information or multiple people completing the questionnaire per household. However, the questionnaire was anonymous therefore, there is a possibility that there was more than one

respondent per household. However, a method to mitigate risks the of over respondents was balancing the number of respondents to the number of questionnaires administered. These interviews were conducted in English although translations into some of the official languages of South Africa such as Xitsonga, isiZulu, Northern Sotho, and Tshivenda, whenever the respondents experienced any difficulties in understanding the interview questions.

The average number of residents per household in Lynwood Park was estimated based on data collected through questionnaires. The equation below was applied to estimate the water demand.

$$Water\ \ Demand = Per - capita - demand\ x\ Population\ x\ Number\ of\ days \qquad Equation\ 2$$

According to a study by Durgasrilakshmi (2019), per capita water demand refers to the average amount of water required per person for various uses, including domestic, industrial, and commercial sectors. Equation 2 mentioned above was employed to calculate the estimated water demand in Lynwood Park. The analysis then compared this demand with the rainwater harvesting potential to assess the sufficiency of rainwater as a water source**.** Significantly, per capita water demand varies according to sectors, industries or water uses. Determining per-capita demand involves a comprehensive analysis of various factors, and the specific uses (domestic, industrial, commercial) play a crucial role in shaping these calculations. Therefore, it is essential to consider the unique characteristics of each sector and the diverse needs of the population to derive accurate per-capita demand figures.

3.6. Data Collection Methods

For the building footprints extraction 20m-by-20m Satellite imagery data was requested from GeoSpace International, a leading aerial photography service provider in Africa. The Microsoft and Google building footprints were downloaded on their respective sites (Microsoft, 2024 and Google Open Building, 2024) and utilised to extract the building footprints. However, Google footprints required pre-processing on QGIS before they can be analysed. As opposed to the Microsoft building footprints, Google are not already processed.

3.7. Data Analysis

3.7.1. Building Footprints Extraction

The data for the building footprints were downloaded from Microsoft's Global Building Footprints and Google's Open Buildings datasets. The google footprints required to be processed before they can be analysed, the preprocessing step was done of QGIS. The pre-processed imagery for Google footprints was then applied to ArcGIS Pro to extract the building footprints, in relation to footprint geometry, Google offers a confidence value with each footprint, as well as guidelines on suggested confidence thresholds to achieve a precision of 80%, 85% or 90%. As a result, this confidence value allows Google to include multiple geometries in their data, most of which may be false detections that can be filtered out by applying the prescribed confidence thresholds (Gonzelaz, 2023 and Sirko et al., 2023). Specifically, in areas where natural building materials are common and the buildings may be confused with rocks and other landscape features (Sirko et al., 2023). In contrast, Microsoft does not include or report confidence values, however, it does report that their data achieves 94.4% precision in Africa (Gonzelaz, 2023), The Microsoft and Google building footprints have both reported a recall of roughly 70% (Google Open Buildings, 2023; Microsoft, 2023).

3.7.2. Mapping potential RWH sites

The datasets used for modelling the rooftop rainwater harvesting structures include, the high satellite imagery of Lynnwood Park, the Digital Elevation model (DEM), the building footprints and rainfall data. The DEM were generated on Google Earth Pro, and then interpolated on ArcGIS Pro. The SAWS rainfall data was processed on QGIS and exported into ArcGIS Pro. As mentioned in section 3.6.1. The building footprints were generated using both Microsoft and Google building Footprints. In addition, to identify the rooftop areas based on the building footprints and elevation data, the building footprints were rasterised and overlayed with the DEM to extract the building footprints. Precipitation data was then incorporated to calculate the potential rainwater accumulation on each rooftop area based on its surface area, slope and rainfall data. The rainfall data was interpolated using the IDW Technique.

The next step was to model surface water flow paths from rooftops to the designated collection points (potential sites), this process involved analysing the slope and direction of the terrain to determine the flow paths. To do this analysis, a DEM was created from Google Earth Pro in the form of a CSV file and an elevation component was created using GPS Visualiser. This was then imported into ArcGIS Pro. This DEM applied hillshade using the symbology tool in ArcGIS Pro as ArcGIS Pro performs an accurate interpolation. This was necessary for understanding the topography of Lynnwood Park. Furthermore, contour lines were generated from the hillshade using the contour tool from the Spatial Analyst toolbox suite. This gave a clear indication of the direction of the terrain to determine flow paths of the rainfall.

3.7.4. Modelling potential rainwater harvesting structures

Building on the initial analysis in section 3.7.3 (above), the next section focused on modelling potential rainwater harvesting sites and depicting the spatial distribution of rainwater collection potential. A crucial step involved modelling surface water flow paths from rooftops to designated collection points. Slope plays a critical role in rainwater harvesting efficiency (Jacovides et al., 2017). Steeper slopes can effectively channel rainwater runoff towards collection tanks, maximising the amount of rainwater captured (Jacovides et al., 2017). In contrast, very flat rooftops may require additional design considerations to ensure proper drainage, while very steep slopes might pose challenges for installing collection systems.

To model these flow paths, a Digital Elevation Model (DEM) was created from Google Earth Pro data in the form of a GPX file. This DEM was then processed in GPS Visualiser to generate an elevation component. Once imported into ArcGIS Pro, Inverse Distance Weighted (IDW) interpolation was applied to create a smooth representation of the terrain's elevation. Finally, contour lines were generated using the Spatial Analyst toolbox suite, providing a clear visual representation of the terrain's slope and direction. By analysing this map, particularly the distribution of steep and gentle slopes, suitable locations for above ground and underground tanks could be identified and mapped. This comprehensive analysis directly addresses the study's aim of identifying optimal locations for rainwater harvesting sites. For instance, rooftops situated on

steeper slopes have the potential to harvest larger volumes of rainwater due to efficient flow towards collection tanks.

3.7.3. Estimating Water Demand

The primary data collected during the questionnaires and the atmospheric data requested from the South African Weather Services were stored in Microsoft Excel. The study also used both descriptive and inferential statistics. According to Leedy and Ormrod (2015), descriptive statistics are used to describe a body of data. The data is presented in the form of descriptive statistics consisting of tables, line graphs, histograms, and bar graphs. It was also presented in the form of inferential statistics, which are known for allowing the researcher to make references to populations from their smaller samples (Leedy and Ormrod, 2001). To analyse and map the potential rainwater harvesting sites, ArcGIS Pro was utilised.

ArcGIS Pro was selected over other software due to its powerful GIS (Geographic Information System) software with capabilities well-suited for mapping potential rooftop rainwater harvesting (RRH) sites. its strength lies in analysing spatial data (roof area, rainfall) and creating suitability maps. ArcGIS Pro excels at integrating various data types and offers robust visualization tools for clear communication. Identifying ideal locations for rooftop rainwater harvesting (RRH) requires analysing factors such as roof area and rainfall patterns. ArcGIS Pro excels with this task due to its robust spatial analysis tools. The roof area can be calculated using the “Measure Area” tool and integrated rainfall data for insightful analysis. It allows for the integration of building footprints, rainfall data and even elevation models for a comprehensive assessment. While alternatives exist, ArcGIS Pro's comprehensiveness makes it a powerful choice for complex RRH mapping projects.

CHAPTER 4: RESULTS

4.1. Introduction

This chapter is dedicated to analysing the results of this study, which were obtained from the data collection phase. It is important to present and discuss the views obtained from the research participants. Each section speaks to the findings of the data collection. The first section is dedicated to presenting the Microsoft and Google building footprints extractions outputs. The purpose of this is to provide a map illustrating the potential rainwater harvesting sites in Lynnwood, Pretoria. The sites were mapped out using the ArcGIS Pro software, applying its various spatial analysis tools. The second section is dedicated to presenting the atmospheric (rainfall and temperature) information in Pretoria for a period of eleven years (2012-2022). The purpose of this is to provide further understanding of the impacts of climate change by analysing the relationship between temperature and rainfall. This will be achieved by indicating the months with increased rainfall amounts for potential rainwater harvesting. In addition, the study will estimate the water demand per capita. In view of the above, this chapter is structured around the research questions, which were stated in chapter one of this dissertation.

4.2. Extraction of the building Footprints

Through the application of Microsoft and Google building footprints, the estimation of roof area catchments was calculated using the "Area Measurement" tool in ArcGIS Pro. This step was crucial in calculating the area of each building’s footprint. This represents the potential rainwater collection area of Lynnwood Park. The application of geospatial techniques to the study area, as shown in the figures 4 and 5 encompasses 146 Microsoft building footprints and 338 Google building footprints.

4.2.1. Lynnwood Park Total Area

As shown in Figure 4 below, the "Measure Area" tool in ArcGIS Pro was used to calculate the area of a residential area, resulting in a value of 203,390.73 square meters.

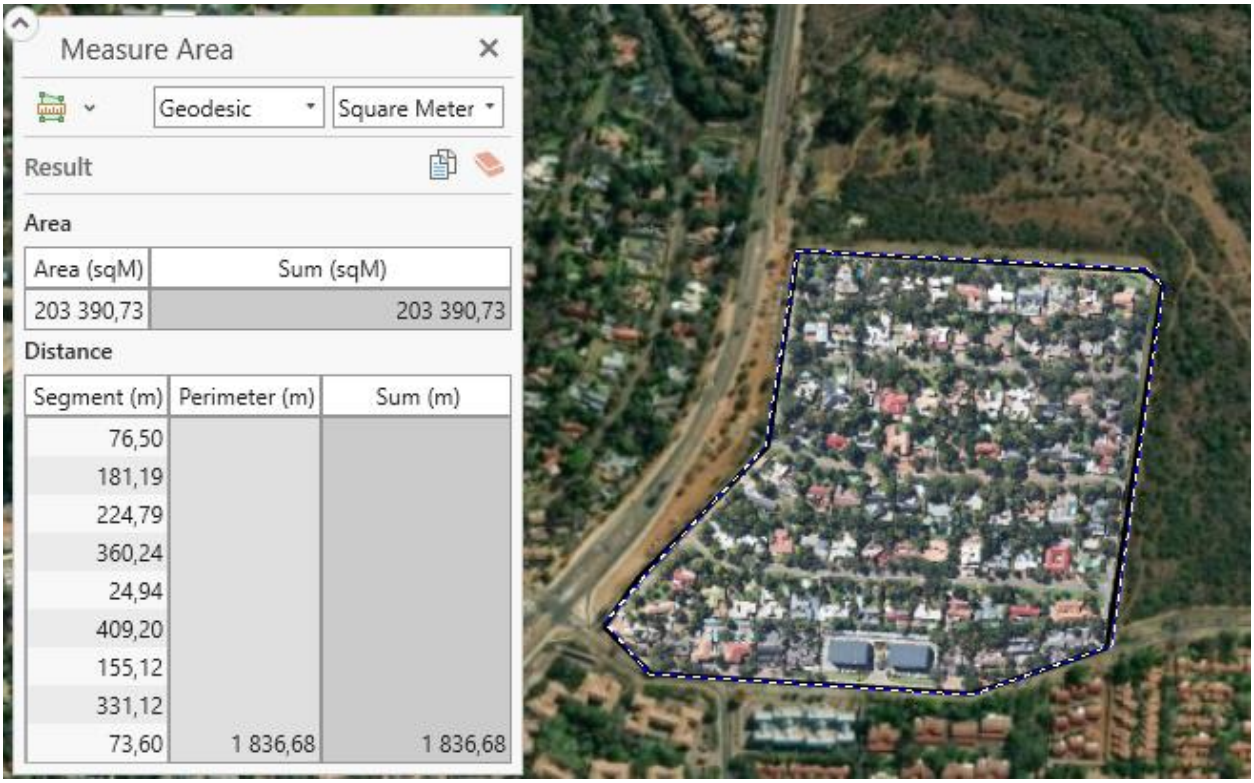

Figure 3: Lynnwood Park Total Area

4.2.2. Lynnwood Park Building Footprints

Building footprints of Lynnwood Park Pretoria were generated using two techniques, the Microsoft and Google building footprints, both of which apply deep learning techniques. The advantages of Google building footprints include its granularity and open access. Due to their granularity, they have the ability to represent individual buildings with greater detail, this is specifically beneficial for applications that require precise building- level analysis (Google Open Buildings, 2023) such as achieving the aim and objectives of this study. Secondly, Google provides its building footprints through a permissive license, this allows for broader use by researchers and developers (Google Open Buildings, 2023). In contrast, limitations include reliance on imagery as well as potential undercounting. The accuracy of Google's building footprints hinges on both the quality and resolution of the underlying imagery. Therefore, in areas with persistent cloud cover or low-resolution, the accuracy may be compromised (Google Open Buildings, 2023). In addition, its focus on individual buildings might lead to undercounting structures that are part of larger complexes (Google Open Buildings, 2023).

Furthermore, the advantages of Microsoft building footprints include LiDAR integration and High Precision (Microsoft, 2024). The incorporation of LiDAR data can potentially enhance footprint accuracy, specifically in capturing complex shapes and building heights (Microsoft, 2024). Its Precision values in Africa, suggest a high success rate in identifying real buildings (Microsoft, 2024). However, unlike Google footprints, its less granular and Limited Open access (Microsoft, 2024).

The main aim of extracting building footprints for rooftop rainwater harvesting (RRH) is to identify potential locations where RRH systems could be implemented effectively. Building footprints provide crucial information about the roof area, spatial distribution and integration of other data such as elevation. The surface area of the roof is a key factor in determining the potential rainwater collection capacity. Extracting building footprints allows for calculating the area of each roof, which directly translates to the potential volume of rainwater that can be harvested. Building footprints reveal the geographic locations of potential RRH sites. This information is essential for understanding the overall rainwater harvesting potential within a specific area and prioritising locations based on factors like water demand or infrastructure needs. Building footprints serve as a base layer for integrating other relevant data for RRH analysis. This can include rainfall data and elevation data. Overlaying rainfall data on top of building footprints allows for estimating the potential rainwater volume based on historical precipitation patterns while the Digital Elevation Models (DEMs) can be used to analyse roof slope, which can influence rainwater collection efficiency.

Figure 4 displays the results related to the Microsoft building footprints, whereas Figure 5 displays the results for the Google building footprints. These deep learning techniques, apply a semi-automated tool for clipping and mapping building footprints to calculate the total land use. In addition, due to Google building providing a more accurate extraction of the study area, they were preferred across the study area. The total rooftop area for Lynnwood Park using Google footprints in relation to the 336 buildings is a sum of 41, 511.50m

Figure 4: Microsoft building footprints.

Figure 5: Google building footprints.

As shown in figure 6 below the Google building footprints extracted more buildings as compared to the Microsoft buildings footprint. Therefore, for the purposes of this study, Google footprints were preferred for this study area.

Figure 6: Combined building footings.

One key difference lies in the level of detail and granularity. Google's building footprints boast higher granularity, allowing for a more precise representation of individual buildings. This is particularly beneficial for studies like this one, where accurate building area measurements are essential for calculating rainwater harvesting potential. Additionally, Google's open-access license allows for broader use by researchers, fostering further exploration of RWH possibilities. However, it is important to acknowledge potential limitations associated with Google's reliance on imagery. Cloud cover or low resolution can compromise accuracy, and a focus on individual buildings might lead to undercounting structures within larger complexes. The selection of Google's footprints over Microsoft's in this study reflects the prioritisation of detail and open access for a comprehensive assessment of RWH potential in Lynnwood Park.

While an ideal scenario would involve validating the extracted footprints using ground-truth data from on-site surveys or high-resolution imagery, this process was not conducted within the scope

of this study. However, Google Earth Pro was employed to visually inspect the satellite imagery used to generate the building footprints. Through this inspection, it was possible to identify some buildings that were not extracted by the automated process. These discrepancies highlight the potential limitations of relying solely on automated footprint extraction and underscore the importance of considering these limitations when interpreting the results. Future studies could benefit from incorporating a more rigorous validation process to enhance the accuracy of the building footprint data.

As shown in table 3 below, Microsoft produced fewer, larger building footprints, some rooftop buildings were not mapped out, covering a total of 146 rooftops. In contrast, Google produced more footprints covering 338 rooftops. In both datasets, the majority of buildings had at least one matching footprint. Therefore, for the purposes of obtaining the objects of this study and the accuracy of the building footprints, this study used Google building footprints. The differences noted in the Microsoft and Google building footprints are less likely be attributed to imagery differences, but rather how the two models have defined and separated buildings and the difficulty associated with matching footprints in dense urban areas.

Table 3: building footprints.

Dataset	Total Buildings
Microsoft	146
Google Building	338

4.2.8.1 Potential Rainwater Harvested (PRWH) Rooftops

In order to determine how much rainfall in volumes (litres) can be harvested by rooftops and building footprints was converted from meters to litres as rainfall coverage in an area was measured per square meter. The equation detailed below was applied for calculating the PRWH by rooftops. Recalling that the buildings footprints accumulate an area of 41, 511.50m, this area was used to calculate the Average Potential Rainwater Harvested (APRWH) by the building footprints from the rainfall data in liters. Equation 3 below was applied:

$$\frac{Area\ of\ catchment\ in\ sq.m}{Rainfall\ in\ (m)}\ x\ Rainfall\ x\ 12\ months\ x\ 11\ years$$

Equation 3

The Equation applies the presumption that every square meter of the building footprints received 10 liters of rainwater with a rainfall of 10 mm.

$$Building\ Footprints = \frac{41{,}511.50m\ (converted\ from\ hectares\ to\ meters)}{10}\ x\ 0.9\ = 3\ 736{,}035\ Litres$$

Where 41 511.50m is the area of the buildings footprints in meters, 10 is the distributed rainfall rate (mm), and the 0.9 is the common runoff coefficient for the rooftops in Lynnwood Park. This implies that the building footprints had a potential of harvesting 3 736, 035 litres of rainfall at a rate of 10mm from 2012-2022. This indicates that's rainwater can be harvested from rooftops.

4.3. Potential Harvested Rainwater

The Atmospheric data requested from the South African Weather Services contained information recorded from two weather stations for the specific study area. Data Station 05133460, Pretoria Unisa located at -25.7660 28.2000 at 1439 meters and data station 0513435A4, Pretoria University Proefplaas located at -25.7520 28.2580 at 1380 meters. The figures below illustrate the results from the two weather stations. The purpose of this was to analyse whether there would be any variations between the weather stations during the study period.

The annual potential of the rainwater harvested was determined by applying Equation 1 from Chapter three

$$S = R\ x\ A\ x\ Cr \qquad \text{Equation 1}$$

This calculation involves multiplying the annual average rainfall, runoff coefficient, and the rooftop catchment area to estimate the potential amount of collected rainwater.

The potential rainwater harvest is shown in table 4 and 5 for the periods of 2012 to 2022 from the two data stations. As indicated in table 4, Lynnwood Park received high rainfall in January, March,

November, and December; the years with the highest recorded rainfall are 2014, 2022, 2021, 2020, 2016, 2017, 2019, 2012 and 2013. On average during the periods 2012 to 2022, the area had received 585,82 mm of consolidated rainfall average per annum. Applying the average rainfall figures derived from the Pretoria Unisa data station into the model equation, the potential rainwater harvested for the years mentioned above with the highest rainfall are 2 513 263 litres.

The potential rainwater harvest is shown in table 4 for the period of 2012 to 2022 from the Pretoria University data station. According to the station, Lynnwood Park received high rainfall between the months January, February, March, April, November, and December, the years with the highest rainfall are 2014, 2021, 2022, 2017, 2020, 2016, 2018, 2019, 2013 and 2012 respectively. On average in the period 2012 to 2022 had 677,45 mm consolidated rainfall average per annum. Applying the average rainfall figures derived from the Pretoria Unisa into the model, the potential rainwater harvested for the years mentioned above with the highest rainfall are 2 849 389 liters.

Table 4: Potential Rainwater Harvested (PRWH), Pretoria Unisa Data Station

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Totals
Jan	81,6	48,0	79	73,4	127,6	148,4	78,4	42,8	91,8	148,8	147,2	**1067**
Feb	46,8	45,8	146,4	25,6	40,0	71,0	39,0	0,0	49,6	65	142,8	**672**
Mar	18,4	40,2	282,4	75,4	199,8	33,0	224,4	5,8	55,4	73	30,6	**1038,4**
Apr	4,2	70,4	12,2	38,8	14	19,2			145,2	41,2	174,4	**519,6**
May	0	0	0,2	0	38,4	20,8			0	0,8	16,6	**76,8**
Jun	0	0	2,4	0,8	11,2	0			5,4	0	2,4	**22,2**
Jul	0	0	0,2	9,4	5	0,2	13,2	0	0	0	0,8	**28,8**
Aug	0	3,2	18,2	0	0	0,0	1,8	0	0	0,2	0,2	**23,6**
Sep	61,6	5	0,6	52,8	4,8	28,4	16,4	0,6	10,2	41,4	0	**221,8**
Oct	78,7	81,8	36,6	10	50,4	69,8	58,2	9,8	93,8	58	61,8	**608,2**
Nov	81,4	83,8	101,2	49,6	85,2	56,6	25,0	142	238,2	137,2	176,6	**1176,8**
Dec	143,2	128,2	241	56,6	77,4	111,4		326,8	117,4	275,6	97,0	**1574,6**
Total	**515,2**	**506,4**	**920,4**	**392,4**	**653,8**	**558,8**	**456,4**	**527,8**	**807**	**841,2**	**850,4**	**5962,2**
Avg	**42,93**	**42,20**	**76,70**	**32,70**	**53,48**	**46,57**	**38,03**	**43,98**	**67,25**	**70,10**	**70,87**	**585,82**
PRWH	**238675**	**234598,2**	**426390,6**	**181785,8**	**302883,7**	**258973,4**	**211434,9**	**244512,1**	**373856,2**	**389699,9**	**393962**	**3256672**

Table 5: Potential Rainwater Harvested (PRWH), Pretoria University Data Station

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Totals
Jan	63	53,6	46	101,4	128,4	195,6	76	74,2	104	206,8	155,8	**1204,8**
Feb	108,4	62,2	178,8	25,4	62,8	179,8	103,4	136,4	29,2	96,4	138,8	**1121,6**

Mar	67,4	31,8	293,6	67	182,4	24,4	238,8	17,2	88	73	80,2	**1163,8**
Apr	15,4	15,4	118	28,6	14,4	107,4	89	76,2	132,4	37,8	155,2	**683,6**
May	0	0,6	0	0	55,8	21,2	15,4	0	0	3	16,8	**112,8**
Jun	0	0	0	0,8	12,8	0	0	0	1,4	0	21	**36**
Jul	0	0	0	7,4	3,2	0	1	0	0	0	0,8	**12,4**
Aug	0	3	0	0	0	0	0,8	0	0	0	0,2	**4**
Sep	48,2	8,4	0,4	43,4	3,6	23,6	12,6	0,4	7,8	52,8	0	**261,2**
Oct	42,6	115,4	34,6	8,2	60,2	96,8	77,8	26,4	83,2	51,6	95,8	**692,2**
Nov	57	121,4	127	49,8	118,8	68	11,8	142,8	222	158,2	171	**1247,8**
Dec	164,2	163,4	290,8	68,2	88,2	122,4	82	208,6	121,4	287,4	52,2	**1648,8**
Total	**566,2**	**575,2**	**983**	**400,2**	**730,6**	**839,4**	**708,6**	**682,2**	**789,4**	**976**	**887,8**	**8129,4**
Average	**47,2**	**47,9**	**81,9**	**33,4**	**60,9**	**69,6**	**59,1**	**56,9**	**65,8**	**80,6**	**74,0**	**677,45**
PRWH	**262301,6**	**266471**	**455391**	**185399,3**	**338462,6**	**388773,4**	**328270,8**	**316040,5**	**365702,7**	**447978,9**	**411288,1**	**3766080**

Figure 7 below shows the average monthly maximum temperatures for a period of 11 years (2012 to 2022). The temperatures range between 0 and 35 °C. According to the figure 8, the years with the highest temperatures are 2015 (28.9°C), 2021 (26.9), 2017 (26.6), 2014 and 2020 (tie with 26.5 °C), 2014 and 2015 (26.5°C). The months with the highest temperatures are October, November, December, January, and February, which are classified as the summer months, indicating that the high amounts of rainwater can be harvested during these months.

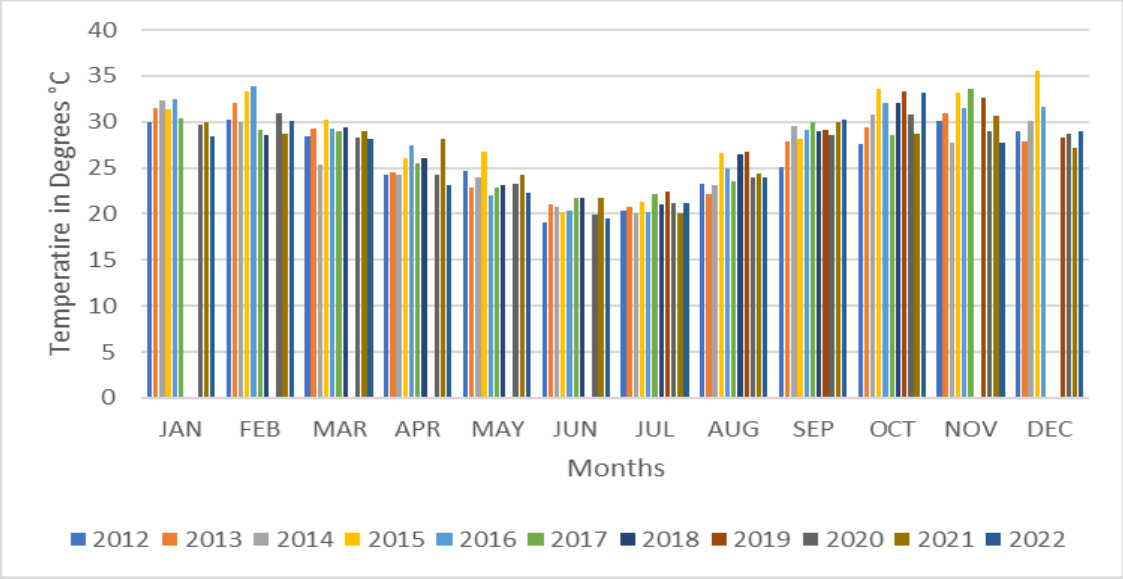

Figure 7: Average Monthly Maximum Temperature- Pretoria Unisa Data Station

Figure 8 shows the average monthly minimum temperatures for a period of 11 years (2012 to 2022). The temperatures range between 0 and 20 °C. According to figure 14, the years with the lowest temperatures are 2019 (6.2°C), 2018 (8.7°C), 2017 (10.9°C), and 2021 with 11.5 °C. The months with the lowest temperatures are June, July, and May, which are classified as the winter months. Therefore, low amounts of rainfall can be harvested during these months.

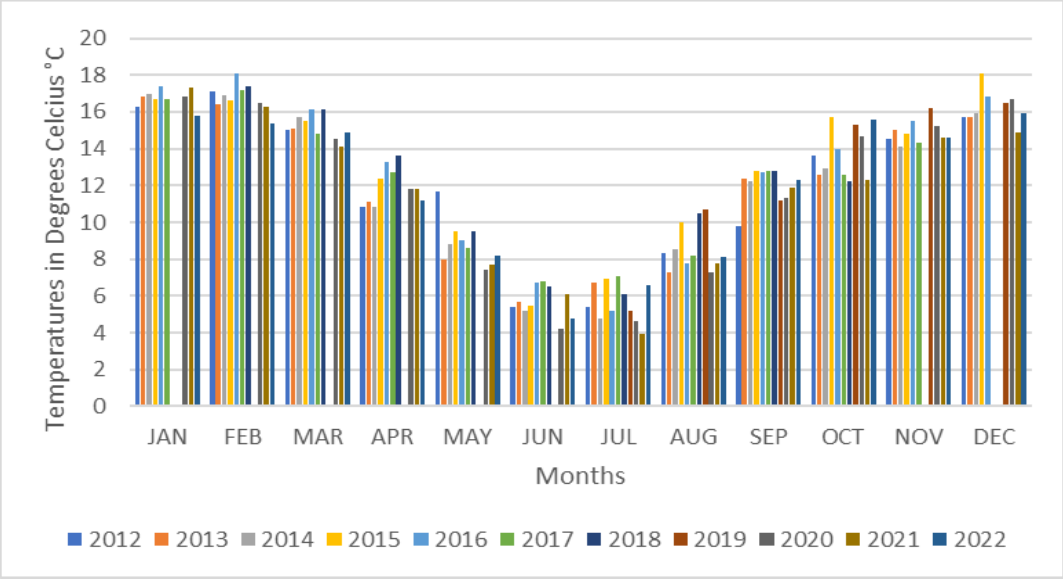

Figure 8: Average Monthly Minimum Temperatures- Pretoria Unisa Data Station

Figure 9 illustrates the Monthly Annual Rainfall for the period of 11 years in the study area. The years with the highest recorded rainfall are 2014, 2022, 2021, 2016, 2017 and 2019 respectively and the months with the highest records are November, December, January, and March respectively. This figure also illustrates the impacts of climate change as rainfall has increased over the years, indicating the need for harvesting rainwater during the months of excessive rainfall (summer months).

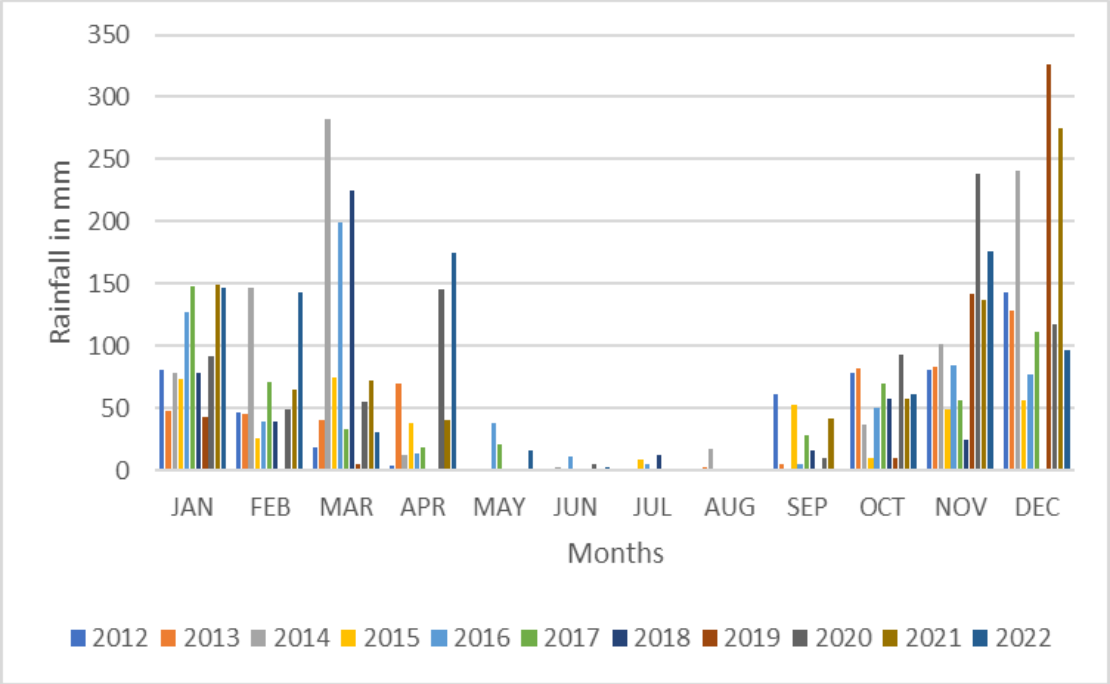

Figure 9: Monthly Annual Rainfall: Pretoria Unisa Data Station

Figure 10 illustrates the relationship between the yearly average maximum temperature (°C) and the annual rainfall (mm). It is observed in figure 10 that when temperatures are high, increased rainfall amounts are recorded. This was shown in 2014, 2020, 2021 and 2022. In contrast, when temperatures are low, decreased rainfall is recorded as observed in 2018, 2017 and 2019.

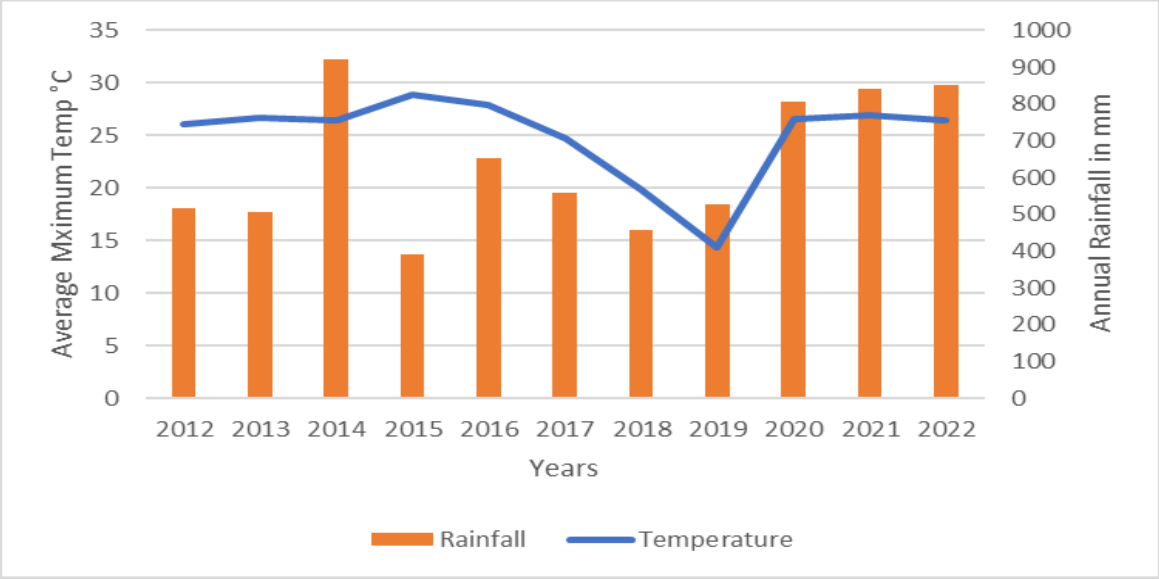

Figure 10: The Relationship Between Temperature and Rainfall- Pretoria Unisa Data Station

To further analyse the relationship between rainfall and temperature descriptive statistics such as the P-value, coefficient was generated using Excel. In a regression analysis involving rainfall and temperature, the coefficients represent the relationship between these variables. In this instance we are assessing how temperature affects rainfall. The statistical analysis indicated that Average Maximum Temperature has a statistically significant relationship with Rainfall in this model. As Average Maximum Temperature increases, Rainfall tends to increase as well. According to the statistical regression analysis indicates a moderately strong correlation (Multiple R: 0.72) between rainfall and temperature. The regression analysis case shows a stronger model (Multiple R = 0.53) compared to the Pretoria Unisa Campus (below). It explains a moderate portion of the variance in rainwater harvesting potential (R-squared = 0.28). However, the adjusted R-squared (0.20) suggests the model might be slightly overfitting the data with the small sample size (n=11).

The F-statistic (3.53) and its corresponding p-value (0.093) indicate a trend towards statistical significance, but it doesn't quite reach the conventional threshold of $p < 0.05$. The intercept (267.62) represents the predicted average rainwater harvesting potential when the average temperature is zero (again, unlikely). The coefficient for average temperature (-7.79) suggests a potential decrease in harvesting with increasing temperature. While the p-value (0.093) is closer to significance than before, it still doesn't definitively confirm this association.

The following results are generated from the atmospheric information recorded from the Pretoria University Proefplaas data station located -25.7520 28.2580 at 1380 meters. The aim was to assess potential differences between the two weather stations throughout the study period. This was because one station would record data for a certain month(s) in a year while the other station would intermittently not do so, and vice versa.

Figure 11 shows the average monthly maximum temperatures for a period of 11 years (2012 to 2022). The temperatures range between 0 and 35 degrees Celsius. According to the figure the years with the highest temperatures are 2015 (27.6 °C), 2019 (27,5 °C) 2016 (27.0°C), 2017 (26.3°C), 2021 (25.8°C), 2014 (25,7°C), 2013 (26.2°C) and 2012 (26.1°C). According to the figure, the months with the highest temperatures are September, October, November, December, January,

February, and March, which are classified as the summer months, indicating that the high amounts of rainwater can be harvested during these months.

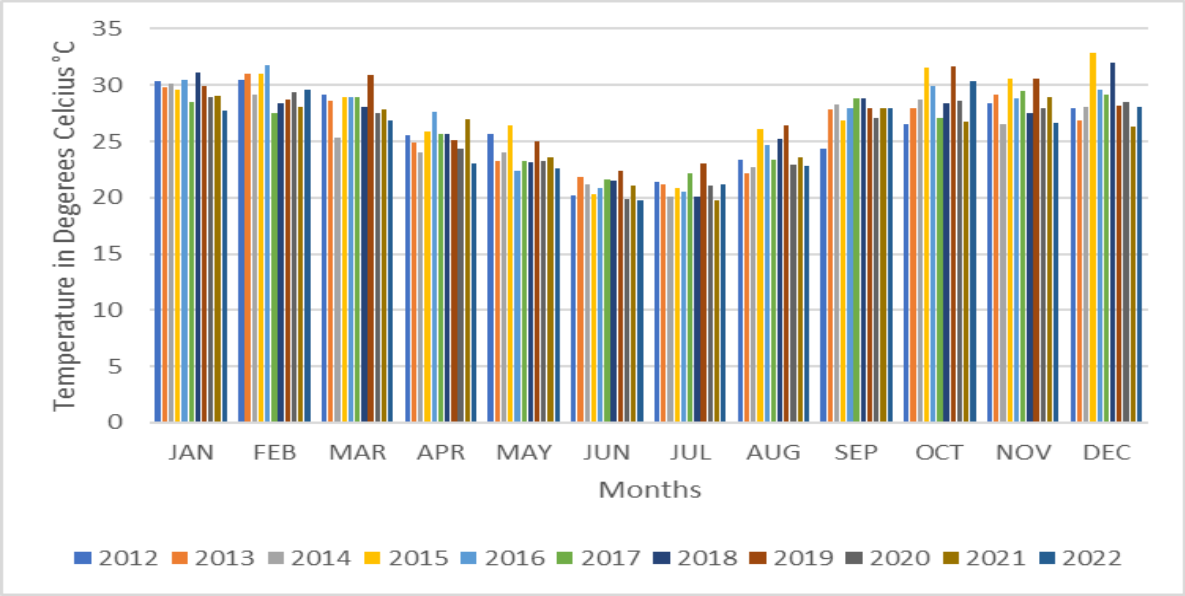

Figure 11: Average Monthly Maximum Temperatures- University of Pretoria Data Station

Figure 12 shows the average monthly minimum temperatures for a period of 11 years (2012 to 2022). The temperatures range between 0 and 20 degrees Celsius. According to the figure the years with the lowest temperatures are below 10 degrees 2018 (8.6°C) and 2022 (9.0°C), The months with the lowest temperatures are June, July and slightly May and August. These differ from the results regenerated from the Pretoria Unisa data station, which are classified as the winter months. Therefore, low amounts of rainfall can be harvested during these months.

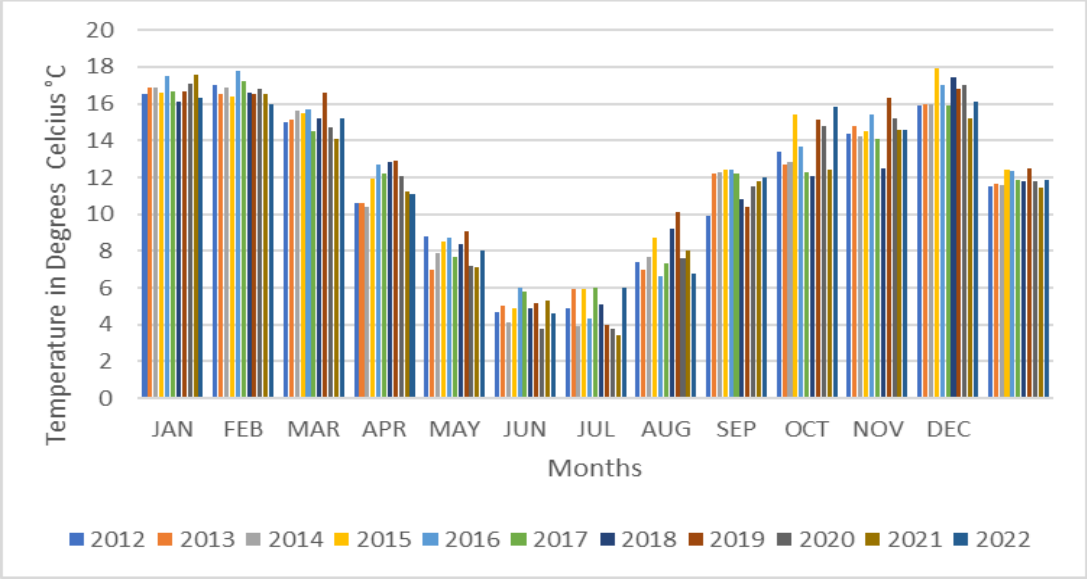

Figure 12: Average Monthly Minimum Temperatures- University of Pretoria Data Station

Figure 13 illustrates the Monthly Annual Rainfall for the period of 10 years in the study area. The years with the highest recorded rainfall are 2014, 2021, 2022, 2017, 2016, and 2018, respectively, and the months with the highest records are December, January, February, and March. This figure also illustrates the impacts of climate change as rainfall has increased over the years, indicating the need for harvesting rainwater during the months of excessive rainfall (summer months). These differ from the results regenerated from the Pretoria Unisa data station.

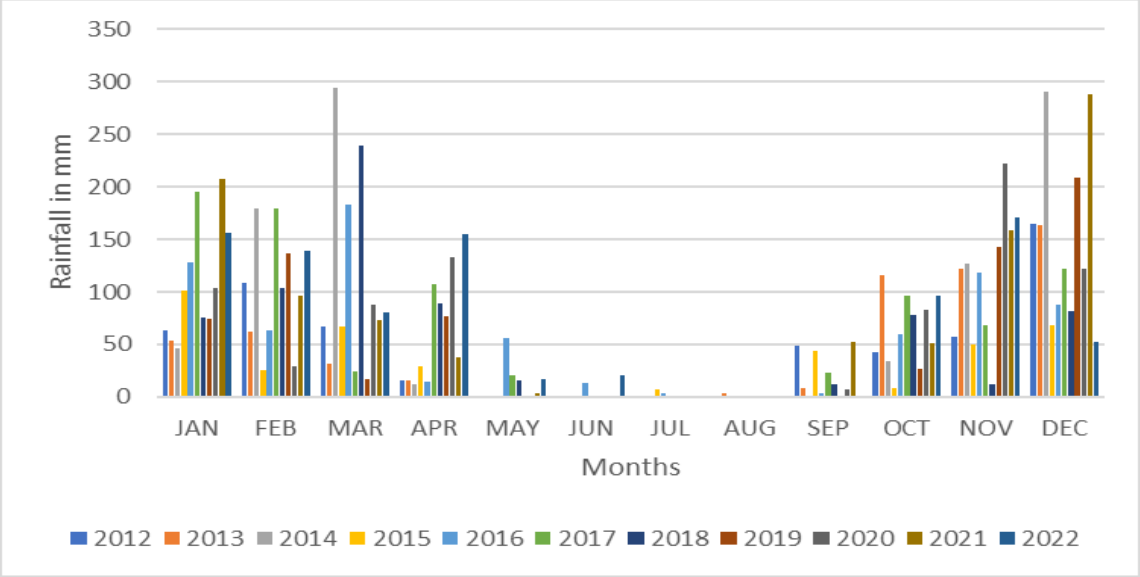

Figure 13: Monthly Annual Rainfall- University of Pretoria Data Station

Figure 14 illustrates the relationship between the yearly average maximum temperature (°C) and the annual rainfall (mm). It is observed in figure 14 that when temperatures are high, increased rainfall amounts are recorded this is shown in 2016, 2018, and 2021. In contrast, when temperatures begun decreasing in 2021 and 2022, low rainfall amounts were recorded.

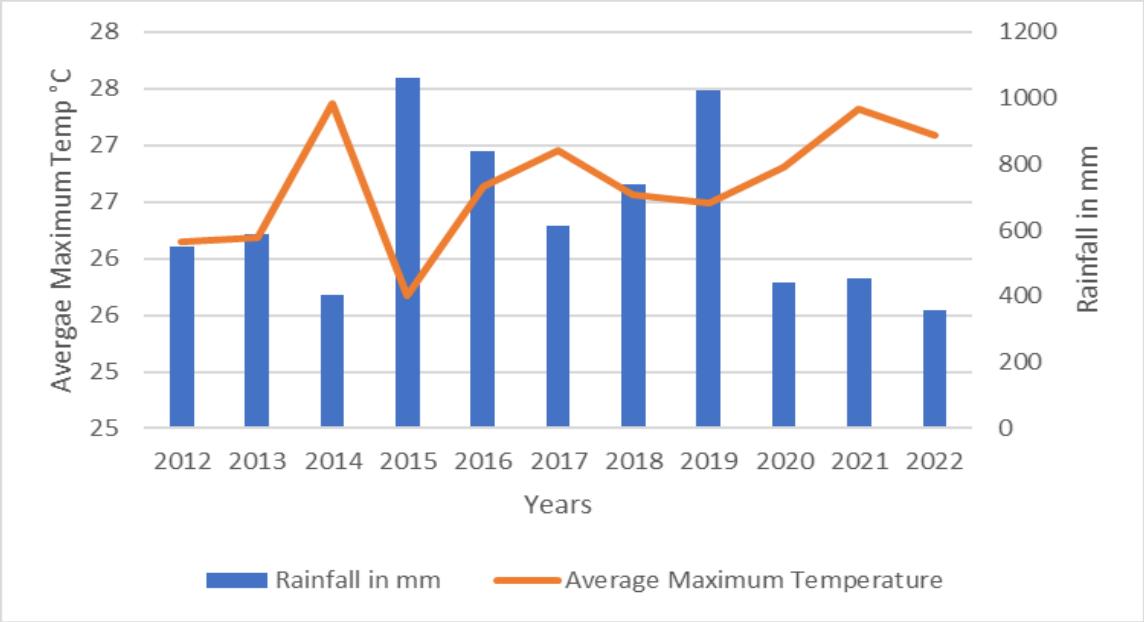

Figure 14: The Relationship Between Temperature and Rainfall- University of Pretoria Data Station

In addition, a statistical regression analysis derived from the University of Pretoria data station The regression analysis indicates a weak model (Multiple R = 0.26) explaining only a small portion of the variance in rainwater harvesting potential (R-squared = 0.068). This suggests other factors beyond average temperature likely have a more significant influence. The F-statistic (0.655) and its corresponding p-value (0.439) further confirm the model's lack of statistical significance. The intercept (84.01) represents the predicted average rainwater harvesting potential when the average temperature is zero (an unlikely scenario). The coefficient for average temperature (-1.10) suggests a potential decrease in harvesting with increasing temperature, but the high p-value (0.439) indicates this association is not statistically significant.

4.2.3. Mapping potential RWH sites

This study aims to identify potential locations for rainwater harvesting in Lynnwood Park, Pretoria. To achieve this, ArcGIS Pro was used for a multi-step process visualised in Figure 18. First, the software displayed the building footprints overlaid on the study area (Frame 1). Next, rainfall data in TIFF format was incorporated, showing the distribution of rainfall across Lynnwood Park (Frame 2). It is important to note that clipping the rainfall data to the building footprints does not directly translate to the amount of rainwater that will be harvested from each rooftop. Rainfall is a continuous phenomenon, with variations occurring even within short distances (Angelis et al., 2017).

Therefore, while the clipped data provides a preliminary assessment, other factors significantly influence rainwater harvesting potential. Larger rooftops generally have the potential to collect more rainwater than smaller rooftops (MacCord et al., 2019). As shown in figure 15, rooftops located in the south would have a higher potential to harvest rainwater, than those located in the north. Slope also plays a role, as steeper inclines can channel rainwater runoff more effectively towards collection tanks, while very flat or very steep roofs may present challenges for collection system installation (Jacovides et al., 2017). However, additional considerations are crucial for a comprehensive analysis. Elevation, for instance, can impact the amount of rainwater reaching a rooftop due to potential evaporation losses at higher altitudes (Shongwe, 2007). Wind direction and speed can also influence rainwater collection efficiency, though these factors were not explored in this initial step. The next section on modeling rainwater harvesting structures will utilise the elevation data captured in the contour lines (Figure 8) to account for this slope. By integrating these factors, the analysis will not only map potential rainwater harvesting sites but also differentiate between suitable locations for above ground and underground tanks.

Figure 15: Steps to model RHW sites.

4.2.3. Modelling for Rainwater Harvestings Structures

The analysis aimed at identifying suitable sites for rainwater harvesting within Lynnwood Park, Pretoria, considering factors like building footprints, rainfall distribution, and elevation (slope). As evident in Figure 8, the spatial distribution of potential rainwater harvesting sites was modeled based on these parameters. Rainfall patterns are known to be continuous across Pretoria (Angelis et al., 2017). However, factors like elevation and wind direction can influence the amount of rain received in specific locations (Shongwe, 2007). The surface flow analysis of the terrain revealed a steeper slope in the southern region of Lynnwood Park, while the northern region comprised a

gentler, plainer slope. This difference in elevation translates to a southerly direction for most surface runoff generated by rainfall events.

According to Jacovides et al. (2017), slope plays a critical role in rainwater harvesting efficiency. Steeper slopes can effectively channel rainwater runoff towards collection tanks, potentially maximising the volume of rainwater captured (Jacovides et al., 2017). In the context of this study, the steeper southern slopes, while having potentially larger rooftops, may be disadvantaged due to this rapid flow of rainwater away from rooftops, reducing the amount of rainwater available for collection.

In contrast, the rooftops in the northern region with a gentler slope present a more favourable scenario for rainwater harvesting. The analysis rightly identified these rooftops for potential tank placement, considering their advantageous position for capturing rainwater runoff. Even though the northern rooftops may have smaller areas compared to their southern counterparts, their location on a gentle slope allows for more efficient collection of rainwater. This highlights the importance of incorporating slope data into rainwater harvesting site selection, as gentle slopes can significantly improve harvesting potential (Yazdani et al., 2012). Therefore, the overlay analysis integrating building footprints, rainfall data, and slope information (via contour lines) provided valuable insights for rainwater harvesting in Lynnwood Park. The resulting map with yellow-plotted points strategically positions tanks near rooftops in the northern region, capitalising on the favourable gentle slope for optimal rainwater collection.

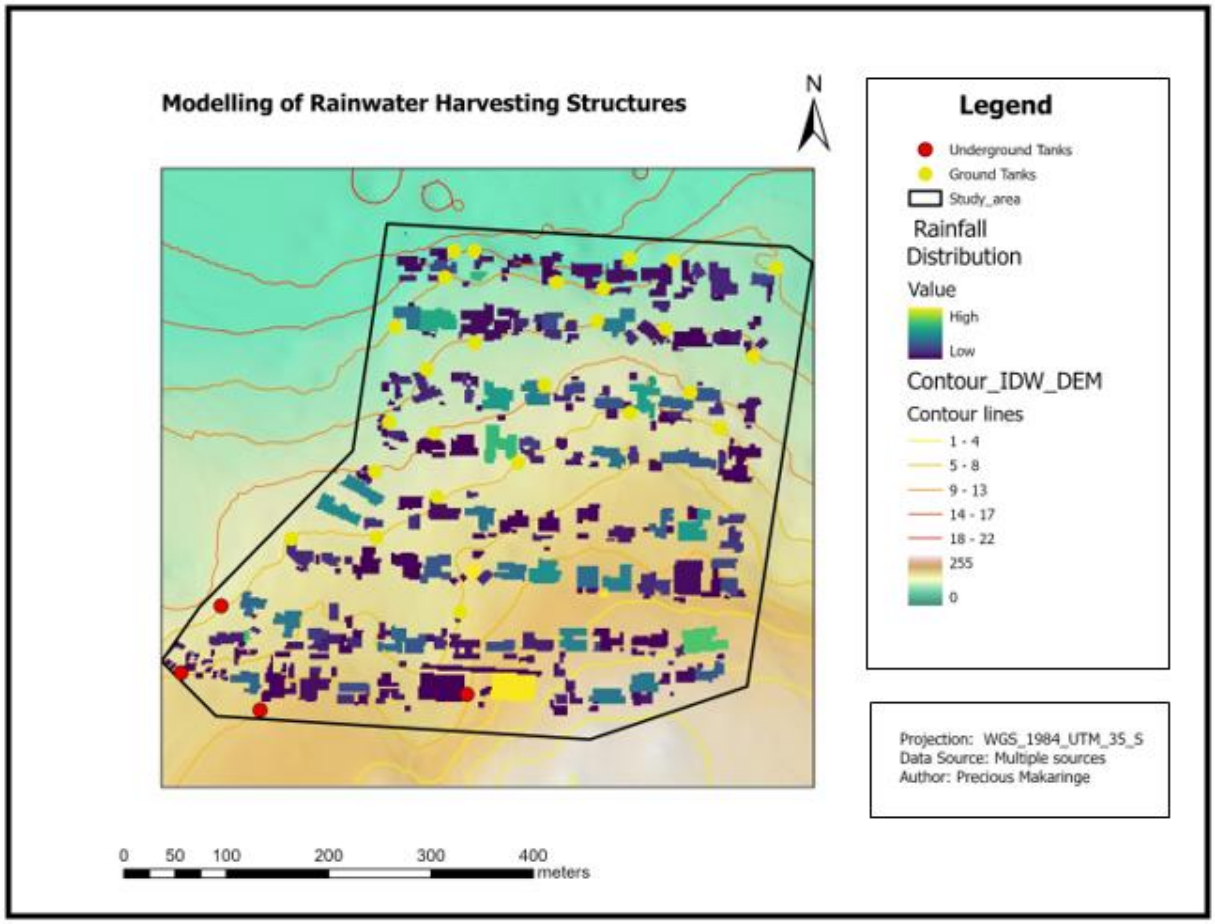

Figure 16: Potential rainwater harvesting sites.

As briefly indicated above that the flow path according to the generated contour lines is Southerly. The southerly water flow as runoff that bypassed being harvested by tanks can be harvesting using underground water tanks where dependent on their use can either be purified for human consumption of redirected to agricultural fields to support food security. A shapefile for underground water tanks was also created and was displayed using red points.

4.4. Estimating water demand

Determining water demand is complex due to variations in household water use. Factors like age and number of occupants can influence consumption, with higher usage typically occurring during summer months (Biswas and Mandal, 2014). Additionally, seasonal celebrations, religious holidays, or extended family visits can cause fluctuations in household occupancy, further

impacting water demand (Biswas and Mandal, 2014). These considerations highlight the importance of evaluating average daily water use. Fortunately, rainwater harvesting offers a versatile source for various household needs, including bathing, cooking, drinking, and washing (Biswas and Mandal, 2014).

The descriptive statistics for the biographical information of the sample population are given in table 5. As observed, the female respondents at 70.4% (n=69) were more than the male respondents at 28.6%. The data shows a higher percentage of female respondents (70.4%) compared to males (28.6%). This highlights the importance of targeting water-saving education programs towards both genders. The highest percentage of respondents was 74% under the 20-29 age category, the least percentage was 1% (n=1) being the pensioners. The study indicates a dominance of younger age groups (74% under 29 years old). Younger demographics may exhibit different water usage patterns compared to older adults (Makwana et al., 2018). Tailoring water conservation messaging to specific age groups could be beneficial.

Table 6: Gender and Age Distribution

Gender Distribution		**Percentage (%)**
Female	69	70.4%
Male	29	28.6%
Age Distribution		
20-29	72	74%
30-39	11	11.2%
40-49	3	3.1%
50-59	8	8.2%
60-65	3	3.1%
Pensioner	1	1%

Many of the respondents that were sampled were employed full-time (37.7%; n=37) while the least number of respondents at 3% (n=3) chose the 'other category'. Respondents for the education level question indicated that the highest level of education for most respondents was a matric qualification (28.6%; n=28) whereas fewer (1%; n=1) respondents only possess primary education.

The data suggests a correlation between education level and water-saving awareness. A lower percentage (1%) of respondents had only primary education, potentially indicating limited exposure to water conservation knowledge. Educational programs aimed at low-income communities could be crucial to promote water-saving practices. Many of the population are not working which indicates that buying water would not be a viable alternative for them.

Table 7: Employment Status and Educational Levels

Employment status		**Percentage**
Full-time	37	37.7%
Part-time	13	13.2%
Self-employed	6	6.1%
Unemployed	6	6.1%
Student	33	33.6%
Other	3	3.1%
Highest level of education		
Primary School	1	1%
Matric	28	28.6%
Post-Matric		
Certificate/Diploma	26	26.6%
Bachelor's Degree	22	22.4 %
Post-Graduate Qualification (Btech, Honours, Masters, Ph.D.	21	21.4 %

As observed in Table 8 (below), nearly 36% (35.8%; n=35) of the respondent's salary ranges between R0 - R50 000, whereas a small percentage of the sample population had a joint income of R1 00000. On the question of the number of people residing within the same household, 24,4% (n=24) answered that 3 people reside within the household, followed closely by 20.4% (n=20) residing as 5 persons within the household. Further, only 1% (n=1) of the population resided as 9 people. Most respondents fell within lower-income brackets. This highlights the need for cost-effective water management strategies like rainwater harvesting, particularly for low-income households who may struggle to afford alternative water sources during scarcity.

Table 8: Household Income and Size

Joint household income per year		**Percentage**
Realised Middle Class (R300 001- R 500 000)	19	19.4%
Lower Income (R0- R50 000)	35	35.8%
Emerging Middle Class (R100 000- R300 000)	22	22.4%
Emerging Affluent (R750 001- R1 000 000)	7	7.1%
Affluent (R1 000 000)	6	6.1%
Number of people residing with the participants		
9 Persons	1	1%
8 Persons	4	4.1%
7 Persons	7	7.1%
6 Persons	8	8.2%
5 Persons	20	20.4 %
4 persons	12	12.2%
3 Persons	24	24.4%
2 Persons	10	10.2%
1 Person	12	12.2%
9 Persons	1	1%

The demographic data of the study participants reflects the varied population of Lynwood Park, Pretoria, suggesting the generalisability of the findings. South Africa's average water consumption (237 liters per person per day) exceeds the global average of roughly 173 liters per person per day, as reported by Ngobeni and Breitenbach (2021). To determine the water demand in Lynwood Park, this study employed Equation 7

$$Water\ demand = Per - capita - demand\ x\ Population\ x\ Number\ of\ days$$

Equation 4

= (9x1) + (4x8) + (7x7) + (8x6) + (20x5) + (12x4) + (24x3) + (10x2) + (12x1)

= 9 + 32+ 49 + 48 + 100 + 48 + 72 + 20 + 12

=***390 people***.

Therefore, the estimated water demand: *237 litres x 390 x 365*
*= **33 736 950 Litres***

Rooftop rainwater harvesting (RRWH) presents a promising strategy to supplement or even replace conventional water sources for specific uses, particularly in low-income communities. The estimated water demand (33,736,950 liters) highlights the overall water requirement. RRWH systems can reduce pressure on municipal water supplies and provide a more sustainable water source for non-potable uses like toilet flushing or irrigation, potentially lowering overall water demand.

The inclusion of building footprints in the rainwater harvesting (RWH) analysis for Lynnwood Park opens doors to a more promising scenario. Herein a comparative analysis of water demand, potential rainwater harvest, and the key factors influencing RWH efficiency. The annual water demand for Lynnwood Park sits at 33,736,950 liters. While the estimated harvest from a single high-rainfall year (2022) was 1,574,600 liters based on the building footprint area and an assumed collection rate, it falls short of meeting the Lynwoods entire water needs. However, this doesn't negate the value of RWH because on certain months the weather station did not record the data or had missing values. In addition, the annual water demand for Lynnwood Park sits at 33,736,950 liters. While the estimated harvest from a single high-rainfall year (2022) was 1,574,600 liters based on the building footprint area and an assumed collection rate, it falls short of meeting the park's entire water needs. However, this doesn’t remove its effectiveness, as the weather stations would on some months not record rainfall.

Rainwater harvesting (RWH) can significantly contribute to Lynnwood Park's water management strategy, but its efficiency hinges on several factors. Storage capacity limitations can lead to overflow during high-rainfall periods, while seasonal variations necessitate strategies to maximise storage during wet seasons and utilise it efficiently during dry periods. Evaporation from storage tanks further reduces usable rainwater.

To optimise RWHs contribution, a more detailed rainwater harvesting equation that considers evaporation, and other losses should be implemented. Additionally, expanding storage capacity and implementing water conservation measures can significantly improve RWH efficiency. By

addressing these factors, Lynnwood Park can leverage RWH to reduce reliance on traditional water sources and promote sustainable water management.

CHAPTER 5: Discussion

5.1. Introduction

This chapter aims to present a discussion of the findings of this study. Rainwater harvesting is an attention-grabbing topic due to the realization of the impacts of climate change, water scarcity, water demand and the need for alternative water sources. The aim of this study was to model the potential rainwater harvesting sites in Lynwood Park, Pretoria. In view of the above, this chapter is presented in a manner, which engages the research objectives, which were outlined in Chapter 1 of this dissertation. The first objective was to apply the Object-Based Image Classification (OBIC) technique for semi-automated building footprints extraction using high resolution satellite imagery, the second was to map the potential RWH sites in the study area using geospatial techniques. Lastly, the objective was to calculate per capita water demand in the study area.

As a result of exploring alternative water sources, several studies around the world have been conducted regarding this issue. However, in South Africa, there is a gap in literature concerning Rainwater Harvesting, specifically at rooftop level in urban areas. To add to the gap in literature or to suggest any recommendations on the application of rooftop rainwater harvesting as an alternative water sourcing method for water scarcity. It is paramount to realise, analyse and capture the contribution of and awareness of rooftops and households meeting our water demands.

5.2. Discussion of Results

Water scarcity is a growing concern worldwide, encouraging the exploration of alternative water management strategies. RWH offers a promising solution by collecting and storing rainwater for later use. Its effectiveness depends on several factors, including rooftop area, elevation, as well as precipitation to meet water demand. This study investigated the potential for RWH in Lynnwood Park, Pretoria, South Africa, leveraging advancements in Geographic Information Systems (GIS) and remote sensing to model potential RWH sites (outlined in the Aims and Objectives in chapter 1).

The use of Google building footprints approach offered several advantages over traditional manual digitisation, including efficiency and reduced human error (Benz et al., 2004). The extracted

building footprints formed the foundation for further analysis. By overlaying them with a Digital Elevation Model (DEM), the study was able to calculate rooftop area and slope – critical factors influencing rainwater collection. This approach aligns with previous studies that have successfully utilised building footprints derived from remote sensing data for RWH assessments. For instance, Sun et al. (2018) employed building footprints extracted from LiDAR data to evaluate the rooftop rainwater harvesting potential in Beijing, China. Similarly, Ramesh et al., (2019) leveraged building footprint data derived from high-resolution satellite imagery to assess urban rainwater harvesting potential in Chennai, India. By incorporating building footprints into the RWH modeling process, this study provides a valuable tool for identifying suitable locations for rainwater harvesting infrastructure and maximising rainwater collection potential.

Among the various applications, generating building footprints from satellite imagery has gained significant attention due to its relevance in urban planning, disaster response, and environmental monitoring. Both Google and Microsoft have invested in developing deep learning models for this purpose (Chen et al., 2018). The traditional methods such as surveying can generate the building footprints more accurately however, it takes more time and requires labour extensive resources. The time cost can increase the feasibility of the task when applying traditional methods (Hongjie, 2021). Building footprints extraction using Microsoft and Google has been proven as an efficient method when compared to traditional methods.

There are many data sources for characterising the built environment. However, building footprints have been regarded as the most useful for several purposes from services such as OpenStreetMap to other population modelling methods such as Worldpop as well as LandScan (Gonzale, 2023; Boo et al., 2022 and Moehl 2021). At large scale, the building footprints are generated from satellite imagery through automated machine learning models such as Continental-Scale Building Detection from High Resolution Satellite Imagery, Convolutional Neural Network and Microsoft global ml footprints (Gonzalez, 2023). Alternatively, volunteers are used to manually digitise building footprints as in the case of OpenStreet (Gonzalez, 2023 and OpenStreet Map Contributors, 2024). In addition, Google and Microsoft have both released expansive datasets of building footprints, the datasets can be used by the general public by various industry professionals such as researchers, analysts among others (Gonzalez, 2023).

The Microsoft and Google building footprints contain massive datasets which cover multiple continents, seeking to expand its continent footprint availability (Gonzalez, 2023). In addition to Micorsofts' 1.2 billion building dataset covering, Europe, the Americas, Africa as well as Asia, they have released several independent country-scale datasets including the 2018 dataset for the United States (Microsoft, 2024) The Google Open Buildings dataset emerged with a near complete mapping buildings of Africa, later expanding to Asia and the Americas covering 1.8 billion buildings (Google Open Buildings 2024). Microsoft and Google building footprints both utilise the convolutional neural network-based semantic segmentation models to identify buildings by classifying pixels in high-resolution satellite imagery (Gonzalez, 2023). The buildings are classified as building or non-building, after the classification, the building footprints polygons are generated from the positively classified pixels (Google Open Buildings, 2024; Microsoft, 2024 and Sirko et al., 2021).

Through the process of extracting building footprints, it assisted in modelling the potential rooftop rainwater harvesting sites. For the study it revealed both the size and the location of the rooftops which were key factors in determining their rainwater collection potential. The building footprints could be incorporated with other data such as rainfall data for Lynnwood Park, Pretoria as well as the elevation data. The combined spatial analytical tools from ArcGIS pro achieved the objectives of the study by modelling the potential rainwater harvesting sites and estimating water demand. Upon extracting the building footprints using Google and Microsoft building footprints, the former covered the area completely while Microsoft building footprints left some patches.

With the next step the extracted building footprints were integrated with a Digital Elevation Model (DEM) within ArcGIS Pro. However, the research had a few challenges which encouraged the use of alternatives to achieve the aims and objectives of the study. Acquiring high-resolution Digital Elevation Models (DEMs) is crucial for analysing rainwater harvesting potential. However, commercially available DEMs were unable not offer the necessary detail due to the size of the study area. As a result, the study encountered limitations with the downloaded DEM from USGS, highlighting the need for alternative data sources (Section 3.6.1). The successful use of GPS data and IDW interpolation within ArcGIS Pro addressed this challenge (Section 3.6.1) creating a DEM

which could be used to understand the elevation of Lynnwood Park. Therefore, it is significant to consider the size of the study area, especially for studies that incorporate elevation to minimise potential DEM challenges. This study's findings on the impact of topography in Lynnwood Park reinforce established theories regarding rooftop rainwater harvesting (RWH) potential. The analysis revealed that steeper slopes in the southern region limited collection from large rooftops, while the flatter north offered greater potential. This aligns with the well-documented influence of terrain on RWH effectiveness (Angelis et al., 2017; Moges et al., 2012). Studies have consistently shown that regions with flatter terrain offer a larger utilisable rooftop surface area, translating to a greater rainwater collection capacity (Omolai et al., 2019). In contrast, steeper slopes result in less usable rooftop area and potentially higher runoff losses (Liu et al., 2017). This highlights the importance of considering topography during RWH site selection and system design. For instance, incorporating slope data into RWH models can help identify areas with optimal collection potential and prioritise resource allocation (Ghosh and Mukhopadhyay, 2019).

In addition, the study briefly explored the use of above ground underground tanks by identifying sites as potential areas to harvest with rainwater, challenging topography aligns with emerging trends in RWH optimisation Previous research has demonstrated the effectiveness of underground storage tanks in enhancing RWH system efficiency, particularly in urban environments with limited space for above-ground storage (Ahn et al., 2015). By capturing runoff that bypasses above-ground tanks due to steeper slopes, underground storage could significantly improve the overall rainwater collection potential in the southern region of Lynnwood Park. This approach could contribute to a more comprehensive model that considers not just slope but also strategies to optimise rainwater harvesting even in less favourable topographical conditions.

By acknowledging the importance of topography and exploring potential mitigation strategies like underground storage, this study adds to the ongoing dialogue on maximising RWH effectiveness in diverse geographical settings. Future research could explore the integration of cost-benefit analysis and social acceptance studies to evaluate the feasibility and wider implementation of underground storage tanks in RWH systems, particularly in areas with complex topography. It should also explore the use of underground tanks to capture runoff in these areas. This approach

considers the Lynwood Parks topography to maximise rainwater harvesting for potential uses like drinking water or agriculture.

Recent advancements in remote sensing and GIS technologies offer valuable tools for identifying suitable locations for rainwater harvesting (RWH) systems. For instance, Abrefa et al., (2013) employed a GIS-based decision support framework to optimise RWH implementation strategies (Abrefa et al., 2013). This approach builds upon the earlier work of Kumar and Viswanadh (2012) who developed a model to assist professionals in locating suitable RWH sites. In this study, remote sensing techniques facilitated the mapping of potential RWH sites in Lynwood Pretoria, demonstrating the potential of rainwater harvesting to meet the area's estimated water demand. These findings suggest that rooftop RWH can serve as a viable alternative water source. Incorporating rainfall data obtained from the South African Weather Services was crucial for achieving the aims and objectives of this study. The annual rainfall averages, obtained from the South African Weather Services atmospheric data demonstrates varying patterns across seasons. The results indicated that higher rainfall amounts were recorded during the summer months and lower rainfall during the winter months. This aligns with existing research on seasonal rainfall patterns in South Africa. Studies by Kruger and Shongwe (2020) utilised precipitation data to create regional maps highlighting seasonal variations, similar to the findings of this study. This knowledge of seasonal fluctuations is essential for RWH design. By understanding the typical wet and dry seasons, RWH systems can be sized to capture sufficient rainwater during wetter periods to meet water demands during drier months (Kruger and Shongwe, 2020).

Climate change has led to some years recording significantly lower average rainfall compared to other years which are experiencing extreme rainfall. Indicating that the months and years with lower or reduced rainfall can potentially harvest low rainfall amounts. Furthermore, the analysis revealed variations in annual rainfall, with some years experiencing significantly lower or higher averages compared to others. This finding highlights the concerning nature of climate change, which is known to disrupt historical precipitation patterns according to the Intergovernmental Panel on Climate Change (2022). Studies by Aerts et al., (2018) in Europe and Xu et al., (2020) in China highlight how climate change can lead to more frequent extreme weather events, including periods of intense rainfall followed by extended droughts. These variations in annual rainfall pose

a challenge for RWH system design. While this study did not analyse long-term rainfall data into the modeling process for a more robust assessment of rainwater availability, it lays the groundwork for future research in this area. This future analysis can enable the design of RWH systems that can account for potential fluctuations and ensure sufficient water capture even during drier years associated with climate change. By considering these climate-driven variations, RWH systems can be designed to be more adaptable and resilient in the face of a changing climate. This highlights the importance of incorporating long-term climate trends into future studies to optimise RWH system design for long-term sustainability.

The potential harvesting sites indicate that water can be harvested using rooftops. In addition, the predicted rainwater harvesting potential indicates that over half of the overall annual water demand can be met by harvesting water using roof catchments. The estimated water demand was 33 736 950 litres and the potential rainwater that can be harvested in Lynnwood Pretoria is 2 849 389 litres (University of Pretoria Station) and 2 513 263 litres for the study period (Unisa Data Station), indicating that rooftop rainwater harvesting can meet the needs of estimated water demand. Therefore, while these figures represent potential and may vary depending on actual rainfall patterns and system efficiencies, they demonstrate the significant contribution that RWH can make towards water security in Lynnwood Park.

This study reinforces the potential of rooftop rainwater harvesting (RWH) as a viable and transformative alternative water source, especially in regions facing climate change-driven water scarcity. Similar findings by Xu et al., (2022) in China and Nia et al., (2019) in Malaysia demonstrate the effectiveness of RWH as a reliable supplemental water source during droughts or water restrictions. By lessening reliance on municipal supplies, RWH can alleviate pressure on stressed water resources and promote more sustainable water management strategies. It is important to acknowledge that this study represents a preliminary assessment, and further research is needed to refine the RWH potential estimates. Factors such as system losses due to evaporation, inefficiencies in collection and storage, and variability in rooftop sizes across different buildings would need to be incorporated into more detailed models. However, the initial findings provide compelling evidence for the potential of RWH to play a significant role in mitigating water scarcity challenges in Lynnwood Park and similar urban environments.

The regression analysis revealed a moderate positive correlation between average maximum temperature and rainfall, with a Multiple R-Squared value of 0.720 (University of Pretoria Station data). This indicates that changes in average maximum temperature can explain a moderate portion of the variability observed in rainfall patterns. This finding aligns with research by Nkuna and Odiyo (2016) who highlighted the pivotal role rainfall plays in shaping hydrological systems and water scarcity, further emphasising the need to understand these relationships. Southern Africa's rainy season typically occurs during the summer months (December, January, and February) coinciding with the southward movement of the Intertropical Convergence Zone (ITCZ) (Shongwe, 2007).

The coefficient of determination (R-Squared) of 0.519 suggests that approximately 52% of the variation in rainfall can be attributed to the variation in average maximum temperature. While this indicates a significant influence, it is important to acknowledge that other factors not included in this model, such as sea surface temperatures (SSTs) and El Niño Southern Oscillation (ENSO) cycles, can also significantly impact rainfall patterns (Nkuna 2016). Future research endeavours could incorporate additional variables to create a more comprehensive model.
The statistically significant p-value (0.012) for the F-statistic (ANOVA) further strengthens the evidence of a relationship between average maximum temperature and rainfall. This suggests that at least one of the independent variables, in this case, average maximum temperature, has a statistically significant association with rainfall. This aligns with the findings of Nkuna (2016) who identified positive correlation coefficients between rainfall and both maximum and minimum temperatures.

The regression coefficient of 25.81 indicates that for each unit increase in average maximum temperature, rainfall is estimated to increase by 25.81 units (on the scale used for measurement). The low p-value (0.012) associated with this coefficient suggests that this relationship is statistically significant. Findings from the Pretoria Campus data station support the existence of a statistically significant positive correlation between average maximum temperature and rainfall in Lynnwood Park. As average maximum temperatures increase, rainfall also tends to increase. However, it is important to acknowledge that this model only explains a portion of the variability in rainfall. Therefore, research incorporating additional climatic factors could provide a more

comprehensive understanding of the complex interplay between temperature and precipitation patterns in this region.

Due to the variations between the two data stations, the statistics summaries were also generated for Pretoria University Proefplaas data station. The regression analysis revealed a weak positive correlation between average maximum temperature and rainfall, with a Multiple R-Squared value of 0.356. This indicates that changes in average maximum temperature explain only a small portion of the variability observed in rainfall patterns. This finding contrasts with findings derived from the UNISA Pretoria Campus data station as well as the research by Nkuna and Odiyo (2016) who highlighted a stronger influence of temperature on precipitation. It is possible that the data used in this analysis, with a potential presence of missing values as suggested by the authors, may have masked the underlying relationship between the variables.

The coefficient of determination (R-Squared) of 0.127 suggests that only about 12.7% of the variation in rainfall can be attributed to the variation in average maximum temperature. This further emphasises the weak explanatory power of temperature on rainfall in this specific model. The p-value of 0.283 for the F-statistic (ANOVA) is statistically non-significant at conventional levels (0.05). This reinforces the notion that the observed correlation between average maximum temperature and rainfall may be due to chance and not a true association.

The regression coefficient of 26.01 indicates that for each unit increase in average maximum temperature, rainfall is estimated to increase by 26.01 units. However, the high p-value (0.283) associated with this coefficient suggests that this relationship is not statistically significant and should be interpreted with caution. Nkuna (2016) highlighted the complex ways in which temperature influences rainfall. Increased temperatures can lead to higher evaporation rates, potentially resulting in lower precipitation and drier conditions (Macatsha, 2006). Conversely, under certain circumstances, high temperatures can also contribute to increased condensation and ultimately higher rainfall. The results from this analysis (UNISA Pretoria campus) suggest a weak and statistically insignificant positive correlation between average maximum temperature and rainfall in Lynnwood Park. The limited explanatory power of temperature on rainfall highlights the need to consider other climatic factors. Therefore, future research endeavours could

incorporate additional variables and potentially utilise different data sources to create a more robust model for understanding the relationship between temperature and precipitation patterns in this region.

CHAPTER 6: Recommendations and Conclusions

6.1. Introduction

This chapter summarises the study's key findings, addressing the research questions posed in Chapter 1. It presents recommendations for stakeholders, emphasising the use of alternative water sources like rainwater harvesting to improve water efficiency, reduce scarcity, and mitigate climate change impacts. Finally, the limitations of the study and research gaps are discussed, paving the way for future investigations in rooftop rainwater harvesting and climate change adaptation.

As discussed in chapter one of this dissertation, the aim of this study is to model the potential rainwater harvesting sites in Lynwood Park, Pretoria South Africa. The objectives of the study included applying the Object-Based Image Classification (OBIC) technique for semi-automated building footprint extraction using high resolution satellite imagery; mapping the potential RWH sites in the study area using geospatial techniques and calculating the per capita water demand in the study area. Significantly, the aim and objectives mentioned above informed the research methodology applied in this study.

The research adopted a multi-step approach that effectively utilised Geographic Information Systems (GIS) and remote sensing techniques. The buildings footprints were extracted using both Google and Microsoft building footprints. Although, several studies indicate that Microsoft Building footprints are more accurate than Google building footprints, this study indicated the latter is applicable in the study with Microsoft extracting 146 building footprints and Google extracted 338, the Google footprints formed the basis for the analysis. Extracting the building footprints was a key factor for calculating rooftop area and potential rainwater collection. These footprints were then integrated with a Digital Elevation Model (DEM) to account for terrain slope, which is another critical factor influencing rainwater collection.

Rainfall data obtained from the South African Weather Services played a vital role in achieving the aim and objectives of the study. The analysis revealed seasonal variations, with higher rainfall amounts recorded during summer months and lower rainfall during winter months. This aligns

with existing research on seasonal rainfall patterns in South Africa. Furthermore, the study found variations in annual rainfall, with some years experiencing significantly lower or higher averages compared to others. Supporting the introductory paragraph in chapter 1 that climate change is known to disrupt historical precipitation patterns,

Spatial modeling of potential RWH sites identified promising possibilities for rainwater collection using rooftops. The estimated rainwater harvesting potential in Lynnwood Park suggests that over half of the overall annual water demand could be met through rooftop rainwater collection. While these figures are estimates and may vary depending on actual rainfall patterns and system efficiencies, they demonstrate the significant contribution that RWH can make towards water security. The analysis revealed that steeper slopes in the southern region of Lynnwood Park have limited collection from large rooftops, while the flatter north offered greater potential.

The analysis of the relationship between rainfall and average maximum temperature yielded contrasting results depending on the data source. One analysis indicated a moderate positive correlation, suggesting that increases in temperature are associated with increases in rainfall. However, another analysis revealed a weak and statistically insignificant positive correlation. This highlights the need for further research to incorporate additional climatic factors and potentially explore data quality issues.

This study investigated the potential of rainwater harvesting (RWH) as a water management strategy in Lynnwood Park, Pretoria, South Africa, emphasising the importance of climate considerations. Applying GIS and remote sensing techniques, indicating the importance of geospatial techniques for natural problems by building footprints from high-resolution satellite imagery and integrating them with elevation data to model RWH potential considering both rooftop area and terrain slope. Rainfall data analysis revealed seasonal variations aligning with existing research, while also highlighting concerning annual variations that suggest potential climate change impacts. Spatial modelling identified promising possibilities for rooftop rainwater collection, with estimates indicating the potential to meet over half of Lynnwood Park's annual water demand. An analysis of the temperature-rainfall relationship yielded contrasting results depending on the data source, highlighting the need for further research to incorporate additional

climatic factors and explore data quality issues. Overall, the study emphasises RWH as a viable strategy for water security, with geospatial techniques and climate considerations allowing for the design of more adaptable and resilient RWH systems in the face of a changing climate.

6.2. Conclusions

This study has achieved its aim and objectives of modelling potential RWH sites in Lynnwood Park, Pretoria, South Africa. The first objective was accomplished through the application of the OBIC methodology, which enabled a detail mapping of rooftops through Microsoft and Google footprints. The accuracy of the building footprints extraction was essential for the subsequent step of identifying the potential RHW in the study area. The second objective of mapping potential RWH sites was achieved by integrating the extracted building footprints with elevation and rainfall data. The integration of different datasets provided a comprehensive analysis of how RWH can be employed to meet water demand in urban environment.

The calculation of per capita water demand was achieved by combining both the demographic data and water usage patterns. Through this, the significant potential of RWHs ability to reduce water stress levels was highlighted, emphasising the viability of RWH as a sustainable water management strategy in Urban Environments. The results of this study demonstrated the effectiveness of geospatial techniques in modelling RWH sites. In addition, the findings can be used to inform water management strategies, urban planning, and sustainable water systems. Further, they provide valuable insights for various industry professionals such as policy makers, sustainability professionals, geographers, engineers as well as water resource managers, offering them a framework for developing more climate resilient water sources. In summation, this research directly addresses SDGs 6, 11, 13, and 15 while also contributing to mitigating the social challenges associated with water scarcity.

6.3. Recommendations

This study's findings on the potential of rainwater harvesting (RWH) in Lynnwood Park translate into actionable recommendations for both policymakers and future research endeavours. For practical implementation, policymakers can leverage these findings to promote widespread

adoption of RWH. The establishment of green building codes that mandate rainwater harvesting infrastructure in new construction projects can significantly increase rainwater collection capacity. Additionally, financial incentives, such as tax rebates or subsidies, can be offered to residents and businesses to offset the initial costs of installing RWH systems. Currently financial institutions fund green projects as part of their commitments toward sustainability in the form of sustainable finance. Public awareness campaigns that highlight the benefits of RWH, such as water security and reduced reliance on traditional water sources, can further encourage widespread participation in this sustainable water management practice.

It is important to acknowledge that this study represents a preliminary assessment, and further research is needed to refine the RWH potential estimates. Factors such as system losses due to evaporation, inefficiencies in collection and storage, and variability in rooftop sizes across different buildings would need to be incorporated into more detailed models. Collaboration with urban planners and engineers is crucial to translate these findings into practical designs for implementation across various building types within Lynnwood Park. This collaborative approach can ensure that RWH systems are appropriately sized and integrated seamlessly into existing infrastructure.

The study's outcomes also pave the way for future research directions that can further strengthen our understanding of RWH and its role in a changing climate. A more comprehensive understanding of the temperature-rainfall relationship can be achieved by incorporating additional climatic factors such as sea surface temperatures (SSTs) and El Niño Southern Oscillation (ENSO) cycles into future modeling efforts. The results from this analysis (UNISA Pretoria campus) suggest a weak and statistically insignificant positive correlation between average maximum temperature and rainfall in Lynnwood Park. The limited explanatory power of temperature on rainfall highlights the need to consider other climatic factors. Therefore, future research endeavours could incorporate additional variables and potentially utilise different data sources to create a more robust model for understanding the relationship between temperature and precipitation patterns in this region. Furthermore, exploring the integration of weather forecasting data into RWH system design could enhance their efficiency by allowing for dynamic adjustments based on predicted precipitation patterns. Finally, research investigating the life-cycle costs and

environmental benefits of RWH systems compared to traditional water sources can provide valuable data for policymakers and stakeholders considering large-scale implementation.

In addition, for future scientific studies it is crucial to consider examining tank storage, capacity, and household reservoir systems. While rainwater collected from roofs is commonly presumed safe for drinking, assessing its biophysical and chemical elements is essential. This evaluation helps detect impurities that might render the water unsafe for consumption. Implementing cost-effective purification methods can often render the water potable. By addressing these research directions, future studies can refine our understanding of RWH potential and contribute to the development of more efficient and sustainable urban water management strategies that are adaptable to a changing climate.

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