

Determining the sensitivity of flood risk assessment to different multiple criteria analysis approaches

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Abstract

Floods, as a prevalent and destructive natural hazard, have globally inflicted substantial human, economic, and environmental losses. With floods affecting approximately 1.6 billion people and accounting for 44% of all disaster events from 2000 to 2021, there is a clear risk associated with residing in areas known for susceptibility to seasonal or flash flooding, as it can result in the loss of lives or property damage. Due to that, the urgency to address flood-related risks is paramount. One approach is through the identification of flood risk areas through multi-criteria decision analysis (MCDA) such as the Analytical Hierarchy Process (AHP) and Triangular Fuzzy Analytical Hierarchy Process (FAHP). To date, numerous flood risk studies have utilized the Analytical Hierarchy Process (AHP) and Triangular Fuzzy Analytical Hierarchy Process (FAHP) but often overlooked the sensitivity of these methods to variations in weighting factors, leading to increased subjectivity in their findings. Consequently, this study focuses on evaluating the sensitivity of both AHP and FAHP to changes in criteria values, aiming to enhance the objectivity and reliability of flood risk assessment. A GIS-based MCDA framework was employed for flood risk estimation, excluding considerations of social vulnerability and exposure, for the eThekweni Metropolitan Municipality in South Africa. The criteria, derived from a literature review, included soil type, elevation, rainfall, slope, drainage density, distance to rivers, and land use/land cover. AHP and FAHP were utilized to assign weights to these criteria, with sensitivity analysis conducted through twenty-eight simulations, involving a 20% increase and decrease in the weights of each parameter. Results, evaluated using ROC-AUC analysis, demonstrated high accuracy for both AHP and FAHP, with AUC values of 94.4% each, placing them within the "Good (Very Good)" range. FAHP demonstrated greater stability compared to AHP in response to sensitivity testing involving changes in weightings. Based on these findings, the study recommends prioritizing FAHP over AHP for flood hazard mapping studies.

Keywords: Flood risk assessment, Flood risk mapping, Sensitivity analysis, Analytical Hierarchy Process (AHP), Triangular Fuzzy Analytical Hierarchy Process (FAHP), Multi-criteria decision analysis (MCDA), Geographic Information System (GIS), and ROC-AUC analysis.

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List of Acronyms

AHP - Analytical Hierarchy Process

AUC - Area Under the ROC Curve

CI - Consistency Index

COL – Cut-Off Low

COA - Centre of Area

CRED - Centre for Research on the Epidemiology of Disasters

CR - Consistency Ratio

CSIR - Council of Scientific and Industrial Research

DEM - Digital Elevation Models

DMA - Disaster Management Act 57

DRR - Disaster Risk Reduction

DIVA-GIS - Data Interpolating Variational Analysis Geographic Information System

EM-DAT - Emergency Events Database

EPoA - Emergency Plan of Action

ESRI - Environmental Systems Research Institute

EU - European Union

FAHP - Triangular Fuzzy Analytical Hierarchy Process

FAO - Food and Agriculture Organization

GDP - Gross Domestic Product

GIS - Geographic Information Systems

HEC-RAS - Hydrologic Engineering Center's River Analysis System

IFRC - International Federation of Red Cross and Red Crescent Societies

IPCC - Intergovernmental Panel on Climate Change

Landsat 8 TIRS/OLI – Landsat 8 Thermal Infrared Sensor/Operational Land Imager

LULC - Land Use/Land Cover

MCDM - Multi-Criteria Decision Making

MCDCA - Multi-criteria Decision Analysis

NCGIA - National Centre of Geographic Information and Analysis

NGOs - Non-Governmental Organizations

OAT - One-At-A-Time

ROC - Receiver Operating Characteristic

ROC-AUC - The Receiver Operating Characteristic Area Under the Curve

ROM - Rank Order Method

SAFFG - South African Flash Flood Guidance

SAWS - South African Weather Service

SADC - Southern African Development Community

SANSA - South African National Space Agency

SRTM - Shuttle Radar Topography Mission

TOPSIS - Technique for Order of Preference by Similarity to Ideal Solution

UNICEF - United Nations International Children's Emergency Fund

UNESCO - The United Nations Educational, Scientific and Cultural Organization

UNECE - United Nations Economic Commission for Europe

UNISDR - United Nations Office for Disaster Risk Reduction

USA – United States of America

USAID - United States Agency for International Development Flood Management

VI - Variance Inverse

WHO - World Health Organization

WGS - World Geodetic System

WMO - World Meteorological Organization

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1. Chapter One: Introduction

GENERAL INTRODUCTION

1.1. Introduction

Every year, floods result in significant loss of life and widespread destruction of property, along with severe environmental damage, globally (UNISDR, 2019). Floods, among the most common and widespread weather-related natural hazards, have significant negative impacts in many countries (CRED and UNISDR, 2017). According to the Emergency Event Database (EM-DAT, 2021), floods have affected approximately 1.6 billion people globally, the biggest number of any disaster type, accounting for 44% of all disaster events between 2000 and 2021. They have also contributed to 13% of all the fatalities caused by natural hazards, as well as major economic losses of almost \$656 billion in the same period (EM-DAT, 2021). The United Nations Office for Disaster Risk Reduction (UNISDR, 2009) defines a ‘natural hazard’ as a *“natural process or phenomenon that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage”*. The Centre for Research on the Epidemiology of Disasters (CRED, 2017) defines a ‘disaster’ as *“a situation or event which overwhelms local capacity, necessitating a request at national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering”*. There is a clear disaster risk if people live in areas that are known to be prone to seasonal or flash flooding (natural hazard) since it may result in the loss of lives or property damage (Cilliers, 2019).

Although floods are the most frequent type of natural disaster that occurs in South Africa annually (Midgley et al., 2005; Le Maitre and Kotzee, 2019), the majority of urban settlers live in unplanned informal settlements, often in flood-prone areas (Busayo et al., 2022; Musungu et al., 2016; Le Quéré et al., 2020). This situation is exacerbated by the rapid growth of the population, leading to the expansion and development of urban and rural settlements along the riverbanks and floodplains (Sauka, 2016). Consequently, numerous communities, especially those residing in low-lying areas, near riverbanks, and in regions susceptible to high rainfall, face a heightened risk of negative impacts from floods (Munyai, 2016). Due to these risks, the establishment of a flood risk assessment method is a suitable approach that can effectively address floods and provide mitigation measures to help reduce their impacts (Ran and Nedovic-Budic, 2016). Implementing such assessment methods can empower communities with early warning systems, evacuation plans, and sustainable land-use practices, enhancing resilience against the recurring threat of floods (Perera et al., 2020).

In the period between 1980 and 2010, South Africa recorded 77 major floods which resulted in 1,068 fatalities (CSIR, 2019). Moreover, since 2010 the country has experienced multiple devastating floods that have caused substantial infrastructure damage, and loss of lives and livelihoods (Mothapo, 2019). As a result, the probability of experiencing a flood in a given year is notably high, given that the frequency and intensity of catastrophic floods continue to rise (Dube et al., 2022). Therefore, it is of utmost importance that investments be made in disaster management processes by updating the infrastructure through building more dams, constructing dykes, and also ensuring proper selection of settlements that are not prone to flooding which implies taking measures to avoid building communities in areas that are known for being susceptible to flooding, to protect the safety and well-being of the residents and to prevent potential flood-related damage (WHO, 2002; Dung et al., 2018; Sapkota, 2017). Furthermore, applying the appropriate mitigation strategies and delineating flood hazard zones can significantly reduce flood-related damages (European Union Flood Directive, 2007; Naulin et al., 2013; Guo et al., 2014).

Over the years, various efforts have been made by individuals, communities, and governments to reduce society's exposure to known environmental hazards (Copolla, 2006). For example, on the assessment and management of flood hazards, the European Union established a Directive 2007/60/EC with the main goal of creating a general framework for flood risk management and mapping (Feroni et al., 2019). The primary aspect of the flood directive is identifying flood-prone areas within the European Union. In alignment with this, Sutanta et al. (2010) argue that spatial development planning functions as a proactive tool with substantial potential for Disaster Risk Reduction (DRR). They emphasize its role in strategically guiding future land uses to avoid areas susceptible to known natural hazards. In this way, the strategic control offered by spatial development planning aligns with the goals of flood risk management, as exemplified by the EU Directive. To effectively implement flood risk management strategies, various tools for mapping flood risk zones are employed to facilitate a comprehensive understanding of vulnerable areas and enable informed decision-making in spatial development planning. As an example, Geographic Information Systems (GIS) emerged as a pivotal tool for mapping flood risk zones in the realm of flood risk management (Ding et al., 2021).

Over time, GIS has gained popularity, offering quicker and more efficient methods to identify and map flood risk zones while also being proposed as a decision support system for effective flood management. Many studies, including those conducted by Allafta and Opp (2021), Cai et al. (2021), Rincon et al. (2018), and Feroni et al. (2019), have employed GIS for flood risk assessment. In most cases, it has been integrated with Multi-criteria Decision Analysis (MCDA) to enhance the quality of decision-making (Cai et al., 2021; Allafta and Opp, 2021;

Feloni et al., 2019). This integration is especially crucial because flood hazard mapping and risk assessment require the use of criteria, as highlighted by Poussin et al. (2014). Consequently, an increasing number of studies have adopted the MCDA approach in conjunction with GIS for comprehensive flood risk assessment. This integrated approach facilitates the incorporation of the three key components of risk assessment—hazard, exposure, and vulnerability—as emphasized by Rincon et al. (2018). It also considers flood risk assessment as a product of comprehensive action of several factors (Cai et al., 2021).

MCDA is defined as: *“a multi-step process consisting of a set of methods to structure and formalize decision-making processes in a transparent and consistent manner”* (Langemeyer et al., 2016:48). The primary objective of employing various methods of MCDA is to enhance the clarity and transparency of the decision-making process by assessing criterion weights. This improved transparency results in more rational and effective decision-making, ultimately yielding decisions that are reasonable and easily understandable (Mateo, 2012). The most common types of MCDA methods that are often applied for mapping flood risk zones are the AHP and FAHP (Hoque et al., 2019; Gigovic et al., 2017; Dahri and Abita, 2017; Lin et al., 2019; Yodying et al., 2019; Cai et al., 2021; Yang et al., 2013; Papaioannou et al., 2015).

AHP is a decision-making support method that allows users to intuitively judge the relative weight of various criteria or options in comparison to a specified criterion (Saaty, 1990). It uses a network structure to represent a problem and pairwise comparisons to establish the relations within that structure (Saaty, 1980). This method has been widely used to map flood risk and susceptibility using a combination of different flood-related parameters (Rincon et al., 2018; Feloni et al., 2019; Cabrera et al., 2019; Valdez and Fernandez, 2014). The purpose of AHP in flood risk mapping is to weigh the criteria based on the relative importance of each parameter towards a flood risk. Despite its popularity in flood risk mapping, it is often considered inferior because of the “subjective” judgments produced by the priorities of decision-makers (Feloni, 2019) and its incompetency when applied to ambiguous problems like the uncertainty of the criteria of the parameters (Tsai et al., 2010; Sadiq and Tesfamariam, 2009). As a result, it has been improved by combining mathematical techniques, like the fuzzy logic methodology to make a FAHP to reduce the uncertainty of the parameters (Pappenberger et al., 2007). In recent years, the two methods have so far, proved to be useful in flood risk mapping as they have drawn considerable interest in problem-solving from scholars as well as decision-makers and practitioners beyond the scientific community (De Brito and Evers, 2016).

An essential component of FAHP, called sensitivity analysis has been identified as a suitable method for understanding flood-related models and reducing their uncertainty (Pappenberger

et al., 2007). This method determines how the selection of alternatives changes when the relative weights of the selection criteria are adjusted (Munz, et al. 2016). It has also been used in various fields of study to measure the consistency of MCDA methods in the weighting of parameters (Dogan, 2021; Feick and Hall, 2002; Pappenberger et al, 2007; Boroushaki and Malczewski, 2009). However, in flood risk assessment many studies adopted the AHP and FAHP but neglected sensitivity, thus leaving more subjectivity. According to Crotto et al. (2000), sensitivity analysis can help to alleviate the uncertainty of multi-criteria analysis methods. This method ensures the stability of the outputs by demonstrating the impacts of small changes to certain input parameters on evaluation outcomes. Criteria weights are mostly identified as the source of uncertainty because they are subjectively defined, as a result, they can affect the decision outcomes (Belton and Hodgkins, 1999).

1.1. Research Aim and Objectives

1.1.1. Aim

The study aims to evaluate the sensitivity of the AHP and the FAHP to changes in criteria values.

1.1.2. Research Objectives

- i. Determine criteria that are needed for identifying and mapping flood risk areas.
- ii. Determine the weights and conduct a multi-criteria analysis using the two methods (AHP and FAHP).
- iii. Map the spatial distribution of flood risk zones within the municipality.
- iv. Adjust the criteria weights by varying percentages and conduct an accuracy assessment to measure the impact of weight adjustments on the outcomes.

1.2. Structure of the dissertation

Chapter One

Chapter one of the study offers an overview by highlighting the global impact of floods as a natural hazard and delving into the specific vulnerability of South Africa, where floods stand out as the most frequent natural disaster. This vulnerability is exacerbated by the rapid growth of informal settlements in flood-prone areas due to a swiftly increasing population. The chapter also explores the growing utilization of Geographic Information Systems (GIS) for the identification and mapping of flood risk zones, emphasizing its role as a decision support system in effective flood management. Furthermore, it emphasizes the significance of Multi-criteria Decision Analysis (MCDA), particularly focusing on the AHP and FAHP, in mapping flood risk zones. AHP's subjective judgments prompted the development of FAHP to address uncertainty. The chapter introduces sensitivity analysis as a method within FAHP to reduce

uncertainty and comprehend flood-related models. The study's ultimate goal is outlined as testing the sensitivity of AHP and FAHP in flood risk assessment using a multi-criteria approach.

Chapter Two

The chapter provides a comprehensive review of existing research on floods, covering various aspects such as flood risks, vulnerabilities, occurrences, spatial distribution, causes, and types. The role of GIS and multi-criteria analysis in flood risk mapping is explored. The chapter extends its focus to flood risk management, delving into strategies and approaches employed to mitigate the impact of floods. Managing floods, a critical component, is discussed in terms of the methods and measures implemented to control, prevent, and respond to flooding incidents. Additionally, the chapter introduces and discusses two key concepts: the concept of weighting, which involves assigning importance to different factors contributing to flood risk, and the concept of sensitivity analysis, which assesses the reliability of methods used in flood risk assessment and identifies areas for improvement.

Chapter Three

Chapter Three of the study details the methodology employed for flood risk assessment, utilizing a GIS-based Multi-Criteria Decision Analysis (MCDA) approach. The methodology integrates the Analytical Hierarchy Process (AHP) and Triangular Fuzzy Analytical Hierarchy Process (FAHP) to assign weights to criteria, enhancing decision-making precision. The chapter outlines the stepwise process of assigning weights and introduces sensitivity analysis, adjusting weights by $\pm 20\%$ to evaluate the methodology's robustness. The ROC-AUC is introduced to quantitatively assess the accuracy of the flood risk assessment model. This chapter establishes a comprehensive framework, combining GIS, AHP, and Triangular Fuzzy AHP, to enhance the accuracy and reliability of flood risk assessment in the study area.

Chapter Four

Chapter Four presents the results of the flood risk assessment methodology outlined in Chapter Three. The GIS-MCDA employing AHP and FAHP successfully produced two flood hazard maps. The sensitivity analysis, involving modifications of weights by $\pm 20\%$, demonstrates the robustness of the methodology and reveals the subtle effects of changes in criteria weights on the ultimate assessment of flood risk. Additionally, the ROC-AUC results quantitatively measure the accuracy of the model, enhancing our understanding of its capability to differentiate between different flood risk scenarios. Chapter Four encapsulates the tangible findings, patterns, and trends derived from the applied methodology, significantly advancing our comprehension of flood risk in the study area.

Chapter Five

This chapter concludes the study by combining and summarizing the valuable information and understanding obtained from the methodology discussed in Chapter Three and the results presented in Chapter Four. Moreover, it offers practical recommendations based on the nuanced insights obtained, aiming to guide informed decision-making in flood risk management.

2. Chapter Two: Literature review

2.1. Introduction

This chapter thoroughly reviews existing research on floods. It covers various aspects such as flood risks, vulnerabilities, and occurrences. The chapter explores the spatial distribution, causes, and different types of floods. Additionally, it further explores the role of GIS and multi-criteria analysis in flood risk mapping. Furthermore, understanding flood risk involves a multifaceted approach, which involves knowledge of flood causes, types, and their spatial distribution. The chapter also delves into historical major flood events in South Africa, providing an understanding of recurring challenges. Recognizing these historical events and the factors contributing to floods is essential for assessing contemporary flood risks.

Moreover, the chapter emphasizes the link between disaster risk management and the broader field of disaster management. It focuses on multi-criteria analysis, a method for comprehensively evaluating factors contributing to flood risk. The effectiveness of these methods is assessed, considering the concept of weighting and how subjective opinions can influence different approaches. Additionally, the concept of sensitivity analysis is also discussed, assessing the reliability of these methods, and identifying potential areas for improvement. This chapter is instrumental in strengthening the ability to address flood risks and lays the groundwork for more informed decision-making in flood risk management.

2.2. Understanding floods and flood risk

Floods are considered a significant disaster, and their frequency and severity are projected to increase in many countries due to socioeconomic developments and global warming (Taguchi et al., 2022; Hirabayashi et al., 2013; Alfieri et al., 2017). One could argue that human activities have enhanced the flooding's strength and suddenness or, at the very least, created the potential for harm (Klijn, 2009). Hence, flood risk is a measure of the likelihood of a flood occurring and the potential negative effects it may have (Taguchi et al., 2022). While floods can have benefits, such as distributing nutrient-rich sediment across floodplains and creating habitats, they can also be catastrophic, causing damage to infrastructure and resulting in loss of life for both humans and animals (Sayers et al., 2013). In recent years, the impacts of floods have become more severe due to human activities such as urbanization and development in flood-prone areas (Cabrera and Lee, 2019). According to the World Bank (2020), approximately 1.47 billion people worldwide are directly at risk of intense floods, and approximately 600 million of them are poor, making them particularly vulnerable to the devastating impacts of flooding. This increasing vulnerability highlights the necessity of

establishing precise definitions and characterizations of floods, thereby facilitating a more comprehensive understanding of the challenges they pose.

2.2.1. Defining floods

In 2007, the European Parliament Council established a fundamental definition of floods as *"the temporary covering by water of land not typically submerged by water."* This overarching conceptualization involves a wide range of flood events (Feloni et al., 2019). Similarly, the IPCC (2012), defines floods as *"the overflowing of the normal confines of a stream or other body of water, or the accumulation of water over areas that are not normally submerged."* However, despite the common association of floods with rainfall, it is important to recognize that floods can manifest through various mechanisms not directly linked to prevailing meteorological conditions, as highlighted by Doswell (2003). As a result, it is imperative to consider processes that may be unrelated to climatic phenomena to provide a holistic understanding of floods, even though it is widely acknowledged that floodwaters, at some point, originate from precipitation in order. Building upon this discourse, Carter (2012) notes that the Australian Government has proposed an alternative definition of floods, stating that *"flood means the covering of normally dry land by water that has escaped or been released from the normal confines of any lake or river, creek, or other natural watercourse, whether or not altered or modified, or from any reservoir, canal, or dam."*

In the context of this study, floods are defined as the temporary inundation of typically dry land by water, irrespective of the source or prevailing meteorological conditions. This definition comprehensively involves scenarios where water surpasses the typical boundaries of natural watercourses, lakes, rivers, reservoirs, canals, or dams, whether they have undergone modifications or remain in their natural state. The adoption of this inclusive definition is imperative for thorough comprehension and assessment of flood risks in the scope of this research. In essence, the definition involves a broad range of situations where an excessive amount of water leads to the inundation of normally dry land. Moreover, floods can have various causes and can impact both natural and human-altered water systems.

2.2.2. Flood causative factors

Floods occur when an excess of water temporarily submerges normally dry ground (Wisner et al., 2004; Martini and Loat, 2007; Klijn 2009; Ali, 2018). They can be caused by various factors which can be divided into natural and man-made causes (Dambe, 2020). According to van Niekerk and Nemaikonde (2017), changes in weather patterns are one of the main causes of natural hazards in Sub-Saharan Africa. The extreme El Niño event, which occurred in 2015–2016, devastated the Sub-Saharan countries with droughts and floods (van Niekerk and Nemaikonde, 2017; Dambe, 2020). However, there are a variety of other factors that cause

floods globally. A summary of some of the factors that cause and contribute to floods is provided below.

2.2.2.1. Natural factors causing floods.

- Meteorological phenomena like prolonged, cyclones, storms, tidal surges, and drainage changes when combined with heavy rain can result in floods (Brahmah et al., 2014). Heavy rainfall that lasts for a long time saturates the soil, making it incapable of storing any more water, as a result, increasing surface drainage.
- Topography and natural drainage obstructions slow the flow and cause backwater effects whereas steep slopes boost flow and runoff, which in turn boosts overland flow thereby causing floods (Dambe, 2020).
- Regarding water movement, soil type is also important. Since shallow soils have less storage capacity, and do not absorb as much water, which increases overland flow and vice versa (Allafta and Opp, 2021). The same holds for impermeable rocks that promote through flow and overland flow while obstructing groundwater movement (Doswell, 2003).
- Increased runoff from snowmelt due to warm temperatures can also cause floods (Musungu et al., 2012; Beven, 2004; Manfreda et al., 2010). In many parts of the world, severe flooding and soil erosion are primarily caused by fast snowmelt on impermeably frozen soil (Flerchinger et al., 2013). The ability of the soil to absorb water can be significantly reduced by soil freezing. Large runoff episodes from otherwise light rainfall or snowmelt events result from ice-blocking soil pores (Flerchinger et al., 2013).
- Flooding along the coast may result from high tides, storm surges, and powerful winds creating high energy waves and causing an increase in wave run-up (Le Maitre and Kotzee, 2019). According to Ebersole et al. (2022), the primary cause of coastal flooding is storm surges. Tropical cyclones can be accompanied by heavy rain, which can also significantly increase the risk of flooding. By delaying the drainage of rainfall off the watershed and toward the coast, storm surges can exacerbate inland floods (Ebersole et al., 2022).
- Earthquakes can influence flooding by changing the flow, volume, and distribution of surface and/or subsurface waters as well as the physical characteristics of naturally occurring and artificial environments such as elevation, topographic relief, and permeability (Quigley and Duffy, 2020; Doswell, 2003). For example, a submarine coseismic landslide or an offshore fault rupture may result in flooding brought on by a tsunami. The lower plate, plate interface, upper crustal, or upper

plate faults may all experience subduction-related tsunami genic earthquakes (Gusman et al., 2009).

2.2.2.2. Anthropogenic factors causing floods.

While natural systems can handle occasional floods, human development across much of the world's geography, coupled with our consumptive lifestyles, have not only increased the frequency of floods but also exacerbated their impacts (Munsaka and Mutasa, 2020; Asiedu, 2020; Braimah et al., 2014). Below are some anthropogenic factors that influence floods.

- Urbanization stands out as the predominant anthropogenic factor contributing to floods, as indicated by Asiedu (2020). Several other scholars, including Kaendler et al. (2018), Eldho et al. (2018), and Feng et al. (2021), have associated urbanization with heightened levels of rainfall and its impact on flooding. Additionally, Doswell (2003) contends that even minimal rainfall can trigger flash floods in highly urbanized regions. This connection between urbanization and flooding is primarily attributed to the expansion of impermeable surfaces within urban areas, which tends to slow down the natural hydrological response time and elevate the risk of flooding, as emphasized by Feng et al. (2021). Furthermore, the pace of urbanization has accelerated to such an extent that many people are deprived of access to safe land with essential services. Consequently, they are compelled to settle in marginal lands situated in proximity to hazardous zones, such as rivers.
- Inadequate natural drainage because of pollution or improper waste disposal that strains the drainage systems also causes flash floods (Dambe, 2020; Karley, 2009; Twumasi, 2002; GBF et al., 2014). For instance, poorly maintained drainage systems are often clogged with garbage which prevents rainwater from draining fast and easily, thus increasing flooding.
- Construction of buildings along floodplains which causes water flow obstruction, careless dumping of municipal waste on floodplains, inside streams, and river systems can also result in flooding (Onifade et al., 2014).
- Due to competition for agricultural land and deforestation brought on by the usage of fuelwood, soil erosion has increased while water retention capacity has decreased, and sedimentation has grown, worsening the risk of flooding (Dambe, 2020).
- Another noteworthy anthropogenic factor that can exacerbate flooding risk is the unethical practice of certain local authorities or officials who, in some instances, sell land in flood-prone areas without adequate consideration of potential risks and

consequences. This may endanger lives and property and, in turn, contribute to the issue of urban flooding.

2.2.3. Types of floods

According to Eleuterio (2012), a flood event is influenced by several factors that help to distinguish between floods in various circumstances. The water source (origin), the geography of the receiving area, the cause, and the speed of onset are all factors that can be used to categorize floods (Klijn, 2009). The different types of floods are described below.

2.2.3.1. Coastal floods

Coastal flooding often occurs during extreme water level events due to the combined influences of various factors, as discussed in the study by Swathy Krishna et al. (2023). These factors encompass astronomical, atmospheric, thermal, oceanographic, and geophysical forces, encompassing elements such as powerful battering waves, storm surges, high tides, and resulting mean sea level anomalies. As an example, in June 2007, South Africa experienced significant coastal and inland flooding, including coastal areas in the Western Cape, KwaZulu-Natal, and Eastern Cape provinces where heavy rainfall and stormy conditions, associated with a severe weather system, led to extensive flooding along the coastal regions of these provinces (Hunter, 2007).

2.2.3.2. Flash floods

The term "flash flood" describes a rapid flooding event that occurs during or immediately following intense precipitation, resulting in a swift surge of water (Ugwuibe et al., 2021). As a result, flash floods more often happen in relatively small catchments where the drainage basin's response time is short. Despite being a subtype of riverine flooding (Wisner et al. 2004; Wright 2008), flash floods are frequently treated separately due to the high death toll and significant damage they can cause (Els, 2011). For instance, intense precipitation and powerful winds impacted South Africa, specifically the Western Cape Province and the Cape Town region, from September 23rd to 26th in 2023. These weather conditions led to flooding, landslides, overflowing rivers, and several significant weather-related incidents, resulting in both casualties and property damage ("South Africa - Floods and Severe Weather, Update (Floodlist, Media, SAWS) (ECHO Daily Flash of 27 September 2023) - South Africa," 2023)

2.2.3.3. Riverine floods

Unlike flash floods, river floods which are also known as fluvial floods typically develop over days or even months. This slower onset is often due to multiple, distinct episodes of rainfall that exceed a river's channel capacity, occurring over extended periods and affecting large basins, including 'main stem' rivers (Doswell, 2003; Wright, 2008; Els, 2011).

2.2.3.4. Urban floods

Urban flooding occurs when stormwater enters a city at an increased rate than it can be absorbed by the soil, transported to a body of water (lake, river, etc.), or collected in a reservoir (Els, 2011; Wright, 2008; Vazhuthi and Kumar, 2020). Rapid snowmelt, flash flooding, coastal flooding, or river flooding are all potential causes of the increased water flow. Urban floods can inflict considerable structural damage, even when water levels are a few inches deep (Klijn, 2009).

2.3. Flooding in Southern Africa

Floods, severe storms, droughts, and wildfires are the most frequent extreme weather occurrences in Southern Africa (Davis-Reddy and Vincent, 2017). Historical evidence also shows that natural disasters like floods have afflicted many African countries, including South Africa (Mothapo, 2019). So far, flooding continues to take its toll on the population of many other African countries, where there has been a sharp rise in the number of flood-related fatalities and economic losses in the last 50 years (Mothapo, 2019; Di Baldassarre et al., 2010). Countries within the Southern region of the Southern African Development Community (SADC) have also witnessed destructive flooding events of different scales in the past. For instance, in recent years, the Southern African region has witnessed several significant flood events, with one notable example being the one caused by Cyclone Idai in March 2019. Cyclone Idai, which is one of the most devastating tropical cyclones in the Southern Hemisphere, made landfall in Mozambique, Zimbabwe, and Malawi, resulting in widespread flooding and destruction of infrastructure (United Nations Office for the Coordination of Humanitarian Affairs, 2021).

More importantly, the International Federation of Red Cross and Red Crescent Societies (IFRC) (2022), indicates that the average number of climate and weather-related disasters has increased by about 35% during the past three decades. In the last ten years alone, extreme weather and climate-related events contributed to 83% of disasters, causing 410,000 fatalities and affecting 1.7 billion people globally and generating a tremendous financial loss in the economies of many countries (Angelakis et al., 2023).

Floods can potentially introduce viruses, parasites, and bacteria into clean water supplies, which can lead to the spread of waterborne illnesses (Brown and Murray, 2013). However, it is important to note that this is not always the case, and the outcome may vary depending on specific circumstances. Southern African communities experience food insecurity because of flood disasters' impact on agricultural production (FAO-SAFR, 2002). According to Musyoki et al. (2016), governments in Southern Africa are developing strategies to deal with the effects of flooding, but these efforts are frequently insufficient and impacted by public views, which, in turn, affect their responses. Moreover, communities frequently oppose relocation because

agriculture depends on flooding and because biological systems are the foundation for the regrowth of crops, plants, and aquatic life (Wisner et al. 2004; Musyoki, 2016)

2.3.1. Overview of floods in South Africa

In South Africa and many other countries, natural hazards are common phenomena, especially floods (Midgley et al., 2005; CSIR, 2019; Ntanganedzeni and Nobert, 2021). The country has experienced floods in the past, from local events through to national disasters caused by widespread flooding brought on by catastrophic storms like tropical cyclones, the most recent one being cyclone Eloise in January 2021 (Mothapo, 2019; van Niekerk et al., 2019; Davis-Reddy and Vincent, 2017; Pharoah et al., 2016; Pyle and Jacobs, 2016). According to the South African Weather Service (SAWS, 2021), the country has recently experienced above-average rainfall, leading to floods. These floods have caused widespread destruction not seen in the country in the past few years. The Food and Agriculture Organization of the United Nations (FAO, 2021), argues that the La Nina event is the reason for these above-average rainfalls which usually occur around November to April. La Nina is defined as a climate phenomenon characterized by the weakening of prevailing trade winds, resulting in reduced upwelling and changes in ocean currents, which lead to a warming of sea surface temperatures and a further weakening of trade winds (IPCC, 2012). This event exerts a significant influence on wind patterns, sea surface temperatures, and precipitation distribution in the tropical Pacific. Its climatic repercussions extend across the Pacific region and impact various parts of the world, including South Africa (IPCC, 2012).

On the 31st of March of 2000, one of the most notable flooding events occurred in South Africa's northeast due to heavy rainfall. The affected areas included the Crocodile River, Sabie River, and the Limpopo River basin, resulting in more than 700 fatalities (Dyson and van Heerden, 2001; Mkhulisa, 2017; Spaliviero, 2014). The flooding displaced approximately 300,000 people in Limpopo and Mozambique (Halsnæs and Trærup, 2009) and caused billions of rands in damage to both public and private infrastructure (du Plessis, 2002; Nethengwe, 2007; Mothapo, 2019).

Subsequently, in the KwaZulu-Natal province of South Africa, severe flooding and landslides occurred due to heavy rainfall caused by a Cut-Off Low (COL) (Mashao et al., 2022) from 11 to 13 April 2022. This event resulted in the deaths of 448 people, the displacement of more than 40,000 people, and the destruction of more than 12,000 homes (UNICEF, 2022). Due to the intensity of the floods, the National Disaster Management Centre declared the floods a national state of disaster in terms of section 23 of the National Disaster Management Act 57 of 2002 (Kunguma, 2022). Moreover, the insurance company named Santam faced a substantial payout of billions of rands as a result of the damage inflicted by the flooding. The estimated damage to infrastructure alone amounts to around R25 billion (Mabaso, 2022).

The common effects of flooding in South Africa include the loss of lives, destruction of agricultural areas, damage to bridges and roadways, sewage-disposal systems, and buildings which lead to a loss of shelter (Musyoki et al, 2016). As a result, people often lose their sources of income, which forces them into even deeper poverty. However, according to Mwape (2009), poverty does not necessarily equate to vulnerability; it does make people more susceptible to disasters because they lack the material, social, and intellectual resources necessary to foresee and respond to dangers and shocks like floods. Other effects of the floods that have been affecting South African countries include contaminated drinking water supplies, which are the main cause of waterborne infections (Okaka and Odhiambo, 2018).

Based on historical flood records, the two most destructive floods to ever hit the country are the ones highlighted above. In the past 60 years, there have been several significant floods in the last ten years that also caused considerable infrastructure damage, as well as loss of lives and livelihoods (Busayo et al., 2022).

Table 1: *A historical record of major flood events in South Africa*

Year	Region	Cause and/or type of floods	Details
1958	Musina	River floods, caused by tropical cyclone Astrid.	Residences and bridges along the Sand and Selati rivers were destroyed (SAWDIS, 1981).
1968	Port Elizabeth	Heavy rainfall	Streets have been destroyed, and buildings, motor vehicles, trees, people, and animals have been washed away. Communication lines have been disrupted. Damage is estimated at R400 million. Eleven people lost their lives to drowning (Grobler, 2003).
1974	The central interior of South Africa	River floods (The Great Fish River, the Orange River)	80% of the homes on the island and along the Orange River in Upington were submerged. Infrastructure damage was estimated to have cost millions of rands (Grobler, 2003).
1977	North-eastern part of South Africa	Tropical cyclone Emilie	There were 300 recorded fatalities in the Limpopo Valley region due to widespread flooding (Grobler, 2003).

Year	Region	Cause and/or type of floods	Details
1981	Laingsburg in the Western Cape	Heavy rains	One of the worst disasters in South African history. At least 100 residents lost their lives, and the bodies of 72 people were never found. Only 21 houses remained after a total of 184 houses were destroyed (Grobler, 2003).
1984	North-eastern part of South Africa.	Tropical cyclone Demoina	This incident resulted in substantial loss of life and widespread damage to infrastructure and property that was estimated at \$200 million. The heavy rains led to catastrophic floods that damaged roads, and buildings across northeastern South Africa, southern Mozambique, and Swaziland (Grobler, 2003).
1987	KwaZulu Natal coastal region	Heavy rains	506 fatalities have been recorded. Over 30,000 homes were damaged by the floods, which also left over 50,000 people homeless. A 500-million-dollar damage estimate was made (Grobler, 2003; Zawad and Smith, 1991).
1988	Central interior of the country	River flood (Orange River)	There were fatalities and more than \$126 million in damage because of this flood (Grobler, 2003; Zawad and Smith, 1991).
1994	Ladysmith	River floods (Klip and Sand River)	For the previous 71 years, it was the biggest flood. Over a thousand families were left homeless. Damage was estimated to be around R67 million (Grobler, 2003).
1995	Pietermaritzburg	Heavy rains, River floods (Msunduzi River)	Approximately 200 people lost their lives. Over 700 houses were washed away due to overflowing of the Msunduzi River.

Year	Region	Cause and/or type of floods	Details
2000	Limpopo province	Tropical cyclone Eline	More than 700 fatalities were recorded and approximately 300 000 people have been displaced. One of the worst floods to ever occur in Limpopo (Mothapo, 2019; Mason, 1998).
2006	Western and Southern Cape	Cold front	Approximately 12 fatalities were recorded. Some farm dams were overflowing, while others had burst. Most houses were submerged in water (EPoA, 2014).
2014	North-eastern region	Heavy rainfall	Over 7000 people were affected by floods. More than 600,000 people were left with no water in Nelspruit. The number of reported fatalities was 8 while 19 were reported missing (Mothapo, 2019).
2019	KwaZulu-Natal and Eastern Cape	Heavy rainfall	Almost 70 people lost their lives. 145 people were displaced. Approximately 235 Homes were damaged. The total property damage was estimated at R650 million (IFRC, 2022; Busayo et al., 2022).
2022	KwaZulu-Natal	Heavy rainfall due to Cut-off Low	The floods destroyed infrastructure, land, and houses. Tragically, 80 people were reported missing, while 435 people lost their lives. The disaster has damaged more than 19,000 homes with more than 120 000 people in total (IFRC, 2022; UNICEF, 2022; RCRCCC, 2022).

The process of recovery has taken years, and it has necessitated constant investment. Nevertheless, despite all these efforts, many communities have not been able to redevelop (Le Maitre et al., 2019).

2.3.2 Factors Contributing to Floods in South Africa

Floods occur when catchment areas, waterways, and rivers are unable to handle the volume of water flowing through them. Rainfall serves as the initial trigger for this process, although many other factors also play a role (Sholihah et al., 2020). However, the factors contributing

to floods in Southern African regions are largely undocumented and this results in a lack of preparedness and increased vulnerability. According to Muofhe et al. (2020), COL pressure systems are among the most significant rainfall-producing systems in the country. For example, on the 11th and 12th of April 2022, the eastern coast of KwaZulu Natal province experienced heavy rainfalls caused by the COL pressure system which resulted in floods that caused massive infrastructure damage and loss of lives (Singh et al., 2022). However, anthropogenic activities such as improper waste disposal, deforestation, and inhabitation of floodplains exacerbate the intensity of floods in many areas across the country.

Furthermore, South Africa has experienced rapid urbanization over the past two decades (Arndt et al., 2018). Due to this increased urbanization, there is overpopulation in some areas, and disregard for environmental rules, as a result, people are forced to settle in low-lying areas and ecosystems with weak foundations (Dube et al., 2022). Moreover, the development of hard, impermeable surfaces brought about by urbanization has decreased the capacity of the land to absorb rainfall (Taylor, 2019). Due to less water soaking into the ground, surface runoff increases in volume and accumulates rapidly filling up drains and roads and resulting in floods. Typically, the drainage systems are blocked by waste and soil in most urban settlements across the country (Dube et al., 2022).

The recent flood events in South Africa proved that settling near waterbodies is also one of the key factors that contribute to the vulnerability of people to flooding because when the amount of water exceeds the capacity of the waterbody, it overflows out into the low-lying grounds adjacent to water bodies (Mashao et al., 2022). According to Tsenkova (2010), the majority of informal settlements are typically found near water bodies. This is also the case for South Africa, for instance, the Setswetla informal settlement in Alexandra, Johannesburg is close to the Juksei River, which often causes flooding during heavy downpours, while the Zwelitsha informal settlement in Dunoon in Cape Town is always inundated anytime Diep River bursts its bank (Gqomfa, 2022). Additionally, the Palmiet River, which is close to the Quarry West informal settlement in Durban, frequently overflows and floods the neighbourhood during periods of high rainfall (Williams et al., 2018). In a nutshell, the inhabitation of areas near water bodies is also one of the key factors contributing to floods in South Africa.

Spatial planning carried out during the apartheid era made a substantial contribution to flooding in many South African informal settlements. Discriminatory practices were put into place during the apartheid era, dividing communities along racial lines and pushing non-white populations particularly Black South Africans to the periphery and underdeveloped areas (Strauss, 2019). These areas were characterized by overcrowding, poor drainage systems,

and subpar housing frequently located in flood-prone areas and lacked basic infrastructure. As a result, these places are more vulnerable to flooding during periods of heavy rain because their inadequate or underdeveloped drainage infrastructure is overloaded. Many communities are still struggling to deal with the effects of floods due to the legacy of apartheid-era spatial design, which highlights the need for inclusive and equitable urban planning.

2.3.3. The spatial distribution of floods in South Africa

South Africa experiences floods in many parts of the country (Dyson, 2009). In recent years, flooding has been featured in the news headlines in South Africa across many regions. A significant number of floods have been seen in the country in addition to the 2014 floods which affected most parts of Limpopo province. The frequency of the occurrence of these flood events varies from region to region as shown in Figure 1 which illustrates the spatial distribution of flood occurrence country across provinces. Table 1 shows that the most common cause of floods in South Africa is heavy rainfall, which often overflows rivers and generates flash floods. These floods can be exacerbated by factors such as man-made surfaces, deforestation, or inadequate drainage systems. However, a range of factors influences the spatial distribution of floods in South Africa, including rainfall patterns, terrain, land use, and infrastructure (Mothapo, 2019). According to Botai et al. (2018), rainfall in South Africa varies greatly from west to east. The eastern Highveld receives much of its annual rainfall between 500 mm and 900 mm, rarely surpassing 2000 mm compared to the northwest, where it frequently falls below 200 mm. For this reason, flooding is more common in the eastern parts of South Africa than in the western regions. This is due to higher rainfall volumes and steeper topography in the eastern parts, which can result in fast runoff and flash flooding. In recent years, both the KwaZulu-Natal and Mpumalanga provinces experienced disasters, particularly due to the floods in March 2019 and 2022, resulting in widespread damage and loss of life.

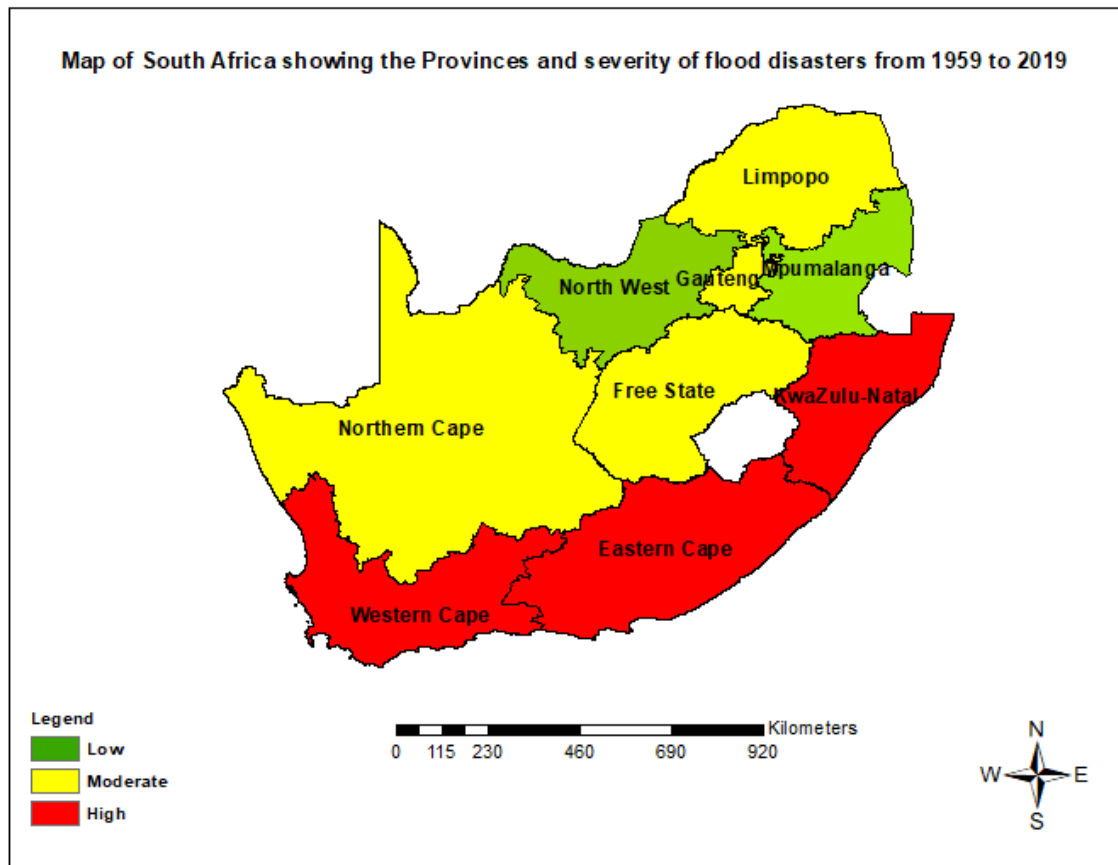


Figure 1: Map of South Africa showing the provinces and severity of flood disasters from 1959 to 2019 (Busayo et al., 2022).

To mitigate the impact of these floods and enhance resilience, several flood risk management strategies have been implemented (Klijn et al., 2009). Consequently, the study will concentrate on the phenomenon of flash flooding, which typically results from intense rainfall events, especially in regions that have been modified by anthropogenic activities.

2.4. Disaster risk management

Disasters, whether caused by human or natural hazards, claim lives and destroy livelihoods (UNISDR, 2015). Based on the findings of a report by the World Meteorological Organization (WMO) (2021), from 1970 to 2019, 91% of all deaths due to weather, climate, and water hazards happened in emerging economies. However, countries have made technical progress in reducing the risk of disasters by shifting from just responding after the event to a higher emphasis on prevention and preparing for shocks, reducing the number of fatalities, and reducing certain economic costs (World Bank, 2015). In the terminology book by the United Nations Office for Disaster Reduction (2009:10), “disaster risk management” is defined as “the application of disaster risk reduction policies and strategies to prevent new disaster risk,

reduce existing disaster risk and manage residual risk, contributing to the strengthening of resilience and reduction of disaster losses.” Additionally, to specifically address the problem of disaster risks, this word is an extension of the more generic term “risk management” (UNISDR, 2009). Also, through activities and methods for prevention, mitigation, and readiness, disaster risk management tries to avoid, mitigate, or transfer the negative consequences of hazards. Cilliers (2019), confirmed that this approach can ensure that the effects of natural hazards, in this case flooding, are either minimized or completely avoided.

2.5. Flood risk management

UNESCO (2013) defines flood risk management as *“the process of data and information gathering, risk analysis and evaluation, appraisal of options, and making, implementing and reviewing decisions to reduce, control, accept or redistribute flood risks”*. According to Klijn et al. (2009), the principle of flood risk management acknowledges that while risks cannot be completely eradicated, they can be mitigated. The primary goal of flood risk management is to reduce the overall impact and damage inflicted by floods of various types on a global scale (Eleuterio, 2012). Then again, flood risk management involves reducing the probability of flooding as well as the vulnerability of society and property in flood-prone areas by using a wide range of measures, such as flood control measures, flood defence measures, and spatial planning (Klijn et al., 2009; Green et al., 2011). In comparison to flood event management, which deals with floods that are happening or about to happen, flood risk management focuses on all possible floods as already indicated, both regular and infrequent, and is therefore basically preventive and usually requires the establishment of flood warning systems and insurance plans that are needed for flood event management (Klijn et al., 2009; Penning-Roswell and Green, 2000a; Eleuterio, 2012; Kreibich and Merz, 2007; Parker et al., 2007a). In conclusion, effective disaster risk management is crucial in achieving the objectives of flood risk management.

2.5.1. Managing floods

Managing floods typically involves a range of techniques and strategies aimed at reducing the risk of flooding and mitigating its impacts. According to Topalovic and Markovic (2018), flood management should be a legal requirement in every country, and it involves both technical and non-technical approaches. Technical flood management techniques include a range of engineered and infrastructure-based strategies aimed at mitigating the impact of flooding (Wang et al., 2022). These techniques typically involve the use of physical structures, technology, and engineering principles to manage and control the flow of water during floods. Whereas non-technical flood management techniques focus on community-based and non-engineered strategies for reducing flood risk and mitigating its impact. These approaches often involve education, awareness, and community participation (Wang et al., 2022).

2.5.2.1. Technical Flood Management

One of the primary technical approaches to flood management is flood risk assessment and mapping, as outlined by the United States Agency for International Development Flood Management (USAID) Report (2015). This method helps identify flood-prone areas and assesses various risk factors such as flood probability, depth, water speed, and submersion duration. Such assessments are vital for improving flood risk management and disaster preparedness. For example, Danumah et al. (2016) conducted a study in the Abidjan district of Cote d'Ivoire, which revealed that 34% of the area had high and very high flood risks. Additionally, a case study from Australia's Hawkesbury-Nepean catchment was also conducted based on flood risk assessment and mapping and the study's findings successfully proved that the catchment has a high risk of flooding, particularly in its urbanized floodplain (Kelly et al., 2023).

Flood forecasts and early warning systems are another essential technical approach, as mentioned by the World Meteorological Organization (WMO, 2013). These systems monitor weather conditions and provide timely alerts to populations in flood-prone areas, enabling decision-makers to make informed assessments and offer early warnings. In South Africa, the Weather Service Act (2001) mandates the South African Weather Service (SAWS), which is a meteorological service under the South African government's Department of Environmental Affairs and Tourism to provide weather and climatic information, including early warnings. The South African Flash Flood Guidance (SAFFG) system, established in 2010, uses meteorological data and hydrological modelling to provide forecasters with information about impending flash floods (Poolman et al., 2015). However, some scholars have argued that disasters are found to be caused by poor communication and reaction capabilities more so than by a lack of forecasts and early warning systems. This is despite communication being a crucial component of flood warning systems (de Perez, 2022; Mashao et al., 2022).

Flood management infrastructure is the third key technical approach, focusing on protecting homes, economically valuable areas, and communities (USAID, 2015). This involves redirecting water flows, delaying and reducing floods, preventing inundation, and maintaining or enhancing the capacity of riverbeds and canals to manage water. These structures are critical for securing communities' economic and social activities by minimizing damage to physical infrastructure. Moreover, Green-grey infrastructure solutions are emerging as innovative interventions in urban planning (Mulligan et al., 2020). These solutions, exemplified by initiatives like bioswales and green sidewalks, aim to enhance the permeability of urban surfaces. They aid in more effective flood management by integrating vegetation and other natural components into urban areas. For instance, bioswales are intended to redirect and treat stormwater runoff, lowering the danger of floods and fostering ecological sustainability

(Mulligan et al., 2020). Similar to this, green sidewalks incorporate vegetation into urban paths, improving both aesthetics and precipitation absorption. These methods indicate a transition towards more resilient and sustainable urban development, where infrastructure and nature collaborate to lessen the effects of flooding in metropolitan areas (Ncube and Arthur, 2021).

Some examples of flood management structures include reservoirs, seawalls, spurs, levees, dikes, and check dams (Wang et al., 2023, USAID, 2015, Mostafazadeh et al., 2017). They are essential for protecting against storm surges by acting as a physical barrier, reducing the impact of waves during a storm surge, while levees and dikes control water flow, preventing inundation of low-lying areas. For example, during flood events, the check dams manage to capture a sizable amount of surface run-off (Mostafazadeh et al., 2017). In Iran's dry and semi-arid regions, as well as other areas, check dams have been successfully used in watershed management practices to control stormwater flows (Zehtabiyan et al. 2011; Mostafazadeh et al., 2017), while levees have been utilized for structural flood prevention for many centuries across many regions (Yen, 1999).

In South Africa, the annual probability of flooding occurrence is approximately 83%. The population is highly vulnerable, facing risks from both economic and geographic factors, as highlighted by Zuma et al. (2012). As a result, the management of floods should be a priority for disaster management centres. However, depending on the extent of decentralization in South Africa, local government (municipalities) is generally regarded as the branch of government that operates in closest proximity to its constituents (van Niekerk, 2014). Municipalities typically have a wide range of obligations in terms of local disaster management and are frequently the first in the line of response when it comes to other spheres of government when disasters occur (van der Berg, 2018). Moreover, municipal local disaster management duties involve the avoidance, reduction, readiness, reaction, recovery from, and rehabilitation of disasters, including floods that have resulted in catastrophic situations.

South Africa has a broad legal framework for disaster management which offers a comprehensive, open, and inclusive disaster management policy that is suitable for the entire country (Vermaak and van Niekerk, 2004; van der Berg, 2018). For instance, the governing legislation for Disaster Risk Management in South Africa is the Disaster Management Act 57 of 2002, as amended (DMA). Yet, van Niekerk (2014) highlights that effective legislation and policy may not always translate into good practice. However, through the efforts of all sectors of government, public society, and the commercial sector, the DMA was established to provide an integrated and coordinated disaster management policy that focuses on preventing and minimizing catastrophe risk (South Africa, 2003).

Despite the legal framework, the effectiveness of disaster risk management depends on various factors, including coordination, communication, and decision-making by relevant authorities (USAID, 2015). Involving local communities and organizations is crucial for success, as collaboration at all levels of society can enhance responsiveness and resilience during disasters. An integrated approach to disaster risk management, involving both the legal framework and practical implementation, is essential for effectively addressing these challenges.

2.5.2.2. Non-Technical Flood Management

The non-technical approaches to flood management, primarily involve community-based and risk assessment methods (Wang et al., 2022). These approaches are equally important in managing and mitigating the impact of floods. To elaborate, non-technical flood management often begins with community mapping exercises. These exercises involve local communities in identifying flood-prone areas, hazards, and vulnerabilities (van Niekerk, 2014). They play a vital role in raising awareness and involving the community in preparedness and mitigation efforts. These exercises empower the communities to take proactive measures by engaging residents in mapping their areas.

Comprehensive disaster risk assessments also form part of the non-technical flood management measures as they are crucial for understanding the vulnerabilities and potential impacts of flooding (Wang et al., 2022). This non-technical approach goes beyond engineering solutions and involves a deep analysis of the socio-economic and environmental factors that contribute to flood risk (USAID, 2015). These assessments help in developing strategies for reducing vulnerability, enhancing community resilience, and targeting resources effectively. Moreover, the DMA in South Africa describes the various disaster risk management structures that should be set up within the various levels of government with a focus on involving local communities (also known as "at-risk" communities), the private sector, government public entities like utility companies, centres of research, and the higher education sector, as well as non-governmental, faith-based, and community-based organizations (also known as NGOs) and traditional leaders (van Niekerk, 2014). The Act also provides comprehensive information on how disaster risk management centres and other intergovernmental organizations might be established at every level of government (South Africa, 2003). Despite this, a study by van Niekerk (2014), indicates that there is a lack of adequate involvement of all sectoral departments in disaster risk management. As a result, it can be argued that disaster risk management is not being taken seriously by all line ministries.

One key aspect highlighted by these legal measures is the importance of disaster risk assessment in the overall disaster risk management strategy. These assessments involve systematically evaluating potential hazards, vulnerabilities, and the capacities of local

communities in specific areas. This process helps identify and analyze risks, enabling the development of suitable strategies and readiness measures. Effective disaster risk assessment forms the foundation for informed decision-making, resource allocation, and the creation of effective disaster response and recovery plans.

Another non-technical aspect involves training and capacity building for both communities and local authorities. It is essential to ensure that communities are educated on flood preparedness, response, and recovery measures (Cvetković et al., 2021). Moreover, local authorities and disaster management agencies must be equipped with the necessary skills to plan, respond, and coordinate effectively during floods. Training can help improve the overall effectiveness of flood management efforts. These non-technical approaches highlight the importance of involving local communities, building their resilience, and ensuring effective communication in the event of a flood. When integrated with technical methods, they contribute to a more extensive and well-rounded flood management strategy, ultimately reducing flood risk and community vulnerability.

2.5.3. Flood Risk and Vulnerability

Several studies have been conducted on flood risk and vulnerability (Zhang et al., 2022; Albertini et al., 2022; Abid et al., 2021a; Baky et al., 2020; Yankson et al., 2017; Salami et al., 2017). However, Baky et al. (2020) argue that so far, flood studies have not adequately addressed the concept of flood risk. On the contrary, different definitions and conceptual frameworks could be used for flood risk and vulnerability depending on how the researcher interprets risk and vulnerability (Mays, 2018). For instance, Sayers et al. (2013), define risk as the outcome of a combination of two factors: the probability that a specific event (like a flood) will occur and its likely consequences. According to Crichton (1999), risk is the probability of a loss, and it can be determined by three factors: hazard, vulnerability, and exposure. The following equation is used to express risk (Su et al., 2005).

$$R = H \times V \times E$$

Where:

R = Risk

H = Hazard, which is a source of possible harm or a circumstance that could result in a loss (UNECE, 2017). In this context, flooding is a hazard because it can damage the community.

V = Vulnerability, the degree of loss sustained by a particular element or group of elements exposed to risk due to a natural catastrophe of a certain intensity (Mays, 2018).

E = Exposure, the elements at risk such as population, property, or other human activities

This study explicitly focuses on completing the hazard assessment within the risk equation. According to Eleuterio (2012), floods have historically been, and at times still are, perceived as a risk with potentially fatal consequences. Moreover, the level of risk and the potential for fatal consequences associated with floods are not solely based on human actions or decisions but are largely influenced by natural factors such as weather patterns, topography, and other environmental conditions. As a result, the term “flood risk” is frequently used to describe the probability that flooding would occur and its potential adverse consequences. However, scientific literature commonly acknowledged that flooding is not a risk by itself because risk involves two components: a catastrophic event and vulnerable systems exposed to it, therefore, floods do not by themselves create a risk; instead, flood risk arises as a result of human habitation in flood-prone areas (Merz et al., 2010b; Torterotot, 1993; Messner et al., 2007; Eleuterio, 2012; Burkham, 1988). In short, the primary objective of flood risk assessments is to identify and estimate the potential effects of flooding in places where vulnerable systems are found (Eleuterio, 2012).

Flood vulnerability is one of the key factors in risk management and flood damage assessment (Nasiri et al., 2016). It involves elements at risk such as people who dwell in flood-prone areas, the built environment or ecosystem that are exposed to flood (Merz et al., 2007; Salami et al., 2017). The term “vulnerability” is used in research on a variety of topics. In this context, the United Nations (1982), defines “vulnerability” as the degree of damage that a certain object might sustain from flood, expressed on a scale from 0 to 1 (no damage to full damage). Furthermore, several researchers agree that vulnerability has three main elements; the level of exposure, susceptibility, and resilience or reaction capacity of a population in a certain area (Wisner et al. 2004; Birkmann 2006; Jean-Baptiste et al., 2013; Parker et al., 2014; Salami et al., 2017). These three elements are described as follows.

Exposure refers to the predisposition of a system to be affected by a flooding event because it is situated in the same region where a hazard is located (Le Maitre and Kotzee, 2019). Unfortunately, a significant portion of urban areas is still within flood zones, which increases the risk of flooding for both people and property, e.g., Kolkata and Mumbai (India), Dhaka, (Bangladesh), and Miami (USA) (Eleuterio, 2012; Nicholls et al., 2007). According to Salami et al. (2017), the majority of flood-related disasters are not primarily caused by natural disasters, as evidence of cities’ vulnerability to flooding grows. Numerous scholars concur that human activities involving socio-political, historical, and cultural relations are the main influencing factors (Milly et al. 2002; Birkmann, 2007; Seyoumet et al., 2011; Vojinović and Abbott, 2012; Vojinović, 2015; Salami et al., 2017).

As described by Cardona et al. (2012), susceptibility is the tendency for people, the environment, and infrastructure to be impacted by a hazard because of society's fragility or the ecosystem's fragility. This suggests that the impact of a hazard is not solely dependent on the hazard itself but is also influenced by the weaknesses or vulnerabilities inherent in the affected society or ecosystem. In other words, the more vulnerable a society or ecosystem is, the greater its susceptibility to harm or damage when a hazard occurs. UNISDR (2009), defines "resilience" as the *"ability of a system, community or society to be exposed to hazards to resist, absorb, accommodate to and recover from the effects, of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions."* Moreover, understanding the vulnerability of a community or ecosystem to specific hazards is crucial for effective risk assessment, resource allocation, mitigation planning, disaster preparedness, and resilience-building. It informs policies and regulations, raises public awareness, and helps protect lives, property, and the environment.

To assess flood vulnerability, a variety of methods have been developed. Previous studies indicate some of the widely used methods which include an indicator-based method, curve method, analytical hierarchy process, disaster loss data method, mapping method, and modelling approaches through GIS (Ebert et al., 2009; Nasiri et al., 2016; Musa and Shabu, 2019; Abid et al., 2021a). An indicator-based vulnerability method that uses locally available data to provide an image of the vulnerable area is frequently employed by many scholars and policymakers due to its clearer spatial representation, which attempts to prioritize actions and prepare for the reaction in a given area (Chan et al., 2022). For instance, Zhen et al. (2022), utilized an indicator-based method to evaluate the risk of buildings affected by flash floods in the Southwest of China's mountainous rural villages, and Yankson et al. (2017), used an indicator-based method to assess the flood vulnerability of coastal floods in Greater Accra Metropolitan area, Ghana. However, vulnerability is difficult to reduce to a single metric and to calculate (Adger, 2006; Nasiri et al., 2016).

To address this issue, multiple factors contributing to floods are incorporated in this study instead of attempting to reduce vulnerability to a single metric. These factors include rainfall, slope, elevation, soil type, drainage density, land use land cover, and distance to rivers (Desalegn and Mulu, 2021). Each of these factors plays a crucial role in influencing vulnerability to flooding. The Geographic Information System (GIS) is subsequently employed to integrate and analyze the various spatial data layers. This involves overlaying and synthesizing the information to create a comprehensive flood risk map that accurately depicts the complex interplay of these diverse factors. The GIS system is instrumental in this process as it offers a powerful set of spatial analysis tools for this comprehensive assessment.

2.6. Geographic Information Systems (GIS)

The term "GIS" is widely used to refer to geographically oriented computer technology, integrated systems utilized in practical applications, and more recently, a brand-new subject that is drawing considerable attention across the globe (Maguire, 1991). Defining GIS is more challenging than one might think for several reasons; consequently, no definitive definition of GIS exists (DeMers, 1997). However, the definition of GIS published by the National Centre of Geographic Information and Analysis (NCGIA) is widely accepted (Escobar et al., 2002). The NCGIA (1990) defines GIS as *"a system of hardware, software, and procedures to facilitate the management, manipulation, analysis, modelling, representation, and display of geo-referenced data to solve complex problems regarding planning and management of resources"*.

According to the "History of GIS: Timeline of Early History and the Future of GIS" (1960), as computers and early ideas of quantitative and computational geography began to take off in the 1960s, the field of geographic information systems was founded. Since then, historical GIS has experienced a significant increase in its application across a variety of topical areas during the past few years. For instance, in disaster management, the use of GIS helps in comprehending the nature of the disaster and helps in resolving challenging management issues whereby decisions can only be taken after careful analysis of the various GIS layers with the aid of geospatial and socioeconomic data (Use of GIS Technology in Disaster Management | GIS for Disaster Management, 2022). In the case of flooding, the identification of flood-stricken areas is made possible by GIS technology. Additionally, this technology aids in the creation of base maps and maps of varying degrees of sensitivity that show the regions that are frequently affected by flooding (Use of GIS Technology in Disaster Management | GIS for Disaster Management, 2022).

2.6.1. The Role of GIS in determining flood risk

Geographic Information Systems simplify the interpretation of patterns, relationships, and spatial context by connecting data to a map and integrating location data with various descriptive information (Esri, 2012). They have been employed in numerous studies on flood risk vulnerability and hazard mapping, providing spatial data for analysing flood maps, displaying the extent of flooding, monitoring floods, and creating flood risk and damage prediction maps (Mays, 2018; Demir and Kisi, 2016; Feloni et al., 2020; Rincon et al., 2018; Wiles and Levine, 2002). The literature indicates that incorporating GIS methodology and maps to integrate risk components is a common practice in many studies and projects related to flood risk assessment (Cai et al., 2021; Rincon et al., 2018; Allafta and Opp, 2021; Feloni et al., 2019). GIS plays a crucial role in this assessment, given its significance in the evaluation procedure, which demands detailed geographical information (Eleutério et al., 2010). As an

illustrative example, the Philippines employs GIS as a primary and distinctive tool on a national scale for modelling flood risk (Gacu et al., 2022).

According to Evans et al. (2007), GIS applications in flood risk mapping include managing and storing hydrological data, as well as creating flood inundation and hazard maps to aid in flood risk management. Typically, flood risk maps provide additional information about potential effects, such as economic loss, human injuries, and environmental impacts. Conversely, flood hazard maps offer information about the probability or magnitude of flood events, such as flood extent and water depth distribution (de Moel et al., 2009).

However, some studies face limitations, using complex models that require expert knowledge for implementation, or assigning weights directly without a theoretical foundation supporting consistent evaluation (Rincon et al., 2018). This can impact the accuracy of flood risk maps during the validation process. Nevertheless, their common advantage lies in using a framework considering static data relevant to flooding, such as topography and land cover. Their ability to produce accurate flood risk maps with minimal time and, in some cases, no financial investments is a key benefit of their adopted flood risk mapping methodology, allowing stakeholders to focus on areas requiring more in-depth evaluation (Rincon et al., 2018).

In flood hazard mapping, GIS applications typically involve assessing Digital Elevation Models (DEM) for various hydrological analyzes (Moglen and Maidment, 2005; Samela et al., 2015). Software tools, like the Hydrologic Engineering Centres River Analysis System (HEC-RAS), are commonly used for flood hazard mapping, providing various applications (Thakur et al., 2017; Loi et al., 2019; Vozinaki et al., 2017; Ongdas et al., 2020). Additionally, hydrodynamic models and techniques simulate floods, but GIS software or integrated GIS-based interfaces are required to represent and analyze the results (Eleuterio, 2012; Buchele et al., 2006). More importantly, it is crucial to recognize that there are several parameters commonly employed to provide significant data for GIS analysis in flood risk assessment. These parameters, including rainfall, distance to a river, slope, land use/land cover, drainage density, and soil (Allafta and Opp, 2021; Naghibi et al., 2015; Ouma and Tateishi 2014; Meyer et al., 2007; Rincon et al., 2018), play a pivotal role in enhancing the effectiveness of GIS in evaluating and mitigating flood risks.

2.6.2. Common GIS approaches in flood risk mapping

Many GIS approaches are successfully used in flood risk studies to aid in the visualization of the extent of flooding, to analyze the flood maps, and to produce flood damage estimation maps as well as flood risk maps (Shamsi, 2002; Demir and Kisi, 2015). The most common approach is the integration of GIS, Remote sensing, and HEC-RAS models for simulating and

monitoring floods (Hadi and Najafzadeh, 2021). HEC-RAS and GIS technology integration has been cited as being effective in modelling, recognizing, and analysing flood events in a geospatial environment (Shamsi, 2002). In this regard, Bajwa and Tim (2002), define the one-dimensional (1D) HEC model as a geospatial hydrology toolkit that acknowledges the potential of the ArcGIS environment for creating and visualizing flood simulations. This approach has been successfully used for identifying the inundated zones in many areas. For example, in a study by Desalegn and Mulu (2021), the Fetam River's floods in Ethiopia were simulated using the HEC-RAS, HEC- GeoRAS, and ArcGIS 10 extension models. Similarly, by combining HEC-RAS and GIS technology, Yerramilli (2012) created a hybrid approach for identifying flood risk areas and determining the impact of the hazard. However, 1D HEC-RAS modelling for flood hazard assessment has several limitations depending on the level of detail in the input data, the characteristics of the area, the complexity of the output data, and project time and budget (Huțanu et al., 2020). Moreover, the results of 1D modelling processing need time and money, and they could underestimate flood risk perception because of the time and money required for processing the data (Huțanu et al., 2020).

Another approach that has gained a lot of attention recently is the combination of geographic information systems (GIS) with multi-criteria decision analysis (Feloni et al., 2019; Rincon et al., 2018; Allafta and Opp, 2021; Cabrera and Lee, 2019). According to Meyer et al. (2007), the approach is capable of considering flood hazards that cannot be quantified in monetary terms, displaying the spatial distribution of these various risks, dealing with uncertainty in the criteria values, and demonstrating how these uncertainties affect the overall assessment. Furthermore, it allows for the integration of the three aspects of risk (hazard, exposure, and vulnerability) in which the environmental, social, and economic vulnerabilities can be considered (Rincon et al., 2018; Allafta and Opp, 2021; Cai et al., 2021; Rahmati et al., 2016). It has also been demonstrated that the approach makes use of the capabilities of GIS for processing geospatial data and the versatility of MCDA to combine factual data with value-based data, e.g., rainfall, soil, slope, land use, drainage density (Yahaya et al. 2010; Seejata et al. 2018; Allafta and Opp, 2021). As a result, numerous studies combined GIS with Multi-Criteria Analysis (MCDA) methods to map flood risk.

According to Malczewski (2017), the integration of GIS and MCDA was primarily driven by the need to increase the geographic information technologies' applicability to the analysis of decision problems. In the context of flood risk assessment, eventually, the approach produces a flood risk map that displays the spatial distribution of flood risk as well as its intensity level, which ranges from extremely high to very low risk (Rincon et al., 2018). Most importantly, the main advantage of using this approach to flood risk is that it offers the possibility to produce an accurate flood risk map with only a modest time and financial investment, enabling

stakeholders to focus solely on the areas that require a more thorough assessment (Rincon et al., 2018). Even though this is a powerful and extensively used method, it has some basic weaknesses including a lack of accuracy assessment, high subjectivity, and computational inefficiency (Radočaj and Jurišić, 2022). However, the literature shows that the benefits of this approach outweigh the drawbacks (Malczewski, 2007; De Brito and Evers, 2016); thus, one can argue that the benefits are more significant than the drawbacks but, the drawbacks have a huge impact on the approach's outcomes. Nevertheless, more research is needed to alleviate the shortcomings of this approach to make its application more dependable. In summary, while GIS MCDA is a useful tool for assessing flood risk, it is critical to realize its drawbacks and enhance its use with other analysis methodologies.

2.6.3. Multi-criteria Analysis (MCDA)

Multi-criteria analysis has gained significant attention in risk assessment, particularly in the context of natural disasters (Meyer et al., 2007; Rincon et al., 2018; Allafta and Opp, 2021; Malczewski, 2018; Kumar, 2010; Aruldoss et al., 2013). MCDA offers a systematic approach to evaluating and selecting decision alternatives based on various competing criteria. Malczewski (2018) defines MCDA as a collection of systematic techniques for generating, assessing, and choosing decision alternatives based on competing and unrelated criteria. The core principle involves aggregating and weighing different criteria to choose the intervention with the best overall rating (Saaty, 1990). MCDA is particularly valuable when dealing with competing environmental, social, and technological objectives, as highlighted by De Montis (2000).

MCDA is employed in situations where there are multiple, often conflicting, objectives involving environmental, social, and technological considerations (De Montis, 2000). While various MCDA methods are applied in disaster management studies, it is worth noting that the choice of method has been a subject of academic debate (Abdulla et al., 2021). One such debate centres around the use of Geographic Information Systems (GIS) in combination with the Analytical Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Allafta and Opp (2021) highlight the effectiveness of using GIS and AHP to assess index-based flood risks by combining geographical data to analyze influencing factors. This approach is advantageous for integrating spatial data into decision-making processes.

For instance, Armenakis et al. (2017) applied MCDA to estimate flood risk by combining geographic coverage of flood hazards, human vulnerability, and exposure. They produced flood risk maps for the Don River watershed in Toronto. However, the study's main limitation was the direct assignment of criteria weights rather than the use of a weighting mechanism in

the framework of MCDA. As a result, the decision-making process is prone to subjectivity and bias with this strategy. However, the robustness and structure of MCDA weighting mechanisms provide a method that can improve the accuracy of the study.

AHP, a commonly used method in flood risk mapping, operates on weighted aggregation and is widely recognized for its seamless integration into GIS environments (Cai et al., 2021). However, its application comes with implications worth noting. AHP relies on subjective pairwise comparisons, introducing the potential for bias. Moreover, conducting extensive pairwise comparisons, especially for large-scale assessments, can be resource intensive. Nevertheless, its strength lies in the flexibility to adjust criteria weights, allowing for the adaptation of evaluations as needed (Mokhtari et al., 2023). This methodology operates by assigning weights to criteria and alternatives through pairwise comparisons, following decision-maker preferences (Saaty, 1990). Despite its recognized limitations, its user-friendly implementation within GIS environments makes it a preferred choice (De Brito and Meyers, 2016). AHP offers the advantage of a straightforward decision-making process, allowing decision-makers to easily adjust criteria weights or add and delete crucial criteria, enabling the updating of evaluations without starting from scratch (Mokhtari et al., 2023). Nonetheless, AHP has its limitations, including subjectivity, extensive pairwise comparisons, and high processing demands (Munier and Honoria, 2021). Researchers have sought to address these limitations by integrating AHP with mathematical approaches, such as fuzzy logic (Cai et al., 2021).

While MCDA methods are applicable in flood risk assessment, their combination with other techniques, like FAHP or GIS, is still relatively rare (Ekmekcioglu et al., 2021). For instance, Hategekimana et al. (2018) developed a framework that integrated FAHP, GIS, and bivariate statistics to determine flood hazard, identifying flood-prone areas with a high level of reliability. Other studies have explored various MCDA methods in the context of water-related natural disaster events (Abdullah et al., 2021). For instance, Sepehri et al. (2020) used Interval Rough AHP and Fuzzy logic to assess flood-prone areas, demonstrating the adaptability of MCDA in diverse applications. Haghizadeh et al. (2017) employed Shannon's entropy model, a form of Multi-criteria Analysis (MCDA), to predict flood-prone areas in the Madarsoo watershed in North-eastern Iran. Notably, this approach is distinct in its ability to handle uncertainties without the need for explicit criteria weighting, making it a valuable choice in addressing limitations related to uncertainties often encountered in Geographic Information System-based MCDA studies. However, weighting is a crucial step in MCDA for flood risk assessment as it allows decision-makers to account for the varying importance of different criteria in the decision-making process.

2.6.3.1. Challenges with MCDA

Although MCDA offers numerous advantages, such as the ability to consider multiple objectives and alternatives, the ability to combine quantitative and qualitative factors during the evaluation process; and the ability to figure out complex issues, it additionally comes with several drawbacks (Zavadskas et al., 2014). The literature also confirms that there are numerous difficulties involved with the assignment of criteria weights as it has also been indicated that this step is the primary source of controversy and uncertainty in MCDA outputs out of a variety of input elements (Feizizadeh and Blaschke, 2013; Chen et al., 2009; de Brito et al., 2019). Specifically, when using subjective approaches like AHP due to the limitations of its pairwise comparison method. For instance, several studies concur that AHP's pairwise comparison is vulnerable to subjectivity in comparison judgments because it is based on expert opinions (Rincon et al., 2018; Cai et al., 2021; Feizizadeh et al., 2014; Saaty, 1990; Chen et al., 2011; de Brito and Meyer, 2016). This is a challenge because decision-makers can be biased, resulting in incorrect and inconsistent weighting judgments, which can affect the outcomes. Overall, all decisions are subject to some degree of uncertainty, and the more confusion there is, the harder it will be to deal with it and come to the best option.

Furthermore, when the number of criteria to be compared is large, there may be uncertainty in the comparisons, resulting in inconsistency because decision-makers may find it challenging to consistently examine and compare all criteria (Sakhardande and Prabhu Gaonkar, 2022). Moreover, the process of conducting and managing pairwise comparisons, a fundamental aspect of AHP, can be a bit difficult and complicated, requiring significant time and effort (Munier and Hontoria, 2021). Lastly, AHP is dependent on the expertise of decision-makers, and the accuracy of results hinges on the knowledge and precision of those involved in the decision-making process (Drescher et al., 2013).

Similarly, navigating through FAHP presents several difficulties. First, the method involves more complex mathematical modelling compared to traditional AHP, leading to increased computational intensity, especially with larger decision matrices (Lima Junior et al., 2014). Making it more complicated, interpreting the results of FAHP may be difficult, as the added fuzziness makes it hard for stakeholders to easily understand the outcomes (Karam et al., 2021). Additionally, FAHP also relies on fuzzy pairwise comparisons, introducing subjectivity and uncertainty, and experts need to evaluate the degree of membership between linguistic terms (Cai et al., 2021). In the midst of these challenges, Zozaya et al. (2018) highlight the importance of effectively managing uncertainty in Multi-Criteria Analysis (MCDA), emphasizing that recognizing and dealing with inherent uncertainties is crucial for making the best decision possible.

Generally, the weights of the assessment criteria have a significant impact on the evaluation process of an MCDM problem, and if the weighting process of an analysis is not completed properly, the inaccurately generated weights can have an impact on the outcome (Bayram, 2020). Subjectivity, as already indicated is also another challenge that MCDA approaches present. Some of these challenges, however, may be overcome if decision-makers identify the decision problem and ensure that the criteria are established and relevant. In addition, using appropriate methods to assign weights and doing sensitivity analysis to assess the results' robustness to other inputs (Malczewski, 2018).

2.7. The concept of weighting

Weighting is a method of ranking criteria that might be subjective, especially when it depends on participants' opinions (Alemi-Ardakani et al., 2016). And yet, MCDA does include subjective procedures, but it is not primarily a subjective decision-making approach where participants' opinions are the deciding factor. In MCDA, there are two aspects to consider when discussing weighting: criteria scores and criteria weights. The process involves both criteria scores, which assess alternative performance on specific criteria and can be subjective, and criteria weights, which determine the relative importance of these criteria in the decision-making process. Assigning criteria weights can be challenging, particularly in MCDA techniques that incorporate them directly into aggregation. Despite that, Vanolya and Jelokhani-Niaraki (2021) indicate that the flood hazard mapping method depends on the accurate calculation of the criteria scores, as these scores influence the flood hazard scores.

The emphasis on precise criteria weighting highlights the complexity of the process, which is further compounded by the fact that several multi-criteria decision-making techniques struggle with determining criteria weights since they frequently employ the weights in their aggregation process (Yin, 2020). As a result, multi-criteria techniques sometimes call for the involvement of experts with unique expertise and experience, as well as varying judgments and evaluations (Zagonari and Rossi, 2013). According to Zardari et al. (2015), there are two types of weighting techniques which are "objective weighting methods" and "subjective weighting methods". Weighting in subjective methods is determined by decision-makers' priorities and judgment (Vanolya and Jelokhani-Niaraki, 2021). The decision-maker's values and priorities regarding the evaluation criteria are reflected in these weights.

Contrary to this, an objective weighting method places more emphasis on the mathematical analysis of the criteria values (Wang et al., 2009; Vanolya and Jelokhani-Niaraki, 2021). Deng et al. (2020) pointed out that the objective weighting approach is especially useful when reliable subjective weights are impossible to determine, such as when decision-makers or stakeholders cannot reach an agreement. Whereas subjective weights can be used when the

objective parameters of interest are extremely undefined. In comparison, subjective weighting methods are less complicated and easier in terms of computation than objective weighting methods. However, the main disadvantage of subjective weighting methods is that the subjectivity of the decision maker in each evaluation situation can frequently bias the evaluation outcomes (Zoraghi et al., 2013; Suh et al., 2019). Thus, the objective weighting method can be used in this case.

On the contrary, for example, while researching the effects of floods on communities, an objective technique for evaluating the effects may not be as effective as a subjective approach; thus, subjective measures will be preferred over objective approaches. Moreover, consider an extreme circumstance in which floods compelled community members to evacuate due to the destruction of their property. In that instance, the total number of observed impacts would be fewer and would not provide a good indication of the extent of the effects that exist. Despite this, the objective weighting method can overcome the drawbacks of the subjective approach by reducing uncertainties caused by decision-makers and producing more realistic results (Mohsen and Fereshteh, 2017). Some of the examples of MCDA methods that use objective methods include Technique for Order of Preference by Similarity (TOPSIS) and Entropy Weighting Method, whereas AHP, Analytic Network Process, and Best Worst Method use subjective approaches based on matrices and also employ pairwise comparisons of the criteria to determine the weights (Arslan, 2017).

2.7.1. Evaluating the effect of subjective weighting on different approaches

Subjective weights are increasingly being employed in empirical studies of an extensive variety of economic issues where objective data is difficult to get (Jahedi and Mendes, 2014). Their evaluation is based on expert opinion, and the analysts typically ask the decision-makers a series of questions to obtain the judgments (Cai et al., 2021). However, this often results in bias. For example, in some of MCDA studies, these weights are assigned to each criterion, ideally reflecting the decision-maker's preferences. To rank alternatives, an overall score is calculated for each option using the weighted total of the various criteria. As a result, MCDA is frequently criticized for being influenced by personal feelings, particularly regarding its weighting process, which is based on the participants' and decision-makers' perceptions. The outcomes are often imprecise and transparent in their predictions due to subjectivity in their weightings (Balasubramaniam et al., 2007). Moreover, the imprecision caused by the subjectivity of weightings in MCDA pairwise comparison influenced the integration of AHP with Fuzzy sets to improve the accuracy of the traditional AHP method since fuzzy sets do not rely on experts' or decision-makers opinions (Liu et al., 2020).

In some applications, the fact that various experts' opinions may differ while making judgments in a group decision-making process presents one difficulty with using subjective values (Liu et

al., 2020). Their viewpoints must therefore be combined to arrive at a final decision, and this might be time-consuming (Odu, 2019). Then again, potential uncertainty in expert judgment is another drawback of subjective approaches (Alemi-Ardakani et al., 2016), because if the judgments are not based on scientific evidence or factual information then the subsequent conclusions may be incorrect. Hence, neglecting uncertainty can lead to incorrect predictions or recommendations, which might have negative implications and weaken the trust among decision-makers (Chen et al., 2011). For that reason, Sun et al. (2020) were able to successfully reduce the uncertainty induced by anthropogenic factors in criteria weightings by combining probability distribution negation with evidence theory. The study rectified subjective inaccuracy to some extent through quantitative evaluation of the fuzzy degree, enhancing the level of multi-criteria decision-making.

Despite their negative effects, subjective weights are fairly useful due to their characteristics, particularly in studies where objective data is difficult to obtain. To elaborate, since their weights are based on the opinions of experts, they can quickly allow decision-makers to adjust the weights allocated to different criteria based on the circumstances or context. In conclusion, subjective weightings can be useful in decision-making processes; however, they should be used cautiously and in combination with objective data and other decision-making tools to ensure that judgments are transparent, reasonable, and based on scientific evidence.

2.7.2. The concept of sensitivity analysis

There are so many definitions of sensitivity analysis in literature. For example, Munoz et al. (2016), define sensitivity analysis as “a systematic process that is used to evaluate the stability or behaviour of the solution to small changes in preferences that occurred during the resolution process or to small changes in the values taken for the parameters”. On the other hand, Boghani et al. (2021), defines sensitivity analysis as “*a method for analysing the effect of uncertainty in the output of a system, subject to uncertainties in the inputs*”. However, according to relevant sources, the main purpose of sensitivity analysis is to evaluate how the selection of alternatives changes when the relative weighting of the selection criteria or project requirements is altered (Munoz et al., 2016; Chen et al., 2009). This method demonstrates the effects of applying changes to particular input parameters on evaluation results, which can assist in minimizing uncertainty in how an MCDA method operates and the stability of its outputs (Crosetto et al., 2000).

Despite its utility in assessing the influence of changes in input variables on model or simulation output, sensitivity analysis has numerous drawbacks that should be noted. For example, in their thorough review of the literature, Saltelli et al. (2019), demonstrated how many studies typically confuse sensitivity analysis and uncertainty analysis and how most papers do not correctly use sensitivity analysis techniques due to technical issues like the

assumption of linearity and the inefficiency of the procedure. This confusion can be a limitation because it is likely to increase the challenge of promoting good practice of sensitivity analysis, so it is crucial to know the difference between the two to avoid incorrect interpretation of results. Also, the sensitivity analysis methodology is dependent on local procedures, which are often incorrect for nonlinear models (Saltelli et al., 2019).

2.7.2.1. Using sensitivity analysis to test

Sensitivity analysis can be used as a tool for testing the robustness of models to changes in parameter values (Broeke et al., 2016). Robust in this case implies that the index estimate does not change considerably when computed over a different sample of model simulations (Pianosi et al., 2015). According to Broeke et al. (2016), a set of model parameter values correlates to a set of assumptions, which leads to certain conclusions. However, for these conclusions to be reasonable, they should not be based on a limited and uncertain set of assumptions. As a result, it is critical to demonstrate that the conclusions are robust to parameter changes. For that reason, Sayl et al. (2020), performed a sensitivity analysis on FAHP and Rank Order Method (ROM) to assess the uncertainty and robustness of the results. The results were then compared using the variance inverse (VI). Consequently, it has been found that the ROM and VI methods affected the ranking priority and considered all the criteria that were sensitive to impact in the ranking process at different levels as compared to FAHP. Importantly, this approach will similarly be employed to comprehensively compare AHP and Triangular FAHP in this study.

Then again, a considerable amount of literature also shows that sensitivity analysis can be used in the calibration and validation of numerical models. Examples of such studies include Cai et al. (2021) and Zhang et al. (2022). Sensitivity analysis has been successfully used in studies to systematically adjust the values of each input variable and assess the consequent changes in output. In the study by Cai et al. (2021), Chongqing municipality is used as an example to test the validity of the FAHP method and effectively identify flood-prone locations. The findings of the sensitivity analysis show that the weights of various components have varying sensitivity, emphasizing the importance of weight consistency. However, it has been indicated that the calculation of the weights with less precision may result in higher inaccuracies in the evaluation results, influencing the judgments made by decision-makers (Cai et al., 2021). Generally, sensitivity analysis can assist in testing the validity of a model by altering the input parameters and comparing the output to observed data. If the model output is sensitive to changes in input parameters, this indicates that the model accurately captures the key variables of the process.

Saltelli et al. (2019), pointed out that while many sensitivity analysis studies tend to copy techniques from widely cited works, some of them lack methodological rigor, which can affect

the quality of the sensitivity analysis. Therefore, if correctly implemented and based on accepted procedures, sensitivity analysis has the potential to contribute to risk analysis (da Silva et al., 2022). For example, analysts can use sensitivity analysis to find areas for improvement, enhance their models, and increase the accuracy of their estimations.

2.8. Conclusion

This chapter provides a comprehensive review of the literature related to floods and their impacts, particularly in the context of South Africa. It shows that flood impacts have become increasingly severe because of human activities such as urbanization and development in flood-prone areas. However, the factors contributing to floods in Southern African regions are largely undocumented and this results in a lack of preparedness and increased vulnerability. For that reason, more flood risk research is needed in Southern Africa and could be essential for enhancing our understanding of the factors that lead to flooding and establishing effective flood management and mitigation techniques. This should focus more on effective flood management strategies to limit the dangers of flooding and preserve the safety and well-being of impacted populations. Additionally, there is a need to increase the application of GIS-based multi-criteria analysis for flood risk mapping as it has been shown that the approach can provide a comprehensive and accurate method of determining flood risk by taking into account multiple factors such as topography, land use and land cover, and rainfall data.

Despite many efforts to combine MCDA methods to improve the accuracy of single MCDA approaches, the majority of the studies used AHP for assigning weights. The review has identified limitations in GIS-MCDA flood risk mapping, particularly in terms of uncertainty and subjectivity. To address these challenges, there is a clear need to enhance the application of mixed MCDA techniques, moving beyond the constraints of single methodologies. Specifically, integrating both subjective and objective methods holds promise for mitigating inconsistencies and enhancing result accuracy. In the context of this study, the chosen approaches for future research, namely AHP and Triangular FAHP, emerge as effective means to minimize the limitations of MCDA, thereby elevating precision, and accuracy in flood risk mapping. The utilization of AHP and Triangular FAHP is strategic in balancing subjective and objective considerations. Moreover, while sensitivity analysis is gaining traction across various fields, it is crucial to acknowledge and clarify the distinction between sensitivity analysis and uncertainty analysis to avoid any potential confusion in their application. Overall, by examining the sensitivity analysis of multi-criteria analysis methods and the concept of weighting, this chapter contributes to understanding how to prioritize flood risk management strategies.

3. Chapter Three: Methodology

3.1. Introduction

This chapter presents the methodological approach that was employed to achieve the aim of the study. A quantitative research approach using a multi-criteria analysis was employed to address the aim, which was to assess the sensitivity of the AHP, and FAHP in mapping flood risk zones. The eThekweni Metropolitan Municipality was selected as study area and will now be discussed.

3.2 Study area description

The eThekweni Metropolitan Municipality is situated in the KwaZulu-Natal province, South Africa (Figure 3). It is located on the south-eastern coast of the province at coordinates -29° 52' S and 31° 01' E. The majority of this region, encompassing an approximate geographical area of 2,556 km², is characterized as rural and peri-urban. The municipality comprises 103 wards and is seamlessly integrated into the city of Durban. The municipality is the third-largest metropolitan region in South Africa and boasts the busiest port on the African continent (eThekweni Municipality, 2013). The population of the region is approximately 3.9 million and the majority of the population is of African origin (Statistics South Africa, 2022). According to Sutcliffe and Banister (2015), the Gross Domestic Product (GDP) of eThekweni was roughly \$20 billion in 2012, with an estimated growth of 3.1% in 2013. Additionally, it constitutes 65% of the province's GDP and 10.7% of the national GDP. These statistics illustrate that in the event of a severe flood hazard affecting the region, its detrimental economic consequences are experienced not only at a local level but also on a national scale.

The municipality is also characterized by a subtropical climate with a mean annual minimum temperature of 13.9° C and a maximum temperature of 24° C (Zungu et al., 2018). The summers are hot and humid, and winters are sunny and moderate. The average annual rainfall is 1,054 mm, with about 80% occurring in the warmer months from October to March, predominantly in summer (Royal Haskoning DHV, 2014). Due to the high average rainfall, the area is often subjected to severe flooding, resulting in significant economic losses and fatalities (Mashao et al., 2022). Additionally, the terrain of the region is mostly rugged, featuring numerous canyons and ravines. Nevertheless, it also boasts a prominent and scenic coastal region along the Indian Ocean. The municipality encompasses 18 major river systems, including notable ones like the Umlazi and Umgeni rivers. The Umgeni River stands as the largest watercourse in Durban, contributing to the coastal city's diverse aquatic landscape (Gairola et al., 2016).

The geological structure of the region is made up of clastic sedimentary sandstone which allows water to percolate, as a result moistening the soil. This metropolitan region is also home to a variety of flora types, such as woody vegetation, shrubs of various sizes, and a medley of grasses (Hlanguza, 2015). The dense shrub and indigenous forest subtypes that make up the bush in the region belong to the Indian coastal belt vegetation type (Zungu et al., 2018; Mucina and Rutherford, 2006; GeoTerraImage, 2014). The bush includes a wide variety of species, a complex of topography, and well-informed tree layers in the canopy and understory, but poorly developed herbaceous layers (Cucina and Rutherford, 2006).

The choice of study area was driven by multiple factors, including its significant susceptibility to recurrent flooding and the urgent requirement for enhanced risk assessment methods. Additionally, the vulnerability of the area to floods, exacerbated by its geographical and climatic attributes, also forms a compelling basis for this research. Moreover, the accessibility of relevant data within the region provides a solid foundation for the application and validation of the methodology in refining flood hazard mapping accuracy. Figure 3 displays the map of the study area.

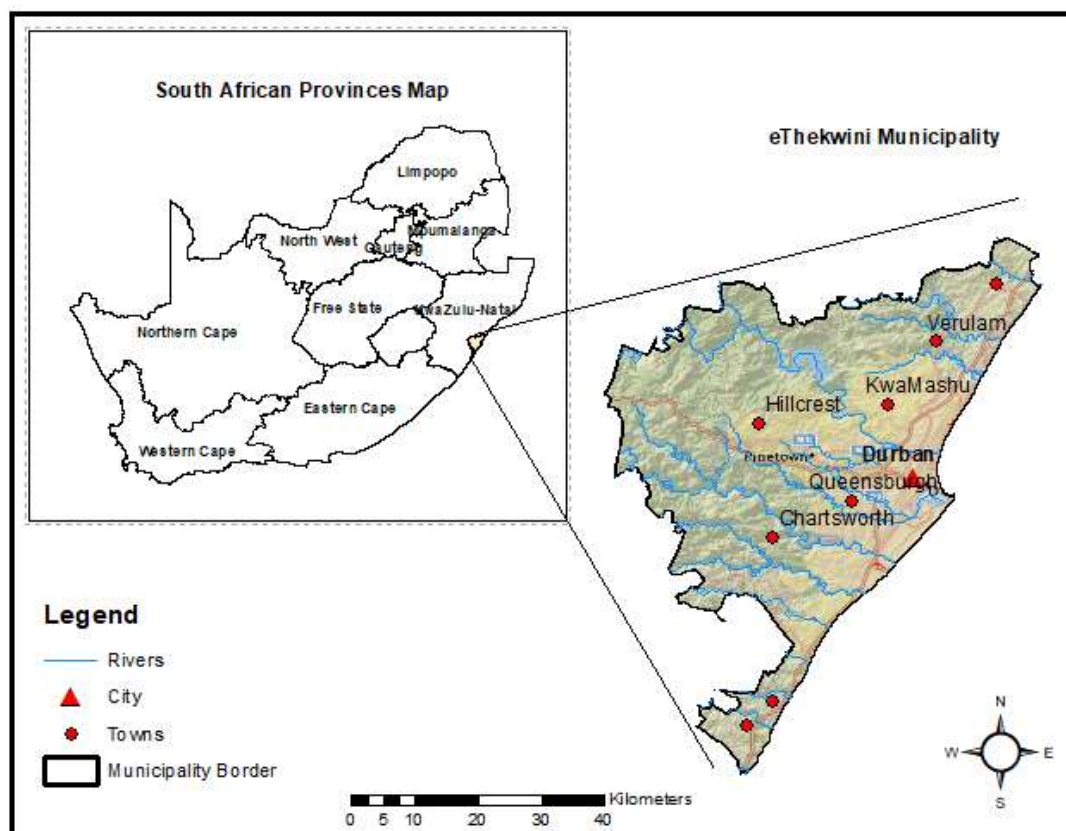


Figure 2: Map of the study area.

3.3 Overview of the methodology

This section provides an overview of the methodology employed in this study; subsequent sections will delve into the individual steps in more detail. The methodology utilizes a GIS-based MCDA framework to assess flood risk. The assessment concentrates solely on evaluating flood hazard without incorporating considerations of social vulnerability and exposure to estimate the overall flood risk. The multi-criteria process follows the steps outlined in the multi-criteria analysis method by Buckley (1985). Furthermore, to determine the appropriate weights for each criterion, two distinct multi-criteria analysis techniques are employed, namely: the AHP and FAHP. These techniques help to assign relative importance to the various criteria used in assessing flood risk.

The criteria used in the study are based on factors that have been identified as significant contributors to flooding (Cai et al., 2021; Rincon et al., 2018; Allafta and Opp, 2021; Feloni et al., 2019). To be sure, these criteria were derived from a thorough review of relevant literature, ensuring that the assessment incorporates well-established factors influencing flood risk. For creating flood hazard maps, a widely used GIS program developed by ESRI called ArcGIS has been used. This software offers a comprehensive suite of tools and capabilities for managing, analysing, and visualizing spatial data. It also provides the necessary functionalities to process the input data and generate accurate flood hazard maps. The input data required for the creation of the flood hazard maps in this study includes a soil type map, digital elevation data obtained from the Shuttle Radar Topography Mission (SRTM), monthly rainfall data from weather stations, Landsat 8 TIRS/OLI satellite images, and the boundary of the eThekweni municipality. Eventually, this methodology allows for a comprehensive assessment of flood hazard in the study area by integrating the GIS-based multi-criteria decision analysis framework, employing appropriate weighting techniques, and utilizing ArcGIS software.

Moreover, each criterion map transformed the corresponding projected coordinate system, specifically the WGS_1984_UTM_Zone_35S and was subsequently converted into a raster format. All datasets were subjected to a reclassification process, utilizing the Reclassify Tool within ArcMap, where a scale ranging from 1 to 5 was employed. This scale was used to assign values to each class, with: 1 representing a very low level of risk; 2 representing low risk; 3 representing moderate level of flood risk; 4 representing high risk; and 5 indicating a very high level of flood risk (Swain et al., 2020). Following the reclassification of the maps, the Weighted Overlay Tool in ArcMap was employed to perform a spatial overlay of the individual maps. As a result, two flood risk maps were generated: one depicting the results of AHP, while the other illustrating that of FAHP. Subsequently, sensitivity analysis for both MCDA methods was carried out by individually adjusting the weights of the criteria, increasing and decreasing each

criterion by 20%, utilizing the one-at-a-time method. As a result, a total of twenty-eight simulations were carried out to analyze the sensitivity of the MCDA methods. The simulations were conducted for each method based on the seven criteria. Subsequently, the outcomes of these simulations are depicted through the presentation of maps.

Lastly, a comparison analysis was done to examine the effectiveness of the two methods. This focused on two aspects: the extent and location of high flood zones and the results of the sensitivity analysis. To elaborate, the flood hazard maps generated by the original weights of both methods were compared in terms of the scope and geographical distribution of areas prone to severe flooding; and secondly, the evaluation of outcomes derived from the sensitivity analysis. The methodological framework for the study is presented in figure 3.

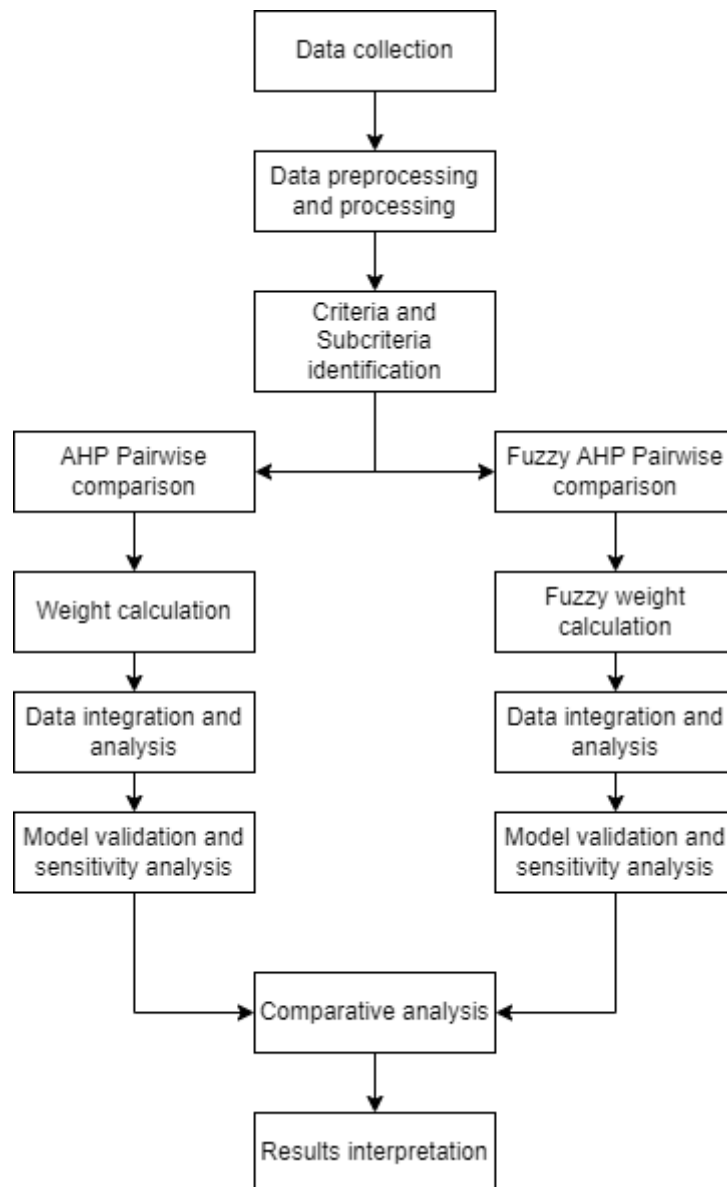


Figure 3: The methodological framework

3.4 Data Collection and Preparation

This section provides an in-depth discussion of the datasets and the data processing methods used for preparing the data for use in this study.

3.4.1 The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM)

Elevation data is essential for understanding an area's topography, with Allafta and Opp (2021) noting it as the primary indicator of topographic features. Topography impact on flood depths as well as the direction that surface water flows (Tehrany et al., 2014; Tang et al., 2018; Rafiei-Sardooi et al., 2021). Moreover, the hydrological response of different zones in an area is greatly influenced by elevation. According to Veerappan et al. (2020), low-elevation locations typically have a gentle or flat slope, making them more vulnerable to flooding and water logging since steep slopes generate greater velocity than flat or gentle slopes and may therefore remove runoff more quickly.

Research shows that slope data is significant for assessing the terrain's gradient and how it influences water flow (Rincon et al., 2018; Allafta and Opp, 2021; Cai et al., 2021). For example, Talukdar et al. (2020) explain that flooding is directly correlated with slope because it affects the water's vertical percolation and runoff velocity. Hence, flooding risks rise as a result of the water infiltration rate and water velocity increasing and decreasing, respectively, with the slope's decline (Chen, 2022).

The SRTM DEM dataset was obtained from the United States Geological Survey (USGS) as shown in table 2 and has seen wide used in flood risk studies (Sharma et al., 2018; Bhuyian et al., 2018; Adesina et al., 2021; Courty et al., 2019). This key dataset holds a particular relevance in the domain of flood hazard mapping. One of its key characteristics is its high-resolution portrayal which captures complex surface details at intervals of approximately 30 meters (Sepuru, 2018). This attribute is important for flood risk mapping, as it allows for a precise understanding of the topography and elevation changes within a given area. Such accuracy is crucial for identifying low-lying regions prone to flooding and assessing the potential extent of floodwaters. As stated in the study by Olusina and Okolie (2018), enhanced resolution in SRTM data contributes to heightened accuracy in input data for applications such as flood mapping, sea level rise models, and volcano hazard assessments, among others. Consequently, the SRTM DEM was employed in this study to extract information on slope, elevation, and drainage density.

SRTM DEM is important for calculating drainage density, as it provides crucial elevation data necessary for delineating watersheds, extracting stream networks, and ultimately determining the density of drainage within a given area. According to Horton (1945), drainage density is defined dimensionally as the inverse of a length, or more specifically, as the proportion of the

network's overall length to its watershed area. Drainage density has a significant impact on the concentration time and, consequently, the peak flow magnitude in the river network because flow velocity is higher there (Pollard et al., 2009). Consequently, increasing drainage density indicates increasing flood peaks. Undoubtedly, this proves that drainage density data is crucial for this study as it indicates the concentration of natural water channels and their ability to manage water flow.

3.4.2 Validation data

Validation data from the South African National Space Agency (SANSA) was used to confirm the high flood risk zones on the maps generated in this study, taking the 2022 flood incident records of the eThekweni Municipality as a point of reference. This data was provided in the form of coordinates which serve as spatial markers, indicating the specific locations of flood-affected regions within the study area. They typically consist of latitude and longitude values, pinpointing precise positions where flood events have occurred. For that reason, the data is essential for the validation process which involves comparing the coordinates data with the flood hazard maps generated during the study. Figure 4 shows the map of flood incidents which is employed for validation of the two MCDA methods.

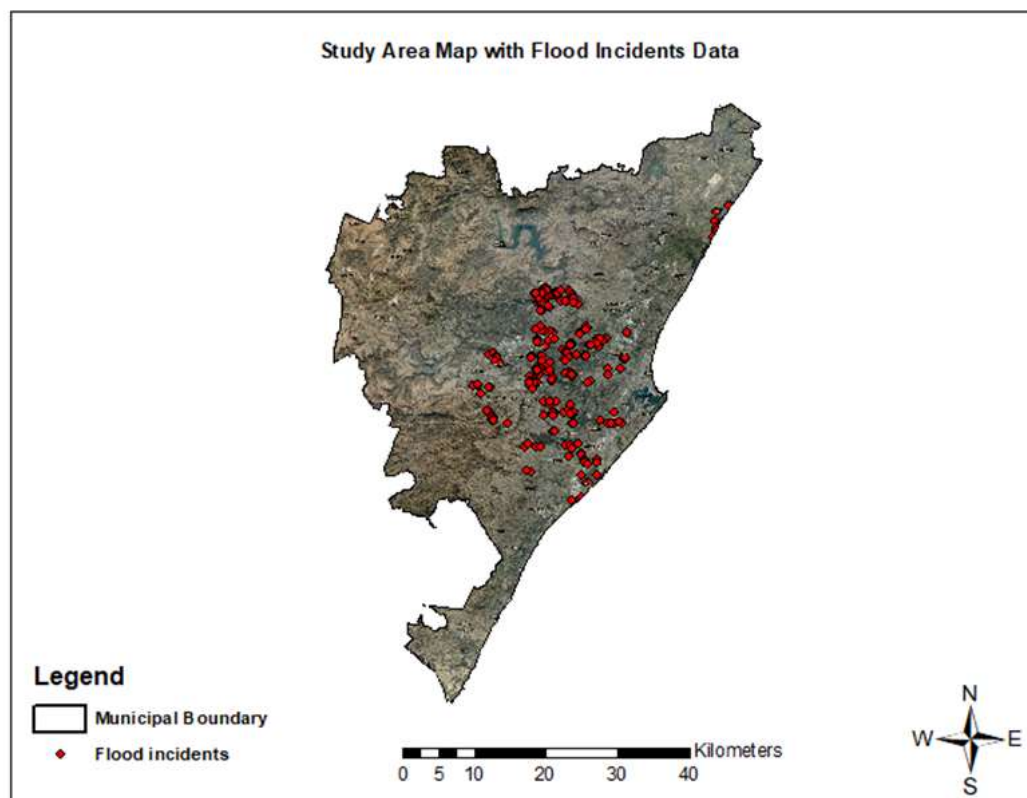


Figure 4: Floods incidents in 2022 used for validation purposes.

3.4.3 Rainfall data

Monthly average rainfall data from 2016 to 2022 was acquired from the eThekweni Data feeds as presented in Table 2. The data holds significance in understanding and predicting flood occurrences as it is commonly known that flash floods happen when excessive rainfall exceeds the ground's capacity to absorb it (Sauka, 2016). In addition, Allafta and Opp (2021) indicate that rainfall plays a significant role in both the frequency and severity of flooding disasters. Moreover, to understand hydrological processes and identify places that are likely to flood, rainfall data can be used to study the patterns, intensities, and duration of rainfall (Allafta and Opp, 2021). Consequently, rainfall data was selected as a fundamental factor in the study due to its significant impact on flood formation. Notably, rainfall data shows variations in precipitation levels across different months, directly influencing the potential for flooding. Despite that, this data helps to delineate potential flood-prone areas on the map, as areas with consistently higher long-term average rainfall are more likely to experience intense runoff and saturation of the ground, which can lead to flooding (Rincon et al., 2018).

3.4.4 Landsat 8 OLI/TIR Imagery Land Cover Analysis

The Landsat 8 Operational Land Imager (OLI) and TIRS (Thermal Infrared Sensor) satellite image obtained from the United States Geological Survey (Table 2) is a valuable tool for diverse applications, particularly in land cover analysis (Sepuru, 2018). The multispectral data captured across a range of wavelengths, from visible light to infrared, provides information on various factors such as land use and land cover, water bodies, and vegetation health (Sepuru, 2018), but it becomes valuable only when subjected to analysis rather than being considered in its raw form. The moderate spatial resolution of Landsat 8 images, typically around 30 meters, enables detailed analysis of land cover and changes over time.

Moreover, Landsat 8's ability to capture near infrared and shortwave infrared data facilitates applications such as flood hazard mapping (Elkhrachy, 2015). This capability allows for the identification of inundated areas and changes in water content within landscapes (U.S Geological Survey, 2023). In this study, the focus is specifically on land cover, which involves the physical characteristics of the Earth's surface, including vegetation, structures, and other features. Land use, referring to human activities on a specific piece of land, is distinct from land cover.

According to Elkhrachy (2015), Land Use Land Cover (LULC) is often categorized based on the quantity and type of vegetation, which directly or indirectly influences flood occurrences and peaks by affecting infiltration, evapotranspiration, and runoff generation. Landsat 8 OLI/TIRS data was chosen for this study due to its superior signal-to-noise levels compared

to Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images. Claverie et al. (2018) note that Landsat 8 OLI/TIRS is a leading platform for moderate-resolution land imagery, offering cost-effective tools for describing landscape processes at large scales. Its application is crucial for creating timely and precise maps, as highlighted by Inglada et al. (2016).

3.4.5 Soil type

Soil data was obtained from DIVA-GIS (Data Interpolating Variational Analysis Geographic Information System) at a global scale as shown in table 2. This data provides information about the composition and properties of soils across different locations including details on soil texture, colour, drainage, and fertility. Additionally, the data usually comes with spatial information, allowing it to be mapped and visualized. That is essential in flood hazard mapping because soil types help to predict how quickly rainwater will be absorbed into the ground, affecting the amount of runoff that can lead to flooding. According to Rahmati et al. (2016), soil properties play an important role in identifying the region's water-holding properties, and hence affect water infiltration. The most important elements of soil are its moisture content and texture (Tariq et al., 2022). For example, sandy soil quickly absorbs water and provides little runoff, soil textures have a substantial impact on floods. In contrast, clay soils are more water-retentive and less permeable than sandy soils. Hence, areas with clay soils have a higher risk of flooding. As a result, soil type data has been used in this study due to the significance of soil texture in determining the drainage characteristics of the soil (Feloni et al., 2019).

3.4.6 Rivers network data

The river shapefile data originating from the South African Department of Water and Sanitation website was also used in the study. The data is often provided in vector format which is compatible with ArcGIS, allowing for precise representation and visualization of river networks. This shapefile data typically contains attributes such as river names, flow direction, and even information on water quality or usage. Moreover, it is crucial for this study because mapping the distance to rivers helps to identify flood-prone areas based on their proximity to water bodies (Rincon et al., 2018). It has been shown that floods are particularly prevalent in areas adjacent to rivers because water flows from higher altitudes and gathers at lower altitudes in the river basin (Tariq et al., 2022). Moreover, the velocity and extent of floods in a region are influenced by the region's distance to rivers, which measures the distance between each cell or pixel and the river (Khosravi et al., 2016; Xu et al., 2018; Chen, 2022). As a result, flooding is common in areas that are near rivers, and as the index value decreases, the likelihood of a flood rises (Rafiei-Sardooi et al., 2021). Due to that, the distance to streams is another important consideration because the susceptibility of an area to flooding is directly influenced by the presence of streams and rivers nearby. Therefore, river data was incorporated as part

of the methodology to help find areas that are more likely to flood because of their proximity to bodies of water. A representation of the data sources is presented in Table 2.

Table 2: Data types and sources

Data type	Source
Average annual precipitation	eThekwini Datafeeds (https://data.ethekwinifews.durban/) accessed on 13 October 2023
SRTM Digital Elevation Model (DEM)	US Geological Survey (https://earthexplorer.usgs.gov/ , accessed on 30 March 2023)
Landsat 8 OLI/TIRS	US Geological Survey (https://earthexplorer.usgs.gov/ , accessed on 30 March 2023)
Soil texture	DIVA-GIS (https://www.diva-gis.org/Data , accessed on 30 March 2023)
Geographic coordinates	SANSA (https://www.sansa.org.za/research/ , accessed on 17 November 2022)
Rivers data	Department of Water and Sanitation (https://www.dws.gov.za/iwqs/gis_data/river/All.html , accessed on 30 March 2023)

3.5. Data Processing

The data utilized in the analysis were standardized to a consistent spatial resolution of 30 meters. This decision was made to ensure uniformity across different datasets and maintain the coherence of the analysis. The 30-meter resolution was deemed appropriate for the study area, allowing for a detailed examination of the various criteria influencing flood risk while aligning with the available data sources.

3.5.1. Elevation

Elevation significantly influences the extent of flooding, particularly in managing the direction of water flow and determining flood depth (Stieglitz et al., 1997; Allafta and Opp 2021). For this study, an elevation map was created using SRTM DEM data in ArcGIS software. The elevation map was reclassified into five categories as follows: Very high (0 – 20 m), High (20

– 50 m), Moderate (50 – 100), Low (100 – 150 m), and (>150) (Souissi et al., 2019; Swain et al., 2020). Each category was assigned a numerical value for use in the weighted overlay analysis, aligning with their elevation characteristics: Very High = 5, High = 4, Moderate = 3, Low = 2, and Very Low = 1. These numerical values were instrumental in the analysis, guiding the software to prioritize areas with certain elevation characteristics based on their assigned weights in the overall flood hazard mapping process.

The studies by Souissi et al. (2019) and Swain et al. (2020) hold significant relevance to flood risk mapping research employing Multi-Criteria Decision Analysis (MCDA) techniques. The studies not only identified and examined key factors contributing to flood risk, but they also assigned weights to these factors and introduced predefined thresholds and intervals for flood susceptibility zones, which served as valuable reference points for this research. This provided a structured approach to understanding the significance of each factor in flood risk assessment and it also facilitates a more precise and standardized assessment of flood risk, enhancing the comparability and accuracy of flood risk mapping projects across different regions and contexts.

3.5.2. Slope

The data was processed using a spatial analysis tool found within the "Surface Tools" category in ArcGIS. Specifically, the "Slope" tool was utilized to generate this map. Through the use of this tool and the SRTM DEM data, the software was able to determine the slope across the area of study. The slope of the terrain was assessed in degrees and then categorized into three specific risk levels concerning the study of Swain et al. (2020): low (>35°), low (15.1°–35.0°) Moderate (5.1° – 15°) High (2.1° – 5.0°) Very high (0.0° – 2.0°). This categorization helped assess the possible effects of floods, with different levels of flood risk being associated with different slope measures in different places. Each slope category was assigned a numerical value to facilitate its integration into the weighted overlay analysis: Very Low (>35°) = 1, Low (15.1° – 35.0°) = 2, Moderate (5.1° – 15°) = 3, High (2.1° – 5.0°) = 4, and Very High (0.0° – 2.0°) = 5. These numerical values align with the inherent characteristics of slope, where higher values correspond to higher degrees of slope.

3.5.3 Drainage density

Drainage density data were processed in ArcGIS using the SRTM DEM dataset and were done so for the entire catchment. After carefully processing the georeferenced SRTM DEM, the flow direction and flow accumulation tools were employed to derive essential flow characteristics from the terrain. The flow accumulation output, representing the number of cells contributing to each location, served as the basis for delineating a stream network. As a result, the areas considered part of the stream network were identified by applying a defined threshold of 500 to the flow accumulation raster, which means that any cell with a flow

accumulation of 500 or more would be classified as part of the stream network, while cells with values below 500 would be excluded. Subsequently, the drainage density for the study area was calculated. Moreover, to assess flood risk, the drainage density values were segmented into three categories. The first category, the very high hazard class ($2 - 2.45 \text{ km/km}^2$), is defined by a notably elevated drainage density and is significantly susceptible to flooding. This is followed by the high class ($1.5 - 2 \text{ km/km}^2$) and moderate hazard class ($1 - 1.5 \text{ km/km}^2$) respectively, while the fourth category falls under the low hazard class ($0.5 - 1 \text{ km/km}^2$) and lastly, the very low class ($0 - 0.5 \text{ km/km}^2$) concerning Souissi et al. (2019) and Swain et al. (2020). This classification is pivotal in identifying areas prone to flooding, where higher drainage density indicates a greater potential for flooding due to increased water flow accumulation. To incorporate these drainage density categories into the weighted overlay analysis, each class was assigned a numerical value: Very High Hazard Class = 5, High Hazard Class = 4, Moderate Hazard Class = 3, Low Hazard Class = 2, and Very Low Hazard Class = 1.

3.5.4. Land use land cover

The 2023 Landsat 8 OLI/TIRS satellite image underwent pre-processing in QGIS before generating composite bands in ArcGIS. Initial QGIS preprocessing involved radiometric and geometric corrections, atmospheric correction, and noise removal. Subsequently, composite bands were generated in ArcGIS using the processed image. The study area was precisely extracted from the image using the "Extract by Mask" tool, ensuring the precise delineation of the area of interest from the source image (Sepuru, 2018). This extraction method focused subsequent image classification and analysis exclusively on the study area, enhancing result accuracy. Supervised image classification procedures were implemented, leading to the creation of distinct training samples for each land use category, including settlement, bare land, water bodies, vegetation, and agriculture (Allafta and Opp, 2021). The supervised classification process, performed in ArcGIS, leveraged these training samples to establish robust classification rules.

Post-classification, five distinct land use categories were derived, each assigned risk levels: water bodies as very high, agriculture as high, settlement as moderate, while bare land and vegetation were classified as low and very low, respectively (Swain et al., 2020; Souissi et al., 2019). To integrate these land use categories into the weighted overlay analysis, each category was assigned a numerical value: Very High (Water bodies) = 5, High (Agriculture) = 4, Moderate (Settlement) = 3, Low (Bare land) = 2, and Very Low (Vegetation) = 1. For accuracy assessment, the Kappa coefficient provided a statistical measure of agreement between the classified land use categories and reference data (Verma et al., 2020). Additionally, the validation process included a comparison with Google Earth imagery,

ensuring independent verification of the accuracy of classified results. Post-classification, the error matrix derived from the confusion matrix was analyzed.

3.5.5. Rainfall

The monthly precipitation data, measured in millimetres, was gathered from five weather stations located within the study area. This dataset underwent processing in ArcGIS through the application of the Inverse Distance Weighted Interpolation tool to create an annual average rainfall map (Allafta and Opp, 2021). This interpolation technique was utilized to estimate rainfall values at locations without direct measurements, relying on the spatial patterns and relationships observed among the available data points. This approach facilitated the development of a continuous surface that represents the distribution of seasonal rainfall across the study area. Monthly average rainfall data from 2016 to 2022 was utilized in the analysis.

Consequently, the resulting rainfall map was categorized into five risk levels: "very high" (300 mm), "high" (250 mm), "moderate" (200 mm), "low" (150 mm), and "very low" (100 mm). These classifications were determined based on historical flood events triggered by heavy rainfall, which have been documented for the KwaZulu-Natal region and are supported by previous research findings from various studies (Mashao et al., 2022; Rincon et al., 2018; Cai et al., 2021; Allafta and Opp, 2021; Swain et al., 2020; Souissi et al., 2019; Cabrera and Lee, 2019). To facilitate the integration of these rainfall categories into the weighted overlay analysis, each category was assigned a numerical value: 'Very High' (300 mm) = 5, 'High' (250 mm) = 4, 'Moderate' (200 mm) = 3, 'Low' (150 mm) = 2, and 'Very Low' (100 mm) = 1. These numerical values, reflective of the historical and research-supported risk levels, were instrumental in guiding the software to appropriately weigh and prioritize areas based on their susceptibility to flooding in response to varying rainfall intensities.

3.5.6 Distance to rivers

The distance to rivers plays a crucial role in identifying flood risk zones. To elaborate, Fernandez and Lutz (2010) demonstrated that flood hazards have a significant impact on regions in close proximity to the river network, with the influence of this factor gradually diminishing as one moves farther away from the riverbed. As result, to create a distance to rivers map that highlights places at risk of flooding, the rivers data was processed in ArcGIS using Euclidean distance analysis (Cai et al., 2021). Subsequently, a gradient was built, with values decreasing as the distance to rivers gets closer through determining the Euclidean distance between each cell and the closest river cell. The thresholds for this data were categorized into five levels of risk, very high (<500 m), high (500 – 1000 m), moderate (1000 – 1500 m), low (1500 – 2000 m) and very low (>2000 m) as per (Souissi et al., 2019; Chaulagain et al., 2023). To facilitate the integration of these distance to rivers categories into

the weighted overlay analysis, each category was assigned a numerical value: 'Very High' (<500 m) = 5, 'High' (500 to 1000 m) = 4, 'Moderate' (1000–1500 m) = 3, 'Low' (1500–2000 m) = 2, and 'Very Low' (>2000 m) = 1.

3.5.7. Soil data

For this dataset, the data processing procedure consisted of modifying a pre-existing global soil map to suit the exact study location. In ArcGIS software, the study area was separated from the larger map using a clipping technique (Allafta and Opp, 2021). Subsequently, the soil data was improved to match the study's specific focus by organizing it into different categories based on distinct soil texture classes. This classification was achieved by adjusting attributes within the ArcGIS software, where texture attributes were assigned based on the relative proportions of sandy loam, clay loam, and clay. As a result, a personalized map displaying soil textures for the study area was produced. The soil textures were classified into very high (clay), moderate (clay loam) and low (sandy loam) (Souissi et al., 2019; Chaulagain et al., 2023; Swain et al., 2020). To enable seamless integration into the weighted overlay analysis, each soil texture category was assigned a numerical value: 'Very High' (Clay) = 3, 'Moderate' (Clay Loam) = 2, and 'Low' (Sandy Loam) = 1. These numerical values, reflecting the specific soil textures and their associated risk levels, played a pivotal role in the analysis, aiding the software in capturing the influence of soil characteristics on flood risk within the study area.

3.6. Data Analysis

3.6.1. Analytical Hierarchy Process

AHP, which was developed by Saaty is a decision-making methodology that provides a structured approach for evaluating and prioritizing alternatives based on a set of criteria (Saaty, 1977). It allows users to establish a hierarchical arrangement of criteria and produce informed evaluations of flood hazards and risk assessments by incorporating local knowledge, expert opinions, and literature-supported prioritization of influencing factors (Wondim, 2016). Furthermore, it breaks down complex decisions into a hierarchical structure consisting of an object layer, index layer, and sub-index layer according to Cai et al. (2021). Furthermore, the pairwise comparison approach is used in AHP to evaluate the relative relevance or preference of elements using integer values from 1 to 9. According to Saaty (1980), the verbal evaluations should be converted into numerical values that represent the values of judgement using a 9-point scale.

As a result, a set of relative weights is developed by comparing all the criteria and alternatives. These pairwise comparison assessments are used by the mathematical model of AHP, which determines the total relevance of each criterion and alternative, to determine the final priorities. Ultimately, a set of matrix calculations and eigenvalue calculations are performed to determine the consistency of the judgements. The definition of a 9-point scale is listed in Table 3.

Table 3: Saaty's scale of relative importance (Adapted from Saaty, 1977)

Scale	Numerical Evaluation	Reciprocal	Description
Equally important	1	1	Both elements have equal importance or preference.
Slightly more important	2	1/2	One element is approximately equal to or slightly more important than the other
Moderately more important	3	1/3	One element has moderate importance or preference over the other.
Significantly more important	4	1/4	One element is between moderately and strongly more important or preferred than the other.
Very strongly more important	5	1/5	One element has strong importance or preference over the other.
Absolutely more important	6	1/6	One element is between strongly and very strongly more important or preferred than the other.
Strongly more important	7	1/7	One element has very strong importance or preference over the other.
Demonstrated importance	8	1/8	One element is between very strongly and extremely more important or preferred than the other.
Extremely more important	9	1/9	One element has extreme importance or preference over the other

i. Pairwise comparison

The first step in determining the weights of the criterion using AHP is to create a matrix for pairwise comparisons of the criteria selected (Rincon et al., 2018), as shown in Table 4, where the factors are listed both in rows and columns. The pairwise comparison judgments were then assigned to each factor to evaluate the relative importance of one criterion in comparison to another using Saaty's scale of relative importance ranging from 1 to 9. These judgements were adopted from different flood risk mapping studies which used almost a similar criterion (Rincon et al., 2018; Cai et al., 2021; Allafta and Opp, 2021; Swain et al., 2020; Souissi et al., 2019; Cabrera and Lee, 2019). For instance, in their research, Rincon et al. (2018) evaluated nearly identical criteria, including rainfall, distance to the river, digital elevation model (DEM), slope, land use/land cover (LULC), drainage density, soils, and lithology. These criteria were integral to their multi-criteria analysis for flood risk mapping in the Greater Toronto Area. The study resulted in a flood hazard map categorizing the area into four zones: high, intermediate, low, and very low flood hazard zones. The decisions made in this study were informed by relevant prior research works, including those by Rincon et al. (2018), Cai et al. (2021), Allafta and Opp (2021), Swain et al. (2020), Souissi et al. (2019), and Cabrera and Lee (2019), which provided valuable insights and served as the basis for comparison.

Table 4: Pairwise comparison scores of the selected criteria

Matrix	Rainfall	Slope	Elevation	DD	Soil	LULC	DFR
Rainfall	1	3	4	2	3	4	3
Slope	1/3	1	2	½	1	3	2
Elevation	¼	1/2	1	1/3	1/2	2	1
DD	½	2	3	1	2	3	2
Soil	1/3	1	2	½	1	2	2
Land use Land cover	¼	1/3	1/2	1/3	1/2	1	1/2
DFR	1/3	1/2	1	½	1/2	2	1
Sum	3	8.333	13.5	5.167	8.5	17	11.5

The pairwise comparisons were then used to create weighted scores that represent the relative importance of each factor. In the calculations, the pairwise comparison matrix was normalized by dividing each factor of the matrix by the sum of its respective column. This normalization process ensures that the values are relative to each other and facilitates comparison as shown in Table 5. The weighted average of the columns was then calculated, and the primary eigenvector was determined. These calculations produced a set of weights that represents the relative importance each factor in determining flood risk.

ii. Normalization

The pairwise comparisons were then used to create weighted scores that represent the relative importance of each factor. In the calculations, the pairwise comparison matrix was normalized by dividing each factor of the matrix by the sum of its respective column. This normalization process ensures that the values are relative to each other and facilitates comparison as shown in Table 5. The weighted average of the columns was then calculated, and the primary eigenvector was determined. These calculations produced a set of weights that represents the relative importance each factor in determining flood risk.

Table 5: Normalized pairwise comparisons of the selected criteria.

Matrix	Rainfall	Slope	Elevation	Drainage density	Soil	Land use Land cover	Distance from rivers	Criteria Weights
Rainfall	0.333	0.360	0.296	0.387	0.353	0.235	0.261	0.318
Slope	0.111	0.120	0.148	0.097	0.118	0.176	0.174	0.135
Elevation	0.083	0.060	0.074	0.065	0.059	0.118	0.087	0.078
Drainage density	0.167	0.240	0.222	0.194	0.235	0.176	0.174	0.201
Soil	0.111	0.120	0.148	0.097	0.118	0.118	0.174	0.127
Land use Land cover	0.083	0.040	0.037	0.065	0.059	0.059	0.043	0.055
Distance from rivers	0.111	0.060	0.074	0.097	0.059	0.118	0.087	0.087

iii. Determining the Consistency Index

The next crucial step is to assess the level of inconsistency using the Consistency Index (CI) to ensure the reliability of the judgments made during the pairwise comparisons. According to Saaty (1977), it is essential for the CI to be less than 0.1 for the pairwise comparisons to be considered reasonably consistent. This is because the AHP method may introduce inconsistencies when establishing values for the pairwise comparison matrix (Rincon et al., 2018). Hence, by assessing the CI, decision-makers can obtain an understanding of the general coherence of the decision-making process and implement any required modifications if deemed necessary. As a result, to calculate the CI, the initial step involves calculating the weighted sum vector. This is achieved by multiplying the criteria weights with the values obtained from pairwise comparisons (Cai et al., 2021).

The expression for CI is defined as equation 1 (Saaty, 1976): CI is equal to $\frac{\lambda_{max}-n}{n-1}$, whereby the symbol " λ_{max} " represents the maximum eigenvalue of a matrix. This matrix is obtained by summing up the column totals of the correlation matrix of each parameter, multiplied by the normalized value of the corresponding parameters as shown in table 6. Additionally, "n" refers to the dimension or order of the matrix.

Table 6: Calculating the CI for the criteria.

Criterion	Weighted Sum Value	Consistency Vector
Rainfall	$(1*0.318)+(3*0.135)+(4*0.078)+(2*0.201)+(3*0.127)+(4*0.055)+(3*0.087) = 2.299$	$\frac{2.299}{0.328} = 7.009$
Slope	0.964	7.141
Elevation	0.554	7.103
DD	1.437	7.149
Soil	0.909	7.157
LULC	0.394	7.164
DFR	0.614	7.057

$$\text{Consistency Index} = \frac{\lambda_{max}-n}{n-1}, \quad (3.1)$$

$$\lambda_{max} = \frac{7.009+7.141+7.103+7.149+7.157+7.164+7.057}{7}$$

$$= 7.111$$

Therefore,

$$CI = \frac{\lambda_{max}-n}{n-1}$$

$$= \frac{7.111-7}{7-1}$$

$$= 0.019233$$

To proceed, the Random Index (RI) and the Consistency Ratio (CR) must be determined to assess the consistency of the judgments made during the pairwise comparisons. As explained by Saaty (1980), the RI depends on the number of criteria used in the pairwise comparison. Ghosh and Kar (2018) define RI as the mean value of the resulting CI. On the other hand, according to Chen et al. (2013), CR represents a measure of how the consistency index of a given matrix compares to that of a purely random matrix. Table 7 presents the RI values.

Table 7: The RI values.

Matrix Size	1	2	3	4	5	6	7	8	9	10
Random Consistency Index	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

To proceed, CR is calculated using Saaty's equation (Saaty, 1980):

$$\begin{aligned}
 \text{Consistency Ratio} &= \frac{\text{Consistency Index}}{\text{Random Index}} & (3.2) \\
 &= \frac{0.019}{1.32} \\
 &= 0.014
 \end{aligned}$$

Since the CR is less than 0.1, this indicates that the level of inconsistency in the pairwise comparisons made during the AHP calculations is within an acceptable range. Due to that, it can be concluded that the judgments provided for the criteria or alternatives are relatively consistent and reliable since the value CR represents a high level of consistency.

3.6.2. Triangular Fuzzy Analytical Hierarchy Process

Previous research has demonstrated that the traditional AHP method often faces criticism for its inadequate ability to effectively handle the uncertainties associated with decision-making processes (Li et al., 2021; Wu et al., 2018; Deng et al., 2014). To address this concern, the application of Triangular FAHP has been incorporated in this research to determine the weights. The objective is to evaluate the sensitivity and compare the effectiveness of using each of these two methods individually in addressing the uncertainties faced by decision-makers. Using crisp numbers, or discrete values, traditional AHP often illustrates the significance of factors. However, in this approach, triangular fuzzy numbers are employed to take into consideration the inherent uncertainty in the decision-making process (Buckley, 1985). These values are ambiguously defined and are indicated by l , m , and u , where l indicates the lower bound, m the most likely value, and u the upper bound, where $l \leq m \leq u$ (Cai et al., 2021). Moreover, in a study by Cai et al. (2021), it can be seen that the incorporation of triangular fuzzy numbers in factor representation allows for greater flexibility and ambiguity rather than relying on a single exact value. As a result, this approach enables researchers to

consider a range of potential hazards, leading to a comprehensive and realistic assessment of the various aspects involved in the decision-making process. The definition of triangular fuzzy numbers is shown in Table 8.

Table 8: FAHP Scale relative of importance (Adapted from Ayhan, 2013)

Linguistic term	Triangular fuzzy numbers	Reciprocal Fuzzy number
Equally Important	(1, 1, 1)	(1, 1, 1)
Moderate Importance	(2, 3, 4)	(1/4, 1/3, 1/2)
Strong Importance	(4, 5, 6)	(1/6, 1/5, 1/4)
Very Strong Importance	(6, 7, 8)	(1/8, 1/7, 1/6)
Extremely Strong Importance	(9, 9, 9)	(1/9, 1/9, 1/9)
Intermediate Values	(1, 2, 3)	(1/3, 1/2, 1)
	(3, 4, 5)	(1/5, 1/4, 1/3)
	(5, 6, 7)	(1/7, 1/6, 1/5)
	(7, 8, 9)	(1/9, 1/8, 1/7)

The triangular membership function can be utilized to illustrate the level of risk or susceptibility associated with specific factors related to flooding. For instance, to model a fuzzy relationship between the value of a factor and the degree to which it contributes to flood risk, the triangular membership function is used as shown in figure 5. This allows decision-makers to make better-informed decisions and promoting the implementation of appropriate flood risk management measures based on the degrees of risk associated with various factors (Zadeh, 1965).

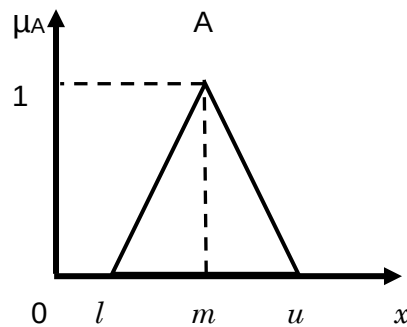


figure 5: Triangular fuzzy membership function

i. Pairwise comparisons

As part of the methodology of the study based on the Triangular FAHP to determine the weights, the first step involved performing pairwise comparisons of the criteria. As a result, the relative importance of each criterion was established using fuzzy preferences. Thereafter, the

linguistic terms used in the comparisons were transformed into triangular fuzzy numbers, encompassing lower bound, midpoint, and upper bound values (Tripathi et al., 2022). To illustrate, Table 9 indicates the relative importance of criteria based on fuzzy preferences transformed into triangular fuzzy numbers.

The formula for determining the reciprocal values is presented as follows (Tariq et al., 2020):

$$\begin{aligned} A^{-1} &= (l, m, u)^{-1} \\ &= \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l}\right) \end{aligned} \quad (3.3)$$

Where, 'l' signifies the lower bound, 'm' denotes the midpoint, and 'u' represents the upper bound of this fuzzy number. The fuzzy reciprocal, A^{-1} , can be understood as a way to deal with imprecision and uncertainty in data. It provides a representation of values in the form of fuzzy intervals, acknowledging the fact that a precise value may not be available, but rather, the value is bounded by a lower and upper limit.

$1/u$ represents the reciprocal of the upper bound, 'u,' in the fuzzy number. It quantifies the degree to which the upper limit influences the reciprocal value.

$1/m$ is the reciprocal of the midpoint, 'm,' which characterizes the central or most probable value within the fuzzy number. It conveys the degree to which the central value impacts the reciprocal outcome.

$1/l$ corresponds to the reciprocal of the lower bound, 'l,' in the fuzzy number. This component assesses the influence of the lower limit on the reciprocal result.

Similarly, the pairwise comparison judgements of the criteria shown in table 9 were drawn from a variety of flood risk mapping studies that employed similar assessment parameters, as documented in the works of Cai et al. (2021), Allafta and Opp (2021), Swain et al. (2020), Souissi et al. (2019), and Cabrera and Lee (2019).

Table 9: FAHP Pairwise Comparison of the selected criteria

Matrix	Rainfall	Slope	Elevation	Drainage Density	Soil	Land use/land cover	Distance from rivers
Rainfall	(1,1,1)	(2,3,4)	(3,4,5)	(1,2,3)	(2,3,4)	(3,4,5)	(2,3,4)
Slope	(1/4,1/3,1/2)	(1,1,1)	(1,2,3)	(1/3,1/2, 1)	(1,1,1)	(2,3,4)	(1,2,3)
Elevation	(1/5, 1/4,1/3)	(1/3, ½,1)	(1,1,1)	(1/4, 1/3, ½)	(1/3,1/2,1)	(1,2,3)	(1,1,1)
Drainage density	(1/3, ½, 1)	(1,2,3)	(2,3,4)	(1,1,1)	(1,2,3)	(2,3,4)	(1,2,3)
Soil	(1/4, 1/3, ½)	(1,1,1)	(1,2,3)	(1/3, ½, 1)	(1,1,1)	(1,2,3)	(1,2,3)
Land use land cover	(1/5, ¼, 1/3)	(¼, 1/3, ½)	(1/3, ½, 1)	(1/4,1/3, ½)	(1/3,1/2,1)	(1,1,1)	(1/3, ½, 1)
Distance from rivers	(1/4, 1/3, ½)	(1/3, ½, 1)	(1,1,1)	(1/3, ½, 1)	(1/3,1/2,1)	(1,2,3)	(1,1,1)

ii. Determining the weights

The next step is to determine the FAHP weights. In this approach the weights are calculated by normalizing the fuzzy geometric mean values using the reciprocal of the summation of the geometric means. The fuzzy geometric mean is a method for combining the triangular fuzzy numbers that come from pairwise comparisons (Buckley, 1985). The formula for calculating the fuzzy geometric mean (r_i) is as follows (Tariq et al., 2020):

$$r_i = (x, y, z) \quad (3.4)$$

where:

$$x = (l_1 * l_2 * \dots * l) ^ { (1/n)} \quad (3.5)$$

$$y = (m_1 * m_2 * \dots * m) ^ { (1/n)} \quad (3.6)$$

$$z = (u_1 * u_2 * \dots * u) ^ { (1/n)} \quad (3.7)$$

The aforementioned calculations involve determining the n^{th} root of the result after multiplying relevant components from the triangular fuzzy numbers of each criterion. To calculate the weights, the formula is present as (Buckley, 1985):

$$W_i = r_i * (r_1 + r_2 + \dots + r_n) ^ { (-1)}, \quad (3.8)$$

To proceed, the fuzzy geometric mean values have to be added using the formula:

$$r_1 + r_2 + \dots + r_7 = (l_1, m_1, u_1) + (l_2, m_2, u_2) + \dots + (l_7, m_7, u_7) \quad (3.9)$$

$$= (l_1 + l_2 + \dots + l_7, m_1 + m_2 + \dots + m_7, u_1 + u_2 + \dots + u_7) \quad (3.10)$$

$$= (1.842 + 0.774 + \dots + 0.512, 2.627 + 1.104 + \dots + 0.701, 3.357 + 1.511 + \dots + 1.060)$$

$$= (5.681, 8.223, 11.365)$$

The reciprocal of the geometric mean sum is presented as follows:

$$(r_1 + r_2 + r_3 + \dots + r_7)^{-1} = (l, m, u)^{-1} \quad (3.11)$$

$$= \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l} \right) \quad (3.12)$$

$$= \left(\frac{1}{11.365}, \frac{1}{8.223}, \frac{1}{5.681} \right)$$

In the next step, each fuzzy geometric mean value must be multiplied with the reciprocal of the geometric mean sum to get the weights using the formula (Buckley, 1985):

$$W_i = r_i * (r_1 + r_2 + \dots + r_n)^{-1}, \quad (3.13)$$

For instance, the FAHP weight for rainfall was calculated as follows:

$$W_i = (1.842, 2.627, 3.357) * \left(\frac{1}{11.365}, \frac{1}{8.223}, \frac{1}{5.681} \right)$$

$$= (0.162, 0.319, 0.591),$$

Similarly, the calculation of the weights for the other criteria followed the method presented in Table 10.

Table 10: Fuzzy Geometric Mean and Fuzzy Weights of different selected criteria

Criteria	Fuzzy Geometric Mean	Fuzzy Weights
Rainfall	(1.842, 2.627, 3.357)	(0.162, 0.319, 0.591)
Slope	(0.774, 1.104, 1.511)	(0.068, 0.134, 0.266)
Elevation	(0.476, 0.635, 0.906)	(0.042, 0.077, 0.159)
DD	(1.042, 1.669, 2.380)	(0.092, 0.203, 0.419)
Soil	(0.701, 1.042, 1.450)	(0.062, 0.127, 0.255)
LULC	(0.334, 0.445, 0.701)	(0.029, 0.054, 0.123)
DFR	(0.512, 0.701, 1.060)	(0.045, 0.085, 0.187)

iii. Defuzzification

After calculating the weights using FAHP, the defuzzification process was applied. This process plays a crucial role in facilitating the ranking of alternatives and reaching a decision. This process involves converting the initially fuzzy calculated numbers into crisp numeric values, allowing for precise comparisons and evaluations (Buckley, 1985). In this study, the Centre of Area (COA) defuzzification method proposed by Zadeh (1965) was employed to achieve this transformation, allowing decision-makers to gain a clearer understanding of the data and make well-informed choices. Moreover, the ambiguity inherent in the triangular fuzzy

numbers is effectively resolved, resulting in a set of crisp values that can be readily compared and ranked. This transformation ensures a more straightforward and intuitive decision-making process, as it provides concrete and interpretable data. To defuzzify the weights using COA, the following formula was used:

$$\text{COA: } w_i = \left(\frac{l+m+u}{3} \right) \quad (3.14)$$

Proceeding with the defuzzification of the fuzzy weight for rainfall using the COA method, the crisp numeric value was obtained as shown below.

Where, $l = 0.162$, $m = 0.319$ and $u = 0.591$,

$$\begin{aligned} \text{COA; } w_i &= \left(\frac{0.162+0.319+0.591}{3} \right) \\ &= 0.357 \end{aligned}$$

iv. Normalizing the fuzzy weights

Similarly, for the rest of the criteria, the weights were defuzzified as presented in Table 11. Weights were normalized by dividing each crisp weight by the sum of all crisp weights. This step ensures that the sum of all weights equals 1 to represent a valid set of normalized weights.

Table 11: Defuzzified and normalized weights

Criteria	Defuzzified Weights	Normalized Weights
Rainfall	0.357	0.306
Slope	0.157	0.134
Elevation	0.093	0.080
Drainage density	0.238	0.204
Soil	0.148	0.127
LULC	0.069	0.059
Distance to rivers	0.106	0.091

3.7. Identifying flood risk zones

After assigning weights to each factor in accordance with their relevance to flood risk—guided by literature (Rincon et al., 2018; Cai et al., 2021; Allafta and Opp, 2021; Swain et al., 2020; Souissi et al., 2019; Cabrera and Lee, 2019) and historical flood event data in the study area—the research progressed to delineate flood hazards zones. This was achieved through a weighted overlay analysis using ArcGIS, where each factor's weight, determined by the AHP and Triangular FAHP methods, played a pivotal role in the spatial identification of these zones. In ArcGIS, these weight scores (Tables 5 and 11) were assigned to the thematic layers and their respective classes for each criterion. To compute the overall risk score for every pixel on

the resulting flood hazard map in ArcGIS, a weighted overlay analysis method was used. This method combines multiple raster layers by applying weights to each layer to generate a composite output raster. The formula for the weighted overlay equation in ArcGIS is as follows (Weighted Overlay Spatial Analyst—ArcGIS Pro | Documentation, n.d.)

$$\text{Weighted Overlay Output} = (w_1 \times R_1) + (w_2 \times R_2) + \dots + (w_n \times R_n) \quad (3.15)$$

where,

Weighted Overlay Output is the final composite raster representing the weighted overlay result,

$w_1, w_2, \dots, w_n$ are the normalized weights assigned to each input raster (factor),

$R_1, R_2, \dots, R_n$ are the raster layers representing the different criteria

Table 12 shows the parameters employed in this study and how they were assigned weights. The ranking was substantiated by literature (Swain et al., 2020; Souissi et al., 2019; Chaulagain et al., 2023; Mashao et al., 2022; Grab and Nash, 2023). After carefully conducting weighted overlay analysis of the two MCDA methods, two flood hazard maps were produced showing risk categories ranging from 1 to 5 (Very low to Very high).

Table 12: Criteria and sub-criteria for assessing flood susceptibility include flood risk.

Flood causative factor	Unit	Class	Susceptibility class or levels of risk	AHP Weight	FAHP Weight
Rainfall	mm	>300 mm	Very high	0.318	0.306
		250 mm	High		
		200 mm	Moderate		
		150 mm	Low		
		100 mm	Very Low		
Slope	Degrees	0.0° - 2.0°	Very high	0.135	0.134
		2.1 ° - 5.0°	High		
		5.1° - 15.0°	Moderate		
		15.1° - 35°	Low		
		>35°	Very low		
Soil	Level	Clay	High	0.078	0.080
		Clay Loam	Moderate		
		Sandy	Low		
Elevation	m	0 – 20 m	Very high	0.201	0.204
		20 – 50 m	High		
		50 – 100 m	Moderate		
		100 – 150 m	Low		
		>150	Very low		
Drainage density	km/km ²	2.00 – 2.45 km/km ²	Very high	0.127	0.127
		1.5 – 2.00 km/km ²	High		
		1.0 – 1.5 km/km ²	Moderate		
		0.5 – 1.0 km/km ²	Low		
		0 – 0.5 km/km ²	Very low		
Distance from rivers	m	<500 m	Very High	0.055	0.059
		500 m – 1000 m	High		
		1000 m – 1500 m	Moderate		
		1500 m – 2000 m	Low		
		>2000	Very low		
Land use Land cover	Level	Waterbody	Very High	0.087	0.091
		Agriculture	High		
		Settlement	Moderate		
		Bare land	Low		
		Vegetation	Very Low		

The table above resulted in two flood hazard maps from the two MCDA methods showing flood risk as values ranging from 1 to 5 (Very low to very high).

3.8. Performing sensitivity analysis

As outlined in Chapter 1, the study's objective was to assess the sensitivity of the Analytic Hierarchy Process (AHP) and FAHP methods. Specifically, it examined how variations in the individual weighting parameters influence the final output — the flood hazard maps. As a result, One-At-A-Time (OAT) sensitivity analysis method was used to examine the impacts of small changes in the criteria weights in both MCDA methods (Fildes, 2022). This method involves changing the weights of individual criteria, one at a time while keeping all other factors constant to observe how these changes affect the final rankings of the alternatives. However, according to Xiao et al. (2017), in order to satisfy the requirement that the sum of all the weights equals one, the remaining criteria weights should be proportionally adjusted as one criterion weight was changed. As a result, the criteria were normalized after every adjustment. Normalizing the increased weight ensures that the overall weighting structure remains valid and proportional, as it should sum up to one as per the sensitivity analysis principle (Cai et al., 2021). This is a valid approach to maintain consistency in the weights after performing sensitivity analysis.

Initiating the analysis, the study began by employing the initial weight values assigned to each criterion, as provided in the flood risk assessment study. These initial weights represented the relative importance of each criterion within the assessment framework. A total of 28 sensitivity simulations were performed to evaluate the sensitivity of the AHP and FAHP methods. In each simulation, one specific criterion's weight was increased by 20% and decreased by 20% in relation to its initial weight value. This choice of 20% variation was based on common practice in sensitivity analysis (Sharifi and Dinpashoh, 2014) allowing an examination of the impact of moderate changes in the criteria's importance on the overall decision-making process.

The adjustment formulas were as follows:

$$\text{Increasing the weight of a factor by 20\%: } W_n = W_c + (W_c * 0.2) \quad (3.16)$$

$$\text{Decreasing the weight of a factor by 20\%: } W_n = W_c - (W_c * 0.2) \quad (3.17)$$

Here, "Wc" represented the initial weight of the factor, while "Wn" denoted the modified weight after the adjustment. This formula is a general method for conducting sensitivity analysis by adjusting the weight of a factor by $\pm$ any percentage. This technique is commonly used in various studies and analyzes involving weighted criteria or decision-making processes, particularly in the field of multi-criteria decision analysis (MCDA) or spatial analysis (Cai et al., 2021). However, these simulations facilitated a comprehensive exploration of the impact of variations in criteria weightings on flood risk assessments.

3.8.1. Weight simulations for Rainfall

Table 13 illustrates the sensitivity simulation results for the AHP method, examining both increased and decreased values for the rainfall criterion.

Table 13: AHP weight simulations for Rainfall

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.359	0.271
Slope	0.135	0.127	0.144
Soil	0.078	0.073	0.083
Elevation	0.201	0.189	0.215
Drainage density	0.127	0.119	0.136
Distance to rivers	0.055	0.052	0.059
LULC	0.087	0.082	0.093

Similarly, table 14 displays the sensitivity simulation results for the FAHP method, considering both increased and decreased values for the rainfall criterion.

Table 14: FAHP weight simulations for Rainfall

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.346	0.323
Slope	0.157	0.126	0.137
Soil	0.148	0.075	0.079
Elevation	0.093	0.192	0.204
Drainage density	0.238	0.120	0.129
Distance to rivers	0.106	0.056	0.056
LULC	0.069	0.086	0.071

3.8.2. Weight simulations for Slope

The sensitivity table for slope values explores how changes in slope affect the decisions made by the AHP method, considering both increased and decreased values.

Table 15: AHP weight simulations for Slope

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.309	0.326
Slope	0.135	0.158	0.111
Soil	0.078	0.076	0.080
Elevation	0.201	0.196	0.206
Drainage density	0.127	0.124	0.130
Distance to rivers	0.055	0.054	0.056
LULC	0.087	0.085	0.089

Similarly, this table shows the sensitivity simulation results for the FAHP method with both increased and decreased values for the slope criterion.

Table 16: FAHP weight simulations for Slope

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.298	0.314
Slope	0.157	0.157	0.110
Soil	0.148	0.078	0.082
Elevation	0.093	0.198	0.209
Drainage density	0.238	0.124	0.130
Distance to rivers	0.106	0.057	0.061
LULC	0.069	0.089	0.093

3.8.3. Weight simulations for Soil

Table 17 presents the sensitivity analysis outcomes for the AHP method, considering both increased and decreased values for the soil criterion.

Table 17: AHP weight simulations for Soil

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.313	0.323
Slope	0.135	0.133	0.137
Soil	0.078	0.092	0.064
Elevation	0.201	0.198	0.204
Drainage density	0.127	0.125	0.129
Distance to rivers	0.055	0.054	0.056
LULC	0.087	0.086	0.088

Similarly, table 18 displays the sensitivity simulation results for the FAHP method, considering both increased and decreased values for the soil criterion.

Table 18: FAHP weight simulations for Soil

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.301	0.311
Slope	0.157	0.132	0.136
Soil	0.148	0.094	0.065
Elevation	0.093	0.201	0.207
Drainage density	0.238	0.125	0.129
Distance to rivers	0.106	0.058	0.060
LULC	0.069	0.089	0.092

3.8.4. Weights simulations for Elevation

Table 19 demonstrates the sensitivity of the AHP method to both increased and decreased values for the elevation criterion.

Table 19: AHP weight simulations for Elevation

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.305	0.331
Slope	0.135	0.130	0.140
Soil	0.078	0.075	0.081
Elevation	0.201	0.232	0.168
Drainage density	0.127	0.122	0.132
Distance to rivers	0.055	0.053	0.057
LULC	0.087	0.084	0.091

On the other hand, table 20 explores the sensitivity of the FAHP method to both increased and decreased values for the elevation criterion.

Table 20: FAHP weight simulations for Elevation

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.294	0.319
Slope	0.157	0.129	0.140
Soil	0.148	0.077	0.083
Elevation	0.093	0.235	0.170
Drainage density	0.238	0.122	0.132
Distance to rivers	0.106	0.059	0.061
LULC	0.069	0.087	0.095

3.8.5. Weights simulations for drainage density

Table 21 shows the sensitivity analysis for drainage density values, evaluating their impact on decisions made by the AHP method.

Table 21: AHP weight simulations for drainage density

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.310	0.326
Slope	0.135	0.131	0.138
Soil	0.078	0.076	0.080
Elevation	0.201	0.196	0.206
Drainage density	0.127	0.149	0.105
Distance to rivers	0.055	0.054	0.056
LULC	0.087	0.085	0.089

Similarly, table 22 shows the sensitivity simulation results for the FAHP method, considering both increased and decreased values for the drainage density criterion.

Table 22: FAHP weight simulations for Drainage density

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.298	0.314
Slope	0.157	0.131	0.137
Soil	0.148	0.078	0.082
Elevation	0.093	0.199	0.209
Drainage density	0.238	0.148	0.105
Distance to rivers	0.106	0.058	0.060
LULC	0.069	0.089	0.093

3.8.6. Weights simulations for Distance to rivers

Table 23 presents the sensitivity analysis results for the AHP method, considering both increased and decreased values for the distance to rivers criterion.

Table 23: AHP weight simulations for Distances to rivers

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.314	0.321
Slope	0.135	0.133	0.136
Soil	0.078	0.077	0.079
Elevation	0.201	0.199	0.203
Drainage density	0.127	0.125	0.128
Distance to rivers	0.055	0.065	0.044
LULC	0.087	0.086	0.088

On the contrary, table 24 explores the sensitivity of the FAHP method to both increased and decreased values for the distance to rivers criterion.

Table 24: FAHP weight simulations for Distance to rivers

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.302	0.309
Slope	0.157	0.132	0.135
Soil	0.148	0.079	0.081
Elevation	0.093	0.201	0.206
Drainage density	0.238	0.125	0.128
Distance to rivers	0.106	0.070	0.048
LULC	0.069	0.090	0.092

3.8.7. Weight simulations for Land use land cover

Table 25 presents the sensitivity analysis for land use land cover values considers both increases and decreases, assessing their impact on decisions made by the AHP method.

Table 25: AHP weight simulations for Land use land cover

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.318	0.312	0.323
Slope	0.135	0.133	0.137
Soil	0.078	0.077	0.079
Elevation	0.201	0.197	0.204
Drainage density	0.127	0.125	0.129
Distance to rivers	0.055	0.054	0.056
LULC	0.087	0.102	0.071

Similarly, table 26 explores the sensitivity of the FAHP method to both increased and decreased values for the land use land cover criterion.

Table 26: FAHP weight simulations for Land use land cover

Criteria	Original Weight	Increased (Normalized)	Decreased (Normalized)
Rainfall	0.306	0.300	0.311
Slope	0.157	0.132	0.134
Soil	0.148	0.079	0.080
Elevation	0.093	0.200	0.204
Drainage density	0.238	0.125	0.129
Distance to rivers	0.106	0.058	0.060
LULC	0.069	0.107	0.074

3.9. Comparative analysis

According to Rincon et al. (2018), validation is a crucial step in the modelling process, as it verifies whether the model accurately represents the real world or observations. Given the absence of prior studies in the study area that specifically delineated flood risks that would be essential for validating the generated maps within this study, the validation process for the mapped areas in this study relied on data from SANSA concerning regions that experienced floods in 2022 April. The comparison between the two MCDA methods was conducted based on sensitivity analysis to assess how changes in input data affect the resulting flood hazard maps, and the extent and location of elevated flood risk zones with reference to the data provided by SANSA to look for areas of agreement and disagreement. To achieve this, the Zonal Statistics tool in ArcGIS was used to generate the total area of locations that has been classified as elevated flood risk zones which is the moderate, high and very high-risk zones.

According to Chang and Fabri (2003), the absence of validation renders any interpretation unattainable and prevents the provision of support for the method or the input data. Therefore, in this study, the ROC-AUC method was used to evaluate the accuracy of flood risk maps. Darabi et al. (2020) and Mashao et al. (2022) have demonstrated that the AHP and Fuzzy logic methods can be readily assessed and justified using the AUC curve. This approach enabled to validate the precision of the flood hazard maps generated using the AHP and FAHP methods. Furthermore, as a comprehensive assessment of model performance, the results were compared on the basis of AUC (Area Under the ROC Curve) (Mashao et al., 2022), providing an additional quantitative measure to evaluate the accuracy of the AHP and FAHP flood hazard maps and their sensitivity in detecting areas with elevated flood risk.

For the ROC-AUC analysis, a binary classification approach was employed to evaluate the flood risk assessment (Mashao et al., 2022). The flood hazard maps categories were consolidated into two classes, where 'very high,' 'high,' and 'moderate' were considered as the positive class, and 'low' and 'very low' were treated as the negative class. This classification scheme was chosen to assess the model's performance in distinguishing areas with elevated flood risk from those with lower flood risk. The twenty-eight weight simulations were also compared using this method. The AUC graphs were derived using the ArcSDM plugin in ArcGIS, a tool that has been previously utilized in studies such as those by Sengani et al. (2022) and Mashao et al. (2022), highlighting its significance and robustness in the field of flood risk mapping and modelling. This approach enabled the study to make data-driven conclusions regarding the model's effectiveness in delineating areas susceptible to flooding and validate its accuracy in accordance with established methodologies and past research. The table below provides a general guideline for interpreting AUC values (Irawan, 2018).

Table 27: AUC Value Interpretations (Adapted from Irawan, 2018)

AUC Range	Interpretation
0.5	Unsatisfactory
0.5 - 0.7	Poor
0.7 - 0.8	Fair (Acceptable)
0.8 - 0.9	Good (Very Good)
≥ 0.9	Excellent

4. Chapter Four: Results and Discussion

4.1. Introduction

In this chapter, the results are presented and discussed. The resulting maps depict the spatial distribution of flood risk across the study area. Moreover, beyond the depiction of these maps, the chapter delves into the results of a sensitivity analysis for both methodologies. This analysis sheds light on how changing input parameters affects the results and emphasizes the resilience of the outcomes.

4.2. Flood hazard maps

The flood hazard maps revealed five distinct risk levels: very low, low, moderate, high and very high. The 'very high' risk category cover only a small fraction, representing a minuscule portion of the overall classification. This scarcity of 'very high' risk areas in the study can be attributed to several important variables. Firstly, the study area typically encounters substantial rainfall, primarily concentrated during specific periods each year, rather than being a consistent occurrence throughout the year. This pattern of intense rainfall is supported by precipitation data from the eThekweni Data feeds and is responsible for the occasional occurrence of major flooding disasters. Secondly, the analysis employed strict criteria for defining 'very high' risk, with thresholds set at levels that are exceptionally uncommon within the study area.

4.2.1. AHP-Generated flood hazard map

The depicted map illustrates the outcomes of the results of using AHP weights. The resulting flood hazard map effectively categorizes distinct regions within the study area into five well-defined flood risk classifications. Among these classifications is the 'Very High Risk' category, occupying a mere 0.003% of the total study area. Furthermore, the 'High Risk' category encompasses an area of 85.03 square kilometres which is equivalent to 3.92% of the overall study area. This category encompasses locales such as Durban Harbour, Congella, Bayhead, Demat, and others, strategically positioned in proximity to low-lying regions, shorelines, and rivers. The specific factors that contribute significantly to the classification of these areas as high flood risk zones are the proximity to rivers, which are the Umlazi River and Umgeni River. The presence of Durban Harbour and the surrounding regions also amplifies this risk due to their close proximity to the water bodies and are mostly in the low-lying areas near the shoreline. Moreover, some of these areas are as close as approximately 500 meters from the Umlazi River and Umgeni River, rendering them highly susceptible to substantial flood risk. As such, immediate attention is imperative in terms of flood mitigation and risk management, particularly in light of their heightened vulnerability to heavy rainfall.

Additionally, the 'Moderate Risk' category spans a significant 82.86% of the entire study area, characterizing regions with a moderate level of flood risk. These regions warrant risk reduction measures, albeit to a lesser extent when compared to the high-risk areas previously discussed. In contrast, the 'Low Risk' category extends over 13.15% of the area, signifying regions with comparatively lower flood risk levels. Consequently, a reduced priority is attributed to flood risk management initiatives within these areas. Finally, the 'Very Low Risk' category encompasses a mere 0.074% of the study area, designating it as the safest region in terms of flood risk within the study region. In order to illustrate the results of flood risk assessment and enable a comparative analysis with the FAHP approach, the AHP-generated flood hazard map is presented in figure 6.

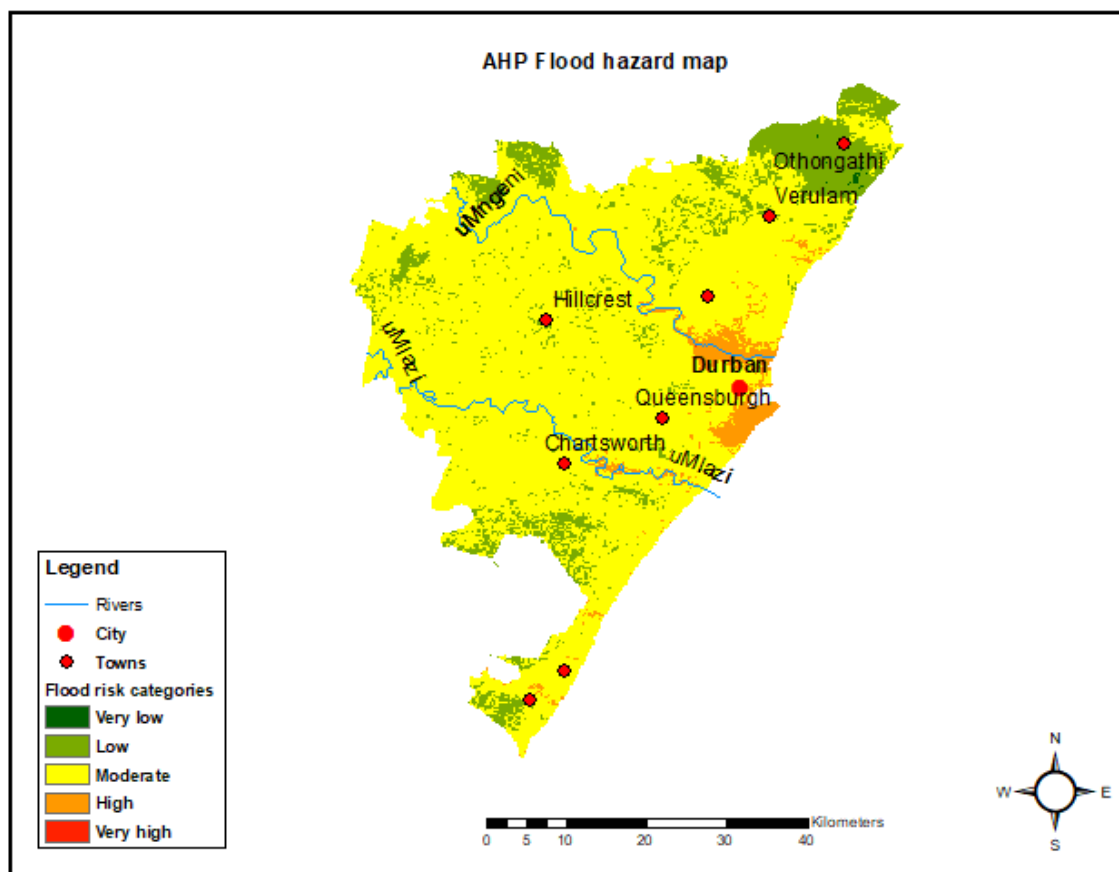


Figure 6: AHP flood hazard map

4.2.2. FAHP-Generated flood hazard map

The flood hazard maps generated by both methods display distinct categorizations and patterns. These differences and similarities shed light on the influence of the selected method and the associated sensitivity of criteria weighting on flood risk assessments. The FAHP flood hazard map classifies flood risk into five distinct levels: very low, low, moderate, high, and very high. These categories highlight specific areas within the study region and are a result of the

FAHP method's sensitivity to criteria variations. In particular, the very high flood risk zones, covering only 0.003% of the study area, are characterized by their extreme vulnerability to flooding (Mashao et al., 2022). Proximity to water bodies and a history of flooding events make them highly susceptible to inundation during heavy rainfall and overflow events.

On the other hand, the FAHP flood hazard map showcases its own unique categorization of flood risk levels. In this case, high flood risk zones cover an area of 3.84% of the total study area, which is slightly lower than that of the AHP, and are primarily situated in close proximity to water bodies, particularly rivers. This proximity to water bodies significantly heightens the flood risk for residents during periods of heavy rainfall. Consequently, residents residing near these water bodies are facing a significantly greater flood risk compared to those living farther away (Mashao et al., 2022). Furthermore, factors such as high drainage density and specific land use and land cover characteristics played substantial roles in designating these areas as high flood risk zones.

The comparison between the two methods reveals that while the FAHP map highlights a small percentage of very high flood risk zones, the AHP map identifies a slightly larger area as high risk. This difference may be attributed to variations in criteria weighting and sensitivity to different factors. Additionally, the moderate flood risk areas, covering 82.10% of the total area, are recognized by both methods and are influenced by complex factors such as slope, soil type, elevation, and land use and land cover characteristics. In summary, the comparison of AHP and FAHP flood hazard maps shows fairly similar results. The extent to which changes in weighting might alter the results will, however, provide insights into the sensitivity of the two methods.

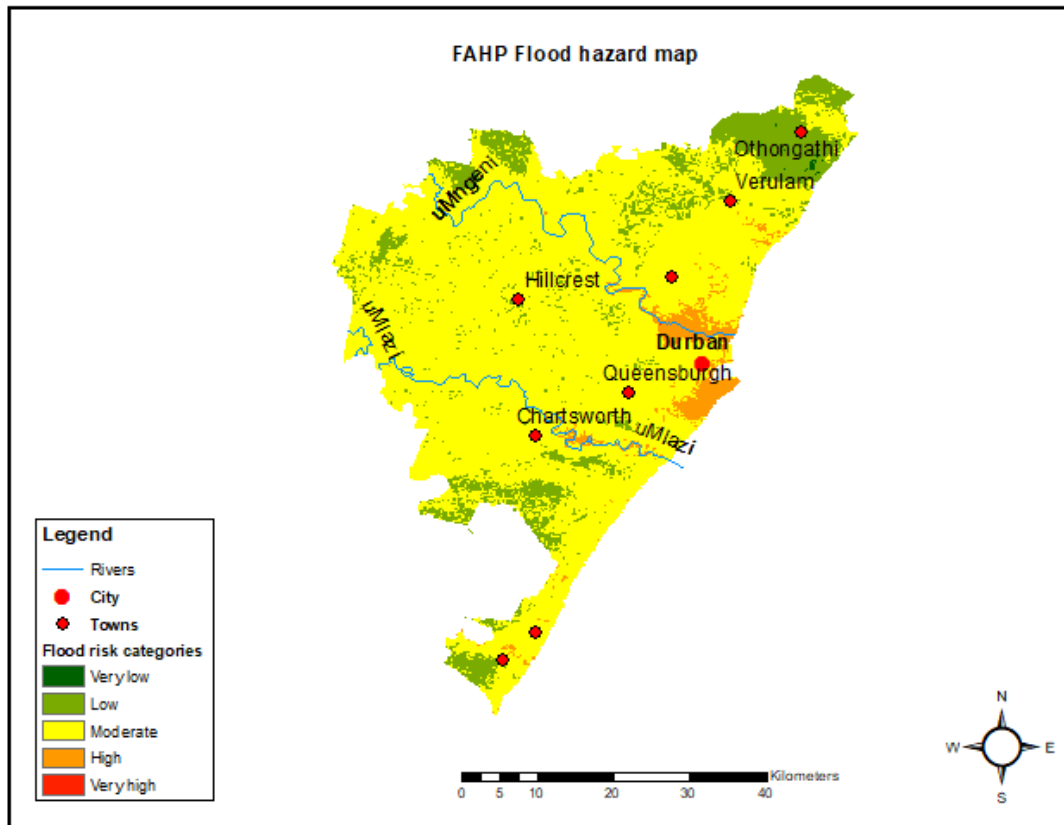


Figure 7: FAHP flood hazard map

4.3. Accuracy of the assessment

Accuracy, a fundamental concept in assessing the quality of predictive models and methodologies, is a critical element that underpins the reliability and credibility of research findings (Carson, 2002). It plays a central role in examining the precision and effectiveness of models, predictions, or classifications by comparing them to external or reference data. In this context, accuracy takes centre stage in the examination of the two MCDA methods, and their ability to predict flood incidents. To complement this assessment, the ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) graphs are presented in the section below. These graphs visually represent the accuracy and performance of the AHP and FAHP methods in mapping flood risk zones (Figure 8-9).

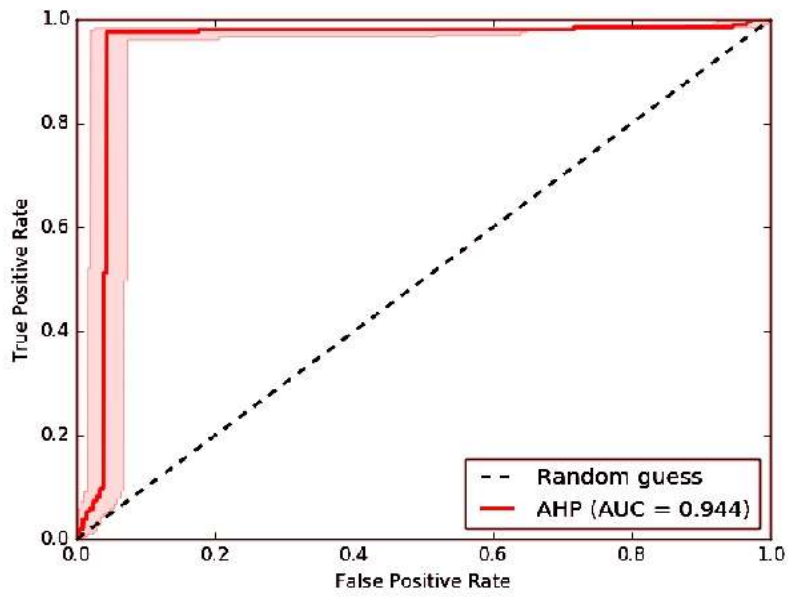


Figure 8: Validation of the AHP method using the ROC- AUC Method

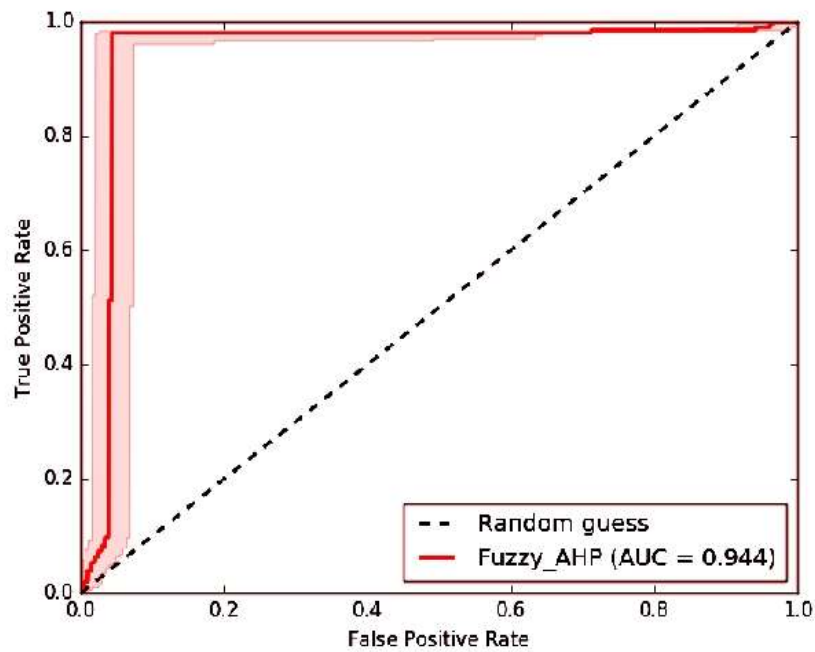


Figure 9: Validation of the FAHP method using the ROC-AUC Method

The AUC curve graphs in figure 9 and figure 10 illustrates the performance of both the AHP and FAHP methods in flood hazard mapping. With AUC values of 0.944 each, at a 95%

confidence level, these methods excel in distinguishing areas prone to flooding from those less vulnerable. Notably, these AUC values place both the AHP and FAHP models within the "Good (Very Good)" range, as shown in Table 27, which means that the methods are making highly accurate predictions. The curves exhibit a steep ascent, highlighting the rapid and precise identification of moderate, high and very high-risk zones when compared to the validation data by both methods. As the ROC curve is traversed, the consistently high upward trajectory reaffirms the capability of both models to deliver accurate classifications. This strong upward slope highlights the reliability of both the AHP and FAHP models, when evaluated against flood incidents data from SANSA. The considerable distance from the diagonal line (representing random guess) further confirms the proficiency of these methods (Mashao et al., 2022). In summary, the AUC curve graph provides unequivocal evidence of the robust performance of the AHP and FAHP models, establishing them as valuable tools for effective flood risk assessment and management.

4.4. Sensitivity analysis of AHP and FAHP

This section presents the results of sensitivity analysis for each parameter in the study using the two MCDA methods.

4.4.1. AHP Sensitivity analysis for rainfall

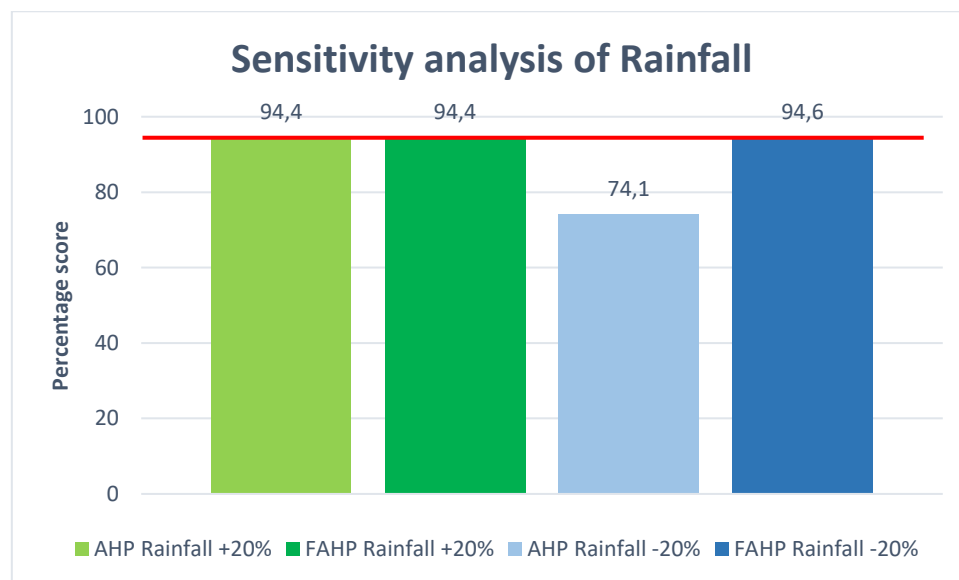


Figure 10: Rainfall sensitivity analysis for AHP and FAHP (red line indicates the baseline accuracy score)

When examining the sensitivity to changes in rainfall, it becomes apparent that both AHP and FAHP are slightly responsive to variations in this criterion. Increasing the rainfall parameter by 20% had no effect on the flood risk scores. Both the AHP and FAHP models yielded the same flood risk score of 0.944 when rainfall is increased by 20%. However, the impact of decreasing

rainfall by 20% is more pronounced in the AHP method, resulting in a substantial decrease in flood risk scores to 0.741. In contrast, FAHP displays a more stable response to reduced rainfall, with a score of 0.946. These findings indicate that AHP exhibits a heightened sensitivity to reductions in rainfall compared to FAHP.

4.3.2. AHP Sensitivity analysis for Slope

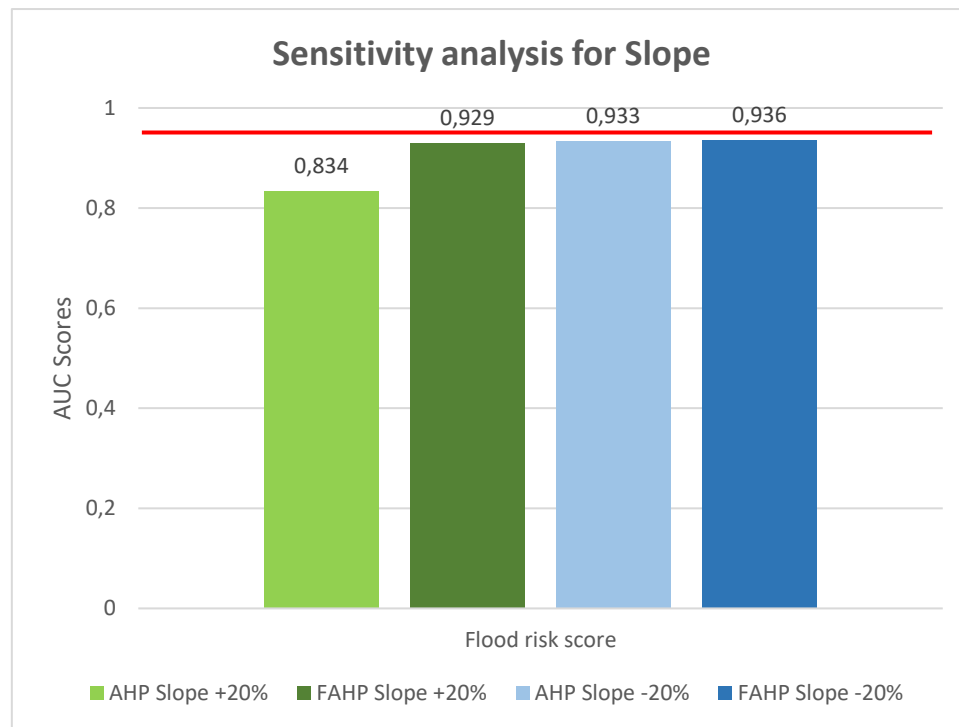


Figure 11: Slope sensitivity analysis for AHP and FAHP (red line indicates the baseline accuracy score)

The sensitivity analysis for slope indicates that both AHP and FAHP respond to changes in this parameter. When the slope is increased by 20%, AHP demonstrates a more pronounced sensitivity, resulting in a reduced flood risk score of 0.834, while FAHP maintains a relatively stable score of 0.929. Conversely, with a 20% decrease in slope, both AHP and FAHP exhibit sensitivity, but AHP scores 0.933 compared to FAHP's 0.936, showcasing a slightly higher sensitivity for AHP. The magnitude of sensitivity in response to slope changes varies, but AHP consistently shows slightly higher sensitivity.

4.3.3. AHP Sensitivity analysis for Soil

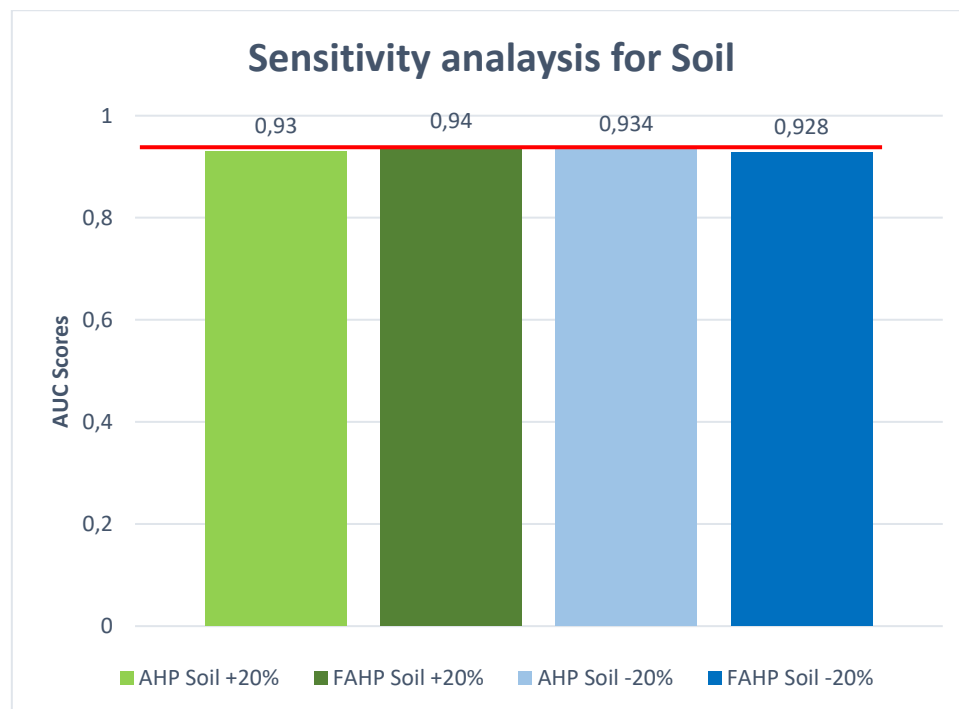


Figure 12: Slope sensitivity analysis for AHP and FAHP (red line indicates the baseline accuracy score)

The sensitivity analysis for soil parameter using both AHP and FAHP methods reveals limited changes in flood risk scores, suggesting a high degree of stability in response to variations. When the soil parameter is increased by 20%, AHP shows a minimal decrease in flood risk score to 0.93, while FAHP remains relatively stable at 0.94. Similarly, a 20% decrease in soil parameter results in slight variations, with AHP scoring 0.934 and FAHP scoring 0.928. Both methods exhibit very little responsiveness to soil changes. The responses to changes in soil parameters are similar for both methods, suggesting balanced sensitivity in this context indicating a consistent behaviour in relation to this specific parameter. This consistency suggests that the soil parameter had a relatively stable and predictable influence on the flood risk scores in both AHP and FAHP, making it one of the more consistent parameters across the methods in your sensitivity analysis.

4.3.4. AHP Sensitivity analysis for Elevation

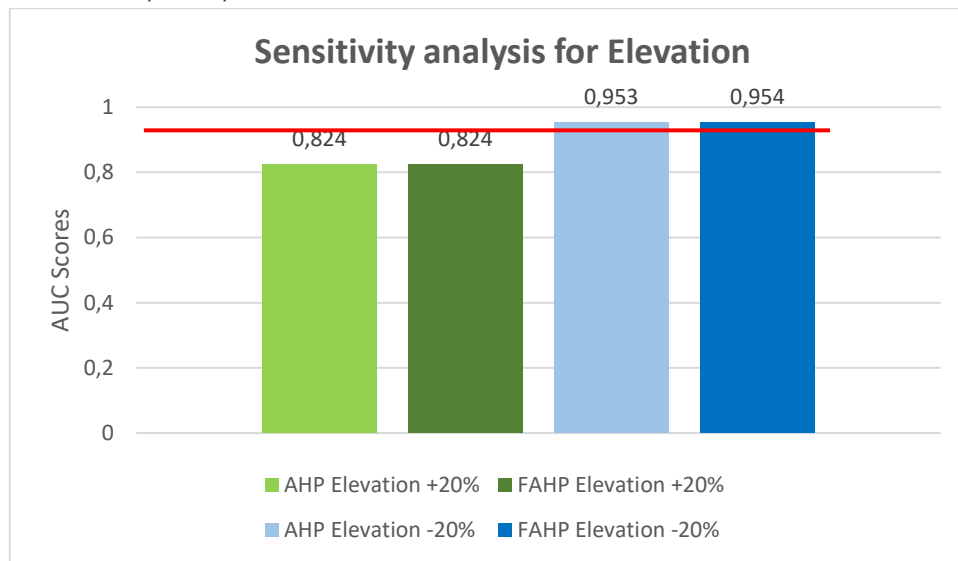


Figure 13: Elevation sensitivity analysis for AHP and FAHP (red line indicates the baseline accuracy score)

The sensitivity analysis for elevation indicates that both AHP and FAHP exhibit higher sensitivity when the parameter is increased (+20%) compared to when it is decreased (-20%). In both cases of an elevation increase, both methods show a substantial decrease in flood risk scores, aligning at 0.824. However, when elevation is decreased by 20%, both methods display relatively more stable sensitivity with AHP at 0.953 and FAHP at 0.954.

4.3.5. AHP Sensitivity analysis for Drainage density

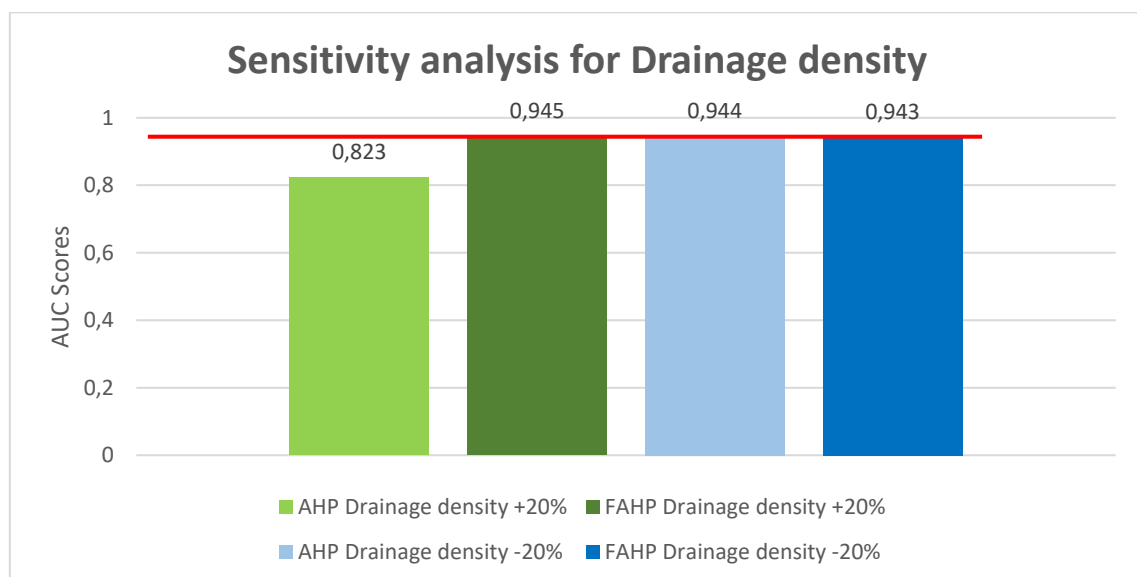


Figure 14: Drainage density sensitivity analysis for AHP and FAHP

The sensitivity analysis for drainage density reveals that AHP shows higher sensitivity to increases in this parameter compared to decreases, while FAHP exhibits a more stable

response. When drainage density is increased by 20%, AHP demonstrates a substantial decrease in flood risk scores to 0.823. In contrast, FAHP displays a less pronounced response, with a flood risk score of 0.945. However, with a 20% decrease in drainage density, AHP and FAHP both show relatively stable flood risk scores, with AHP at 0.944 and FAHP at 0.943

4.3.6. AHP Sensitivity analysis for distance to rivers

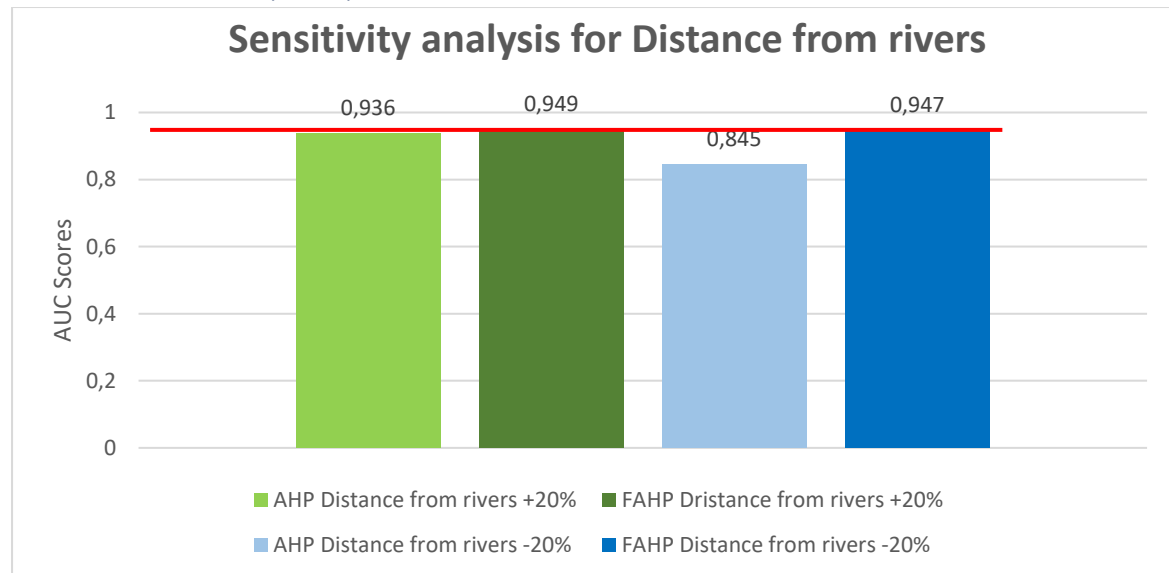


Figure 15: Distance from rivers sensitivity analysis for AHP and FAHP (red line indicates the baseline accuracy score)

When the distance from rivers is increased by 20%, AHP shows sensitivity with a decrease in flood risk scores to 0.936, while FAHP demonstrates a slightly less pronounced response with a score of 0.949. However, the significant difference emerges when the distance from rivers is decreased by 20%. AHP exhibits heightened sensitivity with a flood risk score of 0.845, emphasizing a substantial impact on risk assessments. In contrast, FAHP, while still responsive, shows a more stable response with a score of 0.947.

4.3.7. AHP Sensitivity analysis for land use land cover

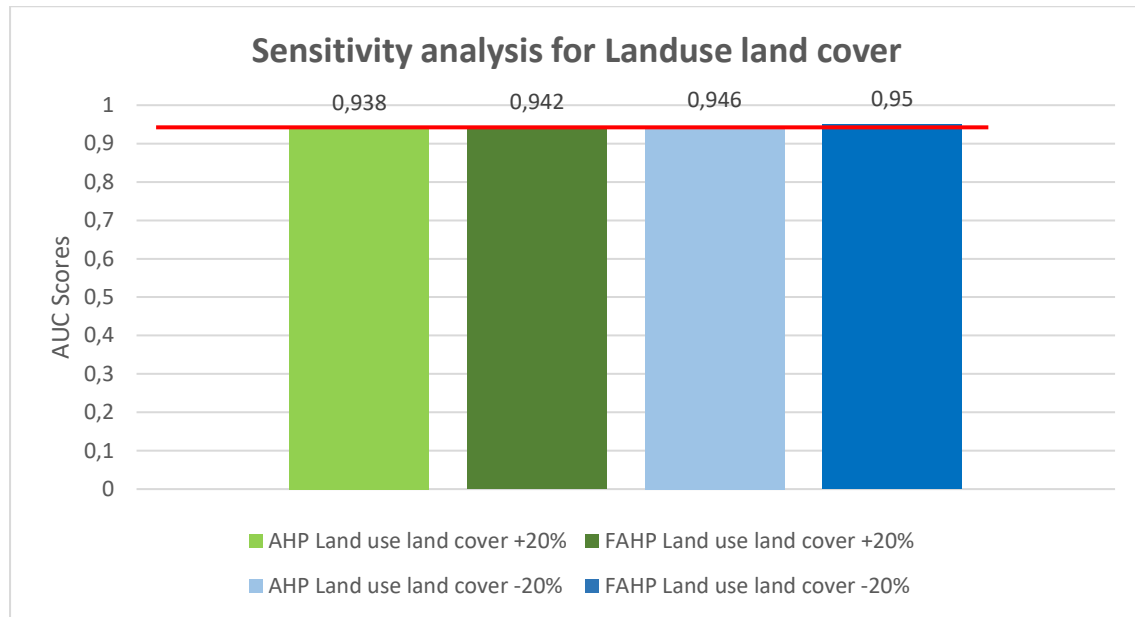


Figure 16: Land use land cover sensitivity analysis for AHP and FAHP (red line indicates the baseline accuracy score)

In the sensitivity analysis for land use land cover parameters, both AHP and FAHP show very slight sensitivity. A 20% increase in land use land cover parameters results in higher flood risk scores, with AHP scoring 0.938 and FAHP scoring 0.942. A 20% decrease in land use land cover parameters leads to sensitivity in both methods, with AHP scoring 0.946 and FAHP scoring 0.95. The responses to changes in land use land cover are similar for both methods, suggesting balanced sensitivity in this context.

In summary, AHP generally display slightly higher sensitivity to criteria changes compared to FAHP, a finding consistent with the outcomes observed across various parameters subjected to sensitivity analysis. Notably, both methods demonstrate robust sensitivity to changes in rainfall when it is increased, with AHP showing a more pronounced response to reductions in this criterion. However, for other parameters, such as soil and land use land cover, both AHP and FAHP display balanced and consistent responses to variations, with similar sensitivity profiles and scores. In contrast, AHP display more pronounced sensitivity in specific instances, such as with the rainfall parameter, where it demonstrates a substantial decrease in flood risk scores when rainfall is decreased. Overall, the key finding is that FAHP proves to be the more stable method. AHP, on the other hand, exhibited the most significant drops in accuracy in instances where the drop was notable, such as -20% Rainfall, +20% Slope, +20% Drainage density, and -20% Distance to rivers. Consequently, one could argue that AHP is more sensitive than FAHP, marking a valuable insight for this study. While FAHP generally provides more consistent responses across various parameters, the selection between AHP and FAHP

should consider specific criteria and data characteristics of the flood hazard mapping project, along with the required level of sensitivity for the analysis.

Chapter Five: Conclusion and Recommendations

5.1. Introduction

This chapter presents the conclusion of the study, summarizing the key findings drawn from an in-depth evaluation of the sensitivity of AHP and FAHP in flood hazard mapping within the eThekweni municipality.

5.2. Concluding remarks

The study sought to evaluate the sensitivity of AHP and FAHP to changes in weightings of the flood risk parameters in mapping flood risk zones within eThekweni municipality. Sensitivity analyzes were conducted for various criteria, revealing that FAHP is more stable and less sensitive to changes in weightings than AHP, aligning with the outcomes observed across multiple parameters. However, AHP exhibited a more pronounced response to a 20% decrease in rainfall compared to FAHP, indicating higher sensitivity to reductions in this parameter. Conversely, for parameters such as soil and land use land cover, both methods displayed balanced and consistent responses to changes, maintaining similar sensitivity scores. However, FAHP showed that it is less sensitive. These findings demonstrate the suitability of FAHP as a more stable and reliable method for accurate flood risk assessment and management within the context of eThekweni municipality. In comparison, AHP exhibited greater sensitivity, with significant drops in accuracy under specific conditions. These insights highlight the recommendation for FAHP as a preferred choice, providing consistent responses and minimizing the impact of variations in the input parameters on the accuracy of the analysis. The choice between these methods should be made considering the specific criteria and data characteristics of the flood hazard mapping project and the required level of sensitivity for the analysis.

5.3. Recommendations

- A recommendation can be made in favour of FAHP when deciding which method to choose for the flood hazard mapping project. The analysis indicates that FAHP exhibits more stability in accuracy across various parameters, suggesting a consistent and reliable performance. Conversely, AHP shows greater sensitivity, with significant drops in accuracy under specific conditions. Therefore, if a more stable and reliable method is preferred for the flood hazard mapping study, FAHP would be a recommended choice.
- Future studies should expand their focus by conducting detailed vulnerability and exposure analyzes, encompassing an in-depth investigation into factors associated with identified flood hazards. This involves understanding the specific vulnerabilities of communities, infrastructure, and ecosystems to flooding, enabling the development of

targeted mitigation strategies. Socio-economic factors, community resilience, and the adaptive capacity of exposed elements should be thoroughly examined. Additionally, a comprehensive exposure assessment is essential for a holistic understanding of flood risk, involving the identification and evaluation of elements at risk, such as population, infrastructure, and economic assets. Using FAHP in mapping flood hazard will lead to improved risk mapping when combined with information on vulnerability and exposure.

- There is a compelling need to expand the application of mixed MCDA techniques in the domain of flood hazard mapping. This recommendation stems from the observed potential of integrating subjective and objective methods, demonstrating the capacity to minimize inconsistencies and improve result accuracy. Future research endeavours should consider adopting mixed MCDA approaches to overcome the limitations associated with single techniques. This integration has the potential to enhance the precision and accuracy of flood hazard mapping, ultimately contributing to more robust and reliable assessments in diverse geographic and environmental settings.
- It is recommended that researchers and decision-makers carefully consider the specific characteristics of the study area before selecting a methodology. The findings of this study highlight the suitability of FAHP for flood hazard assessment in eThekweni municipality. However, it is essential to highlight that the efficacy of this method may not universally apply to regions with differing characteristics. Therefore, future studies are strongly advised to conduct a thorough evaluation of the unique features of their study areas.
- Ultimately, the choice between AHP and FAHP should be driven by the specific requirements of the flood hazard mapping project and the desired level of sensitivity. Researchers need to carefully weigh the advantages and trade-offs associated with each approach based on the characteristics of the study area and the importance of accurately reflecting changes in flood risk parameters. The discussion should consider how the observed sensitivity aligns with the practical needs of flood risk assessment and management within the context of the research areas.

References

- Abdrabo, K. I., Kantoush, S. A., Saber, M., Sumi, T., Habiba, O. M., Elleithy, D., and Elboshy, B. (2020). Integrated methodology for urban flood risk mapping at the microscale in ungauged regions: A case study of Hurghada, Egypt. *Remote Sensing*, 12(21), 3548. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/rs12213548>
- Abdullah, M. F., Siraj, S., and Hodgett, R. E. (2021). An overview of multi-criteria decision analysis (MCDA) application in managing water-related disaster events: Analyzing 20 years of literature for flood and drought events. *Water*, 13, 1358. <https://doi.org/10.3390/w13101358>
- Åberg, I. (2017). Flood mapping: Assessing the uncertainty associated with flood inundation modeling. A case study of the Mora River, Sweden. Published at the Department of Earth Sciences, Uppsala University.
- Abid, S. K., Sulaiman, N., Wei, C. S., and U N. (2021). Flood vulnerability and resilience: Exploring the factors that influence flooding in Sarawak Flood vulnerability and resilience: Exploring the factors that influence flooding in Sarawak. IOP Conf. Ser.
- Adesina, E. A., Musa, A., Ajayi, O. G., Oduosu, J. O., Opaluwa, Y. D., and Onuigbo, I. C. (2021). Comparative Assessment of SRTM and UAV-Derived Dem in Flood Modelling.
- Adger, W. N. (2006). Vulnerability. *Global Environmental Change*, 16, 268–281.
- Albertini, C., Miglino, D., Iacobellis, V., De Paola, F., and Manfreda, S. (2022). Delineation of flood-prone areas in cliffed coastal regions through a procedure based on the geomorphic flood index. *Journal of Flood Risk Management*, 15(1), e12766. <https://doi.org/10.1111/jfr3.12766>
- Alemi-Ardakani, M., Milani, A. S., Yannacopoulos, S., and Shokouhi, G. (2016). On the effect of subjective, objective and combinative weighting in multiple criteria decision making: A case study on impact optimization of composites. *Expert Systems with Applications*, 46, 426-438. doi:<https://doi-org.nwulib.idm.oclc.org/10.1016/j.eswa.2015.11.003>
- Alfieri, L., Bisselink, B., Dottori, F., Naumann, G., de Roo, A., Salamon, P., Wyser, K., Feyen, L. (Year not provided). Global projections of river flood.
- Ali, A. M. (2018). Flood inundation modeling and hazard mapping under uncertainty in the Sungai Johor Basin, Malaysia. Doctoral thesis. Delft University of Technology and of the Academic Board of the UNESCO-IHE Institute for Water Education.
- Allafta, H., and Opp, C. (2021). GIS-based multi-criteria analysis for flood-prone areas mapping in the trans-boundary Shatt Al-Arab basin, Iraq-Iran. *Geomatics, Natural Hazards and Risk*, 12(1), 2087-2116. DOI: 10.1080/19475705.2021.1955755

- Angelakis, A. N., Capodaglio, A. G., Valipour, M., Krasilnikoff, J., Ahmed, A. T., Mandi, L., Tzanakakis, V. A., et al. (2023). Evolution of floods: From ancient times to the present times (ca 7600 BC to the present) and the future. *Land*, 12(6), 1211. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/land12061211>
- Armenakis, C., Du, E. X., Natesan, S., Persad, R. A., and Zhang, Y. (2017). Flood risk assessment in urban areas based on spatial analytics and social factors. *Geosciences*, 7, 123.
- Arslan, H. (2017). Current classification of multi-criteria decision analysis methods and public sector implementations. In (Ed.), *Title of the Book* (pp. 241-261). Publisher. ISBN: 978-1-912503-15-5.
- Arndt, C., Davies, R., and Thurlow, J. (2018). Urbanization, structural transformation, and rural-urban linkages in South Africa. *South African Urbanisation Review, Cities Support Programme (CSP) of the National Treasury*.
- Aruldoss, M., Lakshmi, T. M., and Venkatesan, V. P. (2013). A survey on multi-criteria decision-making methods and its applications. *American Journal of Information Systems*, 2013(1), 31–43.
- Asiedu, B. J. (2020). Reviewing the argument on floods in urban areas: A look at the causes. *Research Centre in Public Administration and Public Services*. Cape Coast-Ghana.
- Australian Institute for Disaster Resilience (AIDR). (2017). Guideline 7-3. Supporting document for the implementation of Australian Disaster Resilience Handbook 7 Managing the Floodplain: A Guide To Best Practice in Flood Risk Management in Australia.
- Aydin, M., and Birincioğlu, E. (2022). Flood risk analysis using GIS-based analytical hierarchy process: A case study of Bitlis Province. *Applied Water Science*, 12. <https://doi.org/10.1007/s13201-022-01655-x>
- Ayhan, M. B. (2013). A FAHP approach for supplier selection problem: A case study in a Gear motor company. *arXiv preprint arXiv:1311.2886*.
- Bajwa, H., and Tim, U. (2002). Toward immersive virtual environments for GIS-based Floodplain modeling and Visualization. In: *22nd Annual ESRI International User Conference*, July 8-12, San Diego, CA: ESRI.
- Baky, M. A. A., Islam, M., and Paul, S. (2020). Flood hazard, vulnerability for different land use classes using a flow model. *Earth System and Environment*, 4, 225-244. <https://doi.org/10.1007/s41748-019-00141-w>

- Balasubramaniam, A., Boyle, A. R., and Voulvoulis, N. (Year not provided). Improving petroleum contaminated land remediation decision-making through the MCA weighting process. *Chemosphere*, 66(5), 791-798. doi:<https://doi-org.nwulib.idm.oclc.org/10.1016/j.chemosphere.2006.06.039>
- Bhuyian, M. N., Kalyanapu, A., and Hossain, F. (2017). Evaluating conveyance-based DEM correction technique on NED and SRTM DEMs for flood impact assessment of the 2010 Cumberland River flood. *Geosciences*, 7(4), 132.
- Birkmann, J. (2006). Measuring vulnerability to promote disaster-resilient societies: Conceptual frameworks and definitions. In J. Birkmann (Ed.), *Measuring vulnerability to natural hazards: Towards disaster resilient societies* (Vol. 1, pp. [Page Range]).
- Boghani, H. C., Ambur, R., Blumenfeld, M., et al. (2021). Sensitivity enriched multi-criterion decision-making process for novel railway switches and crossing – a case study. *European Transportation Research Review*, 13, 6. <https://doi.org/10.1186/s12544-020-00467-x>
- Borouhki, S., and Malczewski, J. (2010). Participatory GIS: A web-based collaborative GIS and multicriteria decision analysis.
- Botai, C. M., Botai, J. O., and Adeola, A. M. (2018). Spatial distribution of temporal precipitation contrasts in South Africa. *South African Journal of Science*, 114(7/8), Art. #2017-0391, 9 pages.
- Broeke, G., Voorn, G., and Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? *Journal of Artificial Societies and Social Simulation*, 19. <https://doi.org/10.18564/jasss.2857>
- Brown, L., and Murray, V. (2013). Examining the relationship between infectious diseases and flooding in Europe: A systematic literature review and summary of possible public health interventions. *Disaster Health*, 1(2), 117–127. doi: 10.4161/dish.25216
- Buchelle, B., Kreibich, H., Kron, A., Thieken, A., Ihringer, J., Oberle, P., Merz, B., and Nestmann, F. (2006). Flood risk mapping: Contribution towards an enhanced assessment of extreme events and associated risks. *Natural Hazards and Earth Systems Sciences*, 6, 485-503. <https://doi.org/10.5194/nhess-6-485-2006>
- Buckley, J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, 17(3), 233-247. [https://doi.org/10.1016/0165-0114\(85\)90090-9](https://doi.org/10.1016/0165-0114(85)90090-9)
- Burkham, D. E. (1988). Methods for delineating flood-prone areas in the Great Basin of Nevada and adjacent states, U.S. Geological Survey, Paper 2316, 20 pp.

Busayo, E. T., Kalumba, A. M., Afuye, G. A., Olusola, A. O., Ololade, O. O., and Orimoloye, I. R. (2022). Rediscovering South Africa: Flood disaster risk management through ecosystem-based adaptation. Department of Geography and Environmental Science, University of Fort Hare, Private Bag X1314, Alice, 5700, Eastern Cape Province, South Africa.

Büyüközkan, G., and Gülleryüz, S. (2016). A new integrated intuitionistic fuzzy group decision-making approach for product development partner selection. *Computers and Industrial Engineering*, 102, 383–395

C. Amoako. (2015). Flood vulnerability and responses in urban informal communities in Accra, Ghana. In: Centre for Geography and Environmental Science Social and Political Sciences Graduate Research Program Faculty of Arts, Monash University.

Cabrera, J. S., and Lee, H. S. (2019). Flood-Prone Area Assessment Using GIS-Based Multi-Criteria Analysis: A Case Study in Davao Oriental, Philippines. Institute of Computing and Engineering, Davao Oriental State College of Science and Technology, Guang-guang, Dahican, Mati City 8200, Philippines.

Cai, S., Fan, J., and Yang, W. (2021). Flooding Risk Assessment and Analysis Based on GIS and the TFN-AHP Method: A Case Study of Chongqing, China. *Atmosphere* 2021, 12, 623.

Canco, I., Kruja, D., and Iancu, T. (2021). AHP, a Reliable Method for Quality Decision Making: A Case Study in Business. *Sustainability*, 13, 13932. <https://doi.org/10.3390/su132413932>

Cardona, O. D., van Aalst, M. K., Birkmann, J., Fordham, M., McGregor, G., Perez, R., et al. (2012). Determinants of risk: Exposure and vulnerability coordinating lead authors: lead

Carson, J. S. (2002). Model verification and validation. In *Proceedings of the Winter Simulation Conference* (Vol. 1, pp. 52-58). IEEE.

Carter, R. A. (2012). Flood risk, insurance and emergency management in Australia. *Australian Journal of Emergency Management*, 27(2), 20-25.

Celik, E., and Akyuz, E. (2018). An interval type-2 FAHP and TOPSIS methods for decision-making problems in maritime transportation engineering: The case of ship loader. *Ocean Engineering*, 155, 371–381.

Çelikbilek, Y., and Tuysuz, F. (2020). An in-depth review of theory of the TOPSIS method: An experimental analysis. *Journal of Management Analytics*, 7, 1-20. <https://doi.org/10.1080/23270012.2020.1748528>

Chakraborty, S. (2022). TOPSIS and modified TOPSIS: A comparative analysis. *Decision Analytics Journal*, 2, 100021. doi:<https://doi.org/10.1016/j.dajour.2021.100021>

- Chan, E. Y. Y. (2017). Public Health Humanitarian Responses to Natural Disasters. In: Hydrological Hazards. New York: Routledge, pp. 97 - 101.
- Chan, S. W., Abid, S. K., Sulaiman, N., Nazir, U., and Azam, K. (2022). A systematic review of flood vulnerability using geographic information system. *Heliyon*, 8(3), e09075. ISSN 2405-8440
- Chaulagain, D., Ram Rimal, P., Ngando, S. N., Nsafon, B. E. K., Suh, D., and Huh, J. (2023). Flood susceptibility mapping of Kathmandu Metropolitan City using GIS-based multi-criteria decision analysis. *Ecological Indicators*, 154, 110653. doi:10.1016/j.ecolind.2023.110653
- Chaves, E. D. M., Picoli, C. A., and Sanches, D. (2020). Recent Applications of Landsat 8/OLI and Sentinel-2/MSI for Land Use and Land Cover Mapping: A Systematic Review. *Remote Sensing*. <https://doi.org/10.3390/rs12183062>
- Chen, H., Wood, M., Linstead, C., and Maltby, E. (2011). Uncertainty analysis in a GIS-based multi-criteria analysis tool for river catchment management. *Environmental Modelling and Software*, 26, 395-405. <https://doi.org/10.1016/j.envsoft.2010.09.005>
- Chen, M., Wood, M. D., Linstead, C., and Maltby, E. (2011). Uncertainty analysis in a GIS-based multi-criteria analysis tool for river catchment management. *Environmental Modelling and Software*, 26, 395–405.
- Chen, Y. (2022). Flood hazard zone mapping incorporating geographic information system (GIS) and multi-criteria analysis (MCA) techniques. *Journal of Hydrology*, 612, 128268.
- Chen, Y., Khan, S., and Paydar, Z. (2010b). To retire or expand? A fuzzy GIS-based spatial multi-criteria evaluation framework for irrigated agriculture. *Irrigation and Drainage*, 59(2), 178–188.
- Chen, Y., Yu, J., and Khan, S. (2013). The spatial framework for weight sensitivity analysis in AHP-based multi-criteria decision-making. *Environmental Modelling and Software*, 48, 129-140. doi:10.1016/j.envsoft.2013.06.010
- Chen, Y., Yu, J., Shahbaz, K., and Xevi, E. (2009). A GIS-based Sensitivity analysis of multi-criteria weights. 18th World IMACS/MODSIM Congress, Cairns, Australia, 13-17 July 2009. Cooperative Research Centre for Irrigation Futures, Australia.
- Cilliers, D. P. (2019). Considering flood risk in spatial development planning: A land use conflict analysis approach. *Jàmbá: Journal of Disaster Risk Studies*, 11(1), a537. <https://doi.org/10.4102/jamba.v11i1.537>

Claverie, M., Ju, J., Masek, J. G., Dungan, J. L., Vermote, E. F., Roger, J. C., ... and Justice, C. (2018). The Harmonized Landsat and Sentinel-2 surface reflectance data set. *Remote Sensing of Environment*, 219, 145–161.

Council for Scientific and Industrial Research. (2019). Annual Report.

Courty, L. G., Soriano-Monzalvo, J. C., and Pedrozo-Acuña, A. (2019). Evaluation of open-access global digital elevation models (AW3D30, SRTM, and ASTER) for flood modelling purposes. *Journal of Flood Risk Management*, 12, e12550.

Crichton, D. (1999). "The Risk Triangle", pp. 102-103 in Ingleton, J. (ed.), *Natural Disaster Management*, Tudor Rose, London.

Crosetto, M., Tarantola, S., and Saltelli, A. (2000). Sensitivity and uncertainty analysis in spatial modelling based on GIS. *Agriculture, Ecosystems and Environment*, 81, 71–79.

Cvetković, V. M., Tanasić, J., Ocal, A., Kešetović, Ž., Nikolić, N., and Dragašević, A. (2021). Capacity Development of Local Self-Governments for Disaster Risk Management. *International Journal of Environmental Research and Public Health*, 18(19), 10406. <https://doi.org/10.3390/ijerph181910406>

da Silva, L. B. L., Alencar, M. H., and de Almeida, A. T. (2022). Exploring global sensitivity analysis on a risk-based MCDM/A model to support urban adaptation policies against floods. *International Journal of Disaster Risk Reduction*, 73, 102898. <https://doi.org/10.1016/j.ijdrr.2022.10289>

da Silva, L. B. L., Humberto, J. S., Alencar, M. H., Ferreira, R. J. P., and de Almeida, A. T. (2020). GIS-based multidimensional decision model for enhancing flood risk prioritization in urban areas. *International Journal of Disaster Risk Reduction*, 48, 101582. <https://doi.org/10.1016/j.ijdrr.2020.101582>

Dahri N, Abida H. (2017). Monte Carlo simulation-aided analytical hierarchy process (AHP) for flood susceptibility mapping in Gabes Basin (southeastern Tunisia). *Environmental Earth Sciences*, 76(7), 302.

Danumah, J. H., Odai, S. N., Saley, B. M., et al. (2016). Flood risk assessment and mapping in Abidjan district using multi-criteria analysis (AHP) model and geoinformation techniques, (Cote d'Ivoire). *Geoenvironmental Disasters*, 3, 10. <https://doi.org/10.1186/s40677-016-0044-y>

Darabi, H., Haghighi, A. T., Mohamadi, M. A., Rashidpour, M., Ziegler, A. D., Hekmatzadeh, A. A., and Kløve, B. (2020). Urban flood risk mapping using data-driven geospatial techniques

for a flood-prone case area in Iran. *Hydrology Research*, 51(1), 127–142.
<https://doi.org/10.2166/nh.2019.090>

Davis-Reddy, C. L., and Vincent, K. (2017). *Climate Risk and Vulnerability: A Handbook for Southern Africa* (2nd ed.). CSIR, Pretoria, South Africa.

de Brito, M. M., Almoradie, A., and Evers, M. (2019). Spatially-explicit sensitivity and uncertainty analysis in a MCDA-based flood vulnerability model. *International Journal of Geographic Information Science*, 33(9), 1788–1806.
<https://doi.org/10.1080/13658816.2019.1599125>.

De Brito, M. M., and Evers, M. (2016). Multi-criteria decision making for flood risk management: a survey of the current state of art. *Natural Hazards and Earth System Sciences*, 16(4), 1019-1033.

De Moel, H., van Alphen, J., and Aerts, J. C. J. H. (2009). Flood maps in Europe – methods, availability and use. *Natural Hazards and Earth System Sciences*, 9, 289-301.

De Montis, A., De Toro, P., Droste-Franke, B., Omann, I., and Stagl, S. (2000). Criteria for quality assessment of MCDA methods. In 3rd Biennial Conference of the European Society for Ecological Economics, Vienna (pp. 3-6).

deMers, M. N. (1997). *Fundamentals of Geographic Information Systems*. John Wiley and Sons.

Demir, V., and Kisi, O. (2016). Flood Hazard Mapping by Using Geographic Information System and Hydraulic Model: Mert River, Samsun, Turkey. Civil Engineering Department, Canik Basari University, Samsun, Turkey.

Deng H., Yeh C, H., Willis R, J. (2000) Inter-company comparison using modified TOPSIS with objective weights. *Computers and Operations Research*, 27, 963–973.

Deng, X., Hu, Y., Deng, Y., and Mahadevan, S. (2014). Supplier selection using AHP methodology extended by D numbers. *Expert Systems with Applications*, 41(1), 156-167.
[doi:10.1016/j.eswa.2013.07.018](https://doi.org/10.1016/j.eswa.2013.07.018)

Department for Communities and Local Government: London. (2009). *Multi-criteria analysis: a manual*. ISBN: 978-1-4098-1023-0

Desalegn, H., and Mulu, A. (2021). Mapping flood inundation areas using GIS and HEC-RAS model at fetam river, upper abbay basin, ethiopia. *Scientific African*, 12, e00834.
[doi:https://doi-org.nwulib.idm.oclc.org/10.1016/j.sciaf.2021.e00834](https://doi-org.nwulib.idm.oclc.org/10.1016/j.sciaf.2021.e00834)

Desalegn, H., and Mulu, A. (2021). Mapping flood inundation areas using GIS and HEC-RAS model at fetam river, upper abbay basin, Ethiopia. *Scientific African*, 12, e00834.

Desalegn, H., and Mulu, A. (2021). Mapping flood inundation areas using GIS and HEC-RAS model at fetam river, upper abbay basin, ethiopia. *Scientific African*, 12, e00834. doi:<https://doi-org.nwulib.idm.oclc.org/10.1016/j.sciaf.2021.e00834>

Desalegn, H., and Mulu, A. (2021). Mapping flood inundation areas using GIS and HEC-RAS model at fetam river, upper abbay basin, Ethiopia. *Scientific African*, 12, e00834.

Desalegn, H., and Mulu, A. (Invalid date). Mapping flood inundation areas using GIS and HEC-RAS model at fetam river, upper abbay basin, ethiopia. *Scientific African*, 12, e00834. doi:<https://doi-org.nwulib.idm.oclc.org/10.1016/j.sciaf.2021.e00834>

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. and Blöschl, G. 2013. Sociohydrology: conceptualising human-flood interactions. *Hydrology and Earth System Sciences*, 17: 3295-3303.

Ding, L., Ma, L., Li, L., Liu, C., Li, N., Yang, Z., Yao, Y., and Lu, H. (2021). A Survey of Remote Sensing and Geographic Information System Applications for Flash Floods. *Remote Sensing*. 13(9):1818. <https://doi.org/10.3390/rs13091818>

Dogan, O. (2021). Process mining technology selection with spherical FAHP and sensitivity analysis. Izmir Bakircay University, Department of Industrial Engineering, Turkey.

Drescher, M., Perera, A. H., Johnson, C. J., Buse, L. J., Drew, C. A., and., Burgman, M. A. (2013). Toward rigorous use of expert knowledge in ecological research. *Ecosphere*, 4(7), 1-26.

Dube, K., Nhamo, G., and Chikodzi, D. (2022). Flooding trends and their impacts on coastal communities of Western Cape Province, South Africa. *GeoJournal*, 87(Suppl 4), 453-468.

Dung, T., Halsem, G., Hoang, L. P., and Kumm, M. (2018). Assessing impacts of dike construction on the flood dynamics of the Mekong Delta. *Hydrology and Earth Systems Sciences*, 22, 1875–1896. <https://doi.org/10.5194/hess-22-1875-2018>

Dyson, L. L. (2009). Heavy daily-rainfall characteristics over the Gauteng Province. *Water SA*, 35(5).

Ebersole, B. A., Richardson, T. W., and Whalin, R. W. (2022). Chapter 3 - Storm surge modeling in the Gulf of Mexico and Houston-Galveston regions. In S. Brody, Y. Lee, and B. B. Kothuis (Eds.), *Coastal Flood Risk Reduction* (pp. 19–31). Elsevier.

Ebert, A., Kerle, N., and Stein, A. (2009). Urban social vulnerability assessment with physical proxies and spatial metrics derived from air- and spaceborne imagery and GIS data. *Natural Hazards*, 48(2), 275–294.

Ekmekcioglu, O., Koc, K., and Ozger, M. (2021). Stakeholder perceptions in flood risk assessment: A hybrid FAHP-TOPSIS approach for Istanbul, Turkey. *Hydraulics Division, Civil Engineering Department, Istanbul Technical University, Istanbul, Turkey*.

Eldho, T. I., Zope, P. E., and Kulkarni, A. T. (2018). Chapter 12 – Urban Flood Management in Coastal regions using numerical simulation and Geographic Information System. In *Integrating Disaster Science and Management*, Elsevier, 205–219. <https://doi.org/10.1016/B978-0-12-812056-9.00012-8>

Eleutério, J., Martinez, D., and Rozan, A. (2010). Developing a GIS tool to assess potential damage of future floods. *WIT Transactions on Information and Communication Technologies*, 43, 381–392.

Els, Z. (2011). Data availability and requirements for flood hazard mapping in South Africa. Stellenbosch University, Stellenbosch. Master's degree thesis.

Escobar, F., Hunter, G., Bishop, I., and Zerger, A. (2002). Department of Geomatics, The University of Melbourne.

Esri. (2012). What is GIS. New York: Esri. <https://www.esri.com/en-us/what-is-gis/overview>

ESRI. (n.d.). History of GIS | Timeline of Early History and the Future of GIS. <https://www.esri.com/en-us/what-is-gis/history-of-gis>

Evaluation of Disaster Risk Management in Flood Prone Areas: A Case Study of Bramfischerville. Nhlanhla Mkhulisa. (2017). A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfillment of the requirements for the degree of Master of Science in Development Planning.

Evans, S. Y., Gunn, N., and Williams, D. (2007). Use of GIS in flood risk mapping. Environment Agency, Orchard House Endeavor Park, London Road, Addington, Kent, ME19 5SH.

FAO–SAFR. (2002). Wetland development and management in SADC countries, paper presented at the proceedings of a sub-regional Workshop, Harare, Zimbabwe, November 19–23, 2001.

- Feizizadeh, B., and Blaschke, T. (2014). An uncertainty and sensitivity analysis approach for GIS-based multicriteria landslide susceptibility mapping. *International Journal of Geographical Information Science*, 28(3), 610–638. <https://doi.org/10.1080/13658816.2013.869821>
- Feizizadeh, B., and Jankowski, P. de T. (2014). A GIS-based spatially-explicit sensitivity and uncertainty analysis approach for multi-criteria decision analysis. *Computers and Geosciences*, 64, 81–95. <https://doi.org/10.1016/j.cageo.2013.11.009>
- Feloni E, Mousadis I, Baltas E. (2020) Flood vulnerability assessment using a GIS-based multi-criteria approach—The case of Attica region. *Journal of Flood Risk Management*, 13.
- Feng, B., Zhang, Y., and Bourke, R. (2021). Urbanization impacts on flood risks based on urban growth data and coupled flood models. *Natural Hazards*, 106(2), 613–627.
- Ferretti, V., and Montibeller, G. (2016). Key challenges and meta-choices in designing and applying multi-criteria spatial decision support systems. *Decision Support Systems*, 84, 41–52. <https://doi.org/10.1016/j.dss.2016.01.005>
- Fildes, S. G., Bruce, D., Clark, I. F., Raimondo, T., Keane, R., and Batelaan, O. (2022). Integrating spatially explicit sensitivity and uncertainty analysis in a multi-criteria decision analysis-based groundwater potential zone model. *Journal of Hydrology*, 610, 127837. <https://doi.org/10.1016/j.jhydrol.2022.127837>
- Flerchinger, G. N., Lehrs, G. A., and McCool, D. K. (2013). Freezing and Thawing | Processes☆. In *Reference Module in Earth Systems and Environmental Sciences*. Elsevier.
- Gacu, J. G., Monjardin, C. E. F., Senoro, D. B., and Tan, F. J. (2022). Flood Risk Assessment Using GIS-Based Analytical Hierarchy Process in the Municipality of Odiongan, Romblon, Philippines. *Applied Sciences*, 12(19), 9456. <https://doi.org/10.3390/app12199456>
- Gairola, S., Procheş, Ş., Gebreslasie, M., and Rocchini, D. (2016). Remote sensing object-oriented approaches coupled with ecological informatics to map invasive plant species. *South African Journal of Geomatics*, 5(3), 285. <https://doi.org/10.4314/sajg.v5i3.2>
- GBF, UNDP, and WB. (2014). *Plan National Multi Risques de Préparation et de Réponse aux Catastrophes: Préparation, Interventions de Premiers Secours, Rehabilitation et Reconstruction*. Ouagadougou, Burkina Faso.
- GeoTerraImage. (2014). The 2013–2014 South African National Land-cover dataset. Geoterraimage, (Pty). Ltd.

- Ghosh, A., and Kar, S. K. (2018). Application of analytical hierarchy process (AHP) for flood risk assessment: a case study in Malda district of West Bengal, India. *Natural Hazards*, 94(2), 349–368. <https://doi.org/10.1007/s11069-018-3392-y>
- Gigovic L, Pamucar D, Bajic Z, Drobnjak S. (2017). Application of GIS-Interval rough AHP methodology for flood hazard mapping in urban areas. *Water*, 9(6), 360–326.
- Goodchild M. F., and Kemp, K. K. (1990). NCGZA Core Curriculum in GIS. Santa Barbara, National Centre for Geographic Information and Analysis, University of California at Santa Barbara.
- Goyal, R. K. (2004). Sensitivity of evapotranspiration to global warming: A case study of arid zone of Rajasthan (India). *Agricultural Water Management*, 69, 1–11.
- Gqomfa, B., Maphanga, T., and Shale, K. (2022). The impact of informal settlement on water quality of Diep River in Dunoon. *Sustainable Water Resources Management*, 8, 27. <https://doi.org/10.1007/s40899-022-00629-w>
- Grab, S. W., and Nash, D. J. (2023). A new flood chronology for KwaZulu-Natal (1836–2022): The April 2022 Durban floods in historical context. *South African Geographical Journal*, Volume Number (Issue Number), Page Numbers. DOI: 10.1080/03736245.2023.2193758
- Green, C., Viavattene, C., and Thompson, P. (2011). Guidance for assessing flood losses: Conhaz report, Flood Hazard Research Centre, Middlesex University WP06, 80, 2011
- Gusman, A. R., Tanioka, Y., Matsumoto, H., and Iwasaki, S.-I. (2009). Analysis of the Tsunami Generated by the Great 1977 Sumba Earthquake that Occurred in Indonesia. *Bulletin of the Seismological Society of America*, 99, 2169–2179. [CrossRef]
- Hadi, F., and Najafzadeh, M. (2021). Flood Risk Mapping by Remote Sensing Data and Random Forest Technique. *Water*, 13(21), 3115. <https://doi.org/10.3390/w13213115>
- Haghizadeh, A., Siahkamari, S., Hagiabi, A., and Rahmati, O. (2017). Forecasting flood-prone areas using Shannon's entropy model. *Journal of Earth System Science*, 126. <https://doi.org/10.1007/s12040-017-0819-X>
- Halsnæs, K., and Trærup, S. (2009). Development and Climate change: A mainstream approach for assessing Economic, Social and Environmental Impacts of Adaptation Measures. *Environmental Management*, 43, 765-78. <https://doi.org/10.1007/s00267-009-9273-0>

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., and Kanae, S. (2013). Global flood risk under climate change. *Nature Climate Change*, 3, 816–821. <https://doi.org/10.1038/nclimate1911>

Hlanguza, N. (2015). Mapping the remnant KwaZulu-Natal sandstone sourveld grass patches in the Ethekwini Municipality using a high-resolution multispectral sensor. MSc Thesis, University of KwaZulu-Natal, Pietermaritzburg.

Hobbs, B., and Meier, P. (2000). *Energy Decisions and the Environment: A Guide to the Use of Multicriteria Methods*. Kluwer Academic Publishers, The Netherlands.

Hoque, M., Tasfia, S., Ahmed, N., and Pradhan, B. (2019). Assessing spatial flood vulnerability at Kalapara Upazila in Bangladesh using an analytic hierarchy process. *Sensors*, 19(6), 1302.

Horton, R. E. (1945). Erosional development of streams and their drainage basins: Hydrophysical approach to quantitative geomorphology. *Bulletin of the Geological Society of America*, 56, 275– 370.

Hunter, I. (2007). Extensive Flooding and Damage to Coastal Infrastructure along the KwaZulu-Natal Coast. South African Weather Services. [Link](#)

Huțanu, E., Mișu-Pintilie, A., Urzica, A., Paveluc, L. E., Stoleriu, C. C., and Grozavu, A. (2020). Using 1D HEC-RAS Modeling and LiDAR Data to Improve Flood Hazard Maps Accuracy: A Case Study from Jijia Floodplain (NE Romania). *Water*, 12(6), 1624. MDPI AG

Inglada, J., Vincent, A., Arias, M., and Marais-Sicre, C. (2016). Improved early crop type identification by joint use of high temporal resolution SAR and optical image time series. *Remote Sensing*, 8, 362.

International Federation of Red Cross and Red Crescent Societies – Humanitarian aid organization. (2022). South Africa, Africa: KwaZulu-Natal Floods and Landslides – Operations update #1, Emergency appeal No. MDRZA012.

IPCC. (2012). Glossary of terms. In: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 555-564.

Irawan, F. (2018). A Comparative Assessment of Random Forest and SVM Algorithms, Using a Combination of Principal Component Analysis and SMOTE For Accounts Receivable Seamless Prediction

Jean-Baptiste, N., Kabisch, S., and Kuhlicke, C. (2013). Urban vulnerability assessment in flood-prone areas in West and East Africa. In S. Rauch, G.M.S. Norra and N. Schleicher (eds.), *Urban Environment*, pp. 203–215. Springer, Heidelberg.

Jozaghi, A., Alizadeh, B., Hatami, M., Flood, I., Khorrami, M., Khodaei, N., and Ghasemi Tousi, E. (2018). A Comparative Study of the AHP and TOPSIS Techniques for Dam Site Selection Using GIS: A Case Study of Sistan and Baluchestan Province, Iran. *Geosciences*, 8(12), 494. MDPI AG

Jusakulvijit, P., Bezama, A., and Thrän, D. (2022). An Integrated Assessment of GIS-MCA with Logistics Analysis for an Assessment of a Potential Decentralized Bioethanol Production System Using Distributed Agricultural Residues in Thailand. *Sustainability*, 14, 9885. <https://doi.org/10.3390/su14169885>

Kaendler, N. A., Ivar; Vassiljev, Anatoli; Puust, Raido and Kaur, Katrin. (2018). Smart In-Line Storage. Facilities in Urban Drainage Network. *Proceedings*, 2. doi: 10.3390/proceedings2110631

Karam, A., Hussein, M., and Reinau, K. H. (2021). Analysis of the barriers to implementing horizontal collaborative transport using a hybrid fuzzy Delphi-AHP approach. *Journal of Cleaner Production*, 321, 128943.

Karley, N. K. (2009). Flooding and Physical Planning in Urban areas of West Africa. Situational analysis of Accra, Ghana. *Theoretical and Empirical Research in Urban Management*, 13(4).

Kelly, M., Schwarz, I., Ziegelaar, M., Watkins, A. B., and Kuleshov, Y. (2023). Flood Risk Assessment and Mapping: A Case Study from Australia's Hawkesbury-Nepean Catchment. *Hydrology*, 10(2), 26. MDPI AG

Klijn, F. (2009). Flood risk assessment and flood risk management: An introduction and guidance based on experience and findings of FLOOD site, FLOOD site-Report T29-09-01.

Klijn, F. (2009). Flood risk assessment and flood risk management: An introduction and guidance based on experience and findings of FLOODsite (an EU-funded Integrated Project). Delft: Deltares, Delft Hydraulics.

Klijn, F., de Bruijn, K., Ölfert, A., Penning-Rowsell, E., Simm, J., and Wallis, J. (2009). Flood risk assessment and flood risk management; An introduction and guidance based on experiences and findings of FLOODsite (an EU-funded Integrated project).

Kodoatie, R. J., and Roestam Sjarief. (2006). *Pengelolaan Bencana Terpadu [Integrated Disaster Management]*. Penerbit Yarsif Watampone, Jakarta.

Kreibich, H., and Merz, B. (2007). Lessons learned from the Elbe River floods in August 2002 – with a special focus on flood warning. In: Extreme hydrological events. New concepts for security, edited by: Vasiliev, O. F., van Gelder, P. H. A. J. M., Plate, E. J., and Bolgov, M. V. NATO science series iv, Earth and environmental sciences, 69-80.

Kumar, D.N. (2010). Multicriterion Analysis in Engineering and Management. PHI Learning: New Delhi, India.

Kunguma, O. (2022). KZN flooding disaster: transitioning from response and relief to recovery and rehabilitation. Disaster Management Training and Education Centre for Africa, University of Free State, South Africa.

Landsat 8 | U.S. Geological Survey. (2023, February 21). Retrieved from <https://www.usgs.gov/landsat-missions/landsat-8>

Langemeyer, J., Gómez-Baggethun, E., Haase, D., Scheuer, S., and Elmqvist, T. (2016). Bridging the gap between ecosystem service assessments and land-use planning through multi-criteria decision analysis (MCDA). *Environmental Science and Policy*, 62, 45-56. doi:10.1016/j.envsci.2016.02.013

Le Maitre, D., and Kotzee, I. (2019). Green Book – The impact of climate change on flooding. Technical report, Pretoria: CSIR.

Le Quéré, C., Clarke, J., Dhakal, S., Goodess, C., Shrestha, A., Tebboth, M., and Sutherland, C. (2020). Foundations for climate resilient and sustainable growing settlements (U-RES).

Li, Y., Wei, M., Liu, L., Yu, B., Dong, Z., and Xue, Q. (2021). Evaluation of the effectiveness of VOC-contaminated soil preparation based on AHP-CRITIC-TOPSIS model. *Chemosphere*, 271, 129571. doi:10.1016/j.chemosphere.2021.129571

Lima Junior, F. R., Osiro, L., and Carpinetti, L. C. R. (2014). A comparison between FAHP and Fuzzy TOPSIS methods to supplier selection. *Applied Soft Computing*, 21, 194-209. 10.1016/j.asoc.2014.03.014

Lin, L., Wu, Z., Liang, Q. (2019). Urban flood susceptibility analysis using a GIS-based multi-criteria analysis framework. *Natural Hazards*, 97, 455–475.

Liu, Y., Eckert, C. M., and Earl, C. (2020). A review of FAHP methods for decision-making with subjective judgments. *Expert Systems with Applications*, 161, 113738. doi:https://doi-org.nwulib.idm.oclc.org/10.1016/j.eswa.2020.113738

Loi, N.K.; Liem, N.D.; Tu, L.H.; Hong, N.T.; Truong, C.D.; Tram, V.N.Q.; Nhat, T.T.; Anh, T.N.; Jeong, J. Automated procedure of real-time flood forecasting in Vu Gia –Thu Bon River basin, Vietnam by integrating SWAT and HEC-RAS models. *J. Water Clim. Chang.*, 10, 535–545

LP DAAC. (n.d.). Societal Benefits of Higher Resolution SRTM Products.

Lyu, H., Zhou, W., Shen, S., and Zhou, A. (2020). Inundation risk assessment of the metro system using AHP and TFN-AHP in Shenzhen, *Sustainable Cities and Society*, 56, 2020, 102103. DOI

Mabaso, N. (2022). Santam admits KZN April floods the biggest disaster it's ever had to deal with. Retrieved from <https://ewn.co.za/2022/11/23/santam-admits-kzn-april-floods-the-biggest-disaster-its-ever-had-to-deal-with>

Madi, E. N., Garibaldi, J., Wagner, C. (2016). An exploration of issues and limitations in current methods of TOPSIS and fuzzy TOPSIS. doi:10.1109/FUZZ-IEEE.2016.7737950.

Maguire, D.J. (1991) An Overview and Definition of GIS. In: Maguire, D.J., Goodchild, M.F. and Rhind, D.W., Eds., *Geographical Information Systems: Principles and Applications*, Wiley, Hoboken, Vol. 1, 9-20.

Mahmoody Vanolya, N., Jelokhani-Niaraki, M. (2021). The use of subjective–objective weights in GIS-based multi-criteria decision analysis for flood hazard assessment: a case study in Mazandaran, Iran. *GeoJournal*, 86, 379–398. DOI

Malczewski, J. (2007). GIS-based multicriteria decision analysis: a survey of the literature. *International Journal of Geographical Information Science*, 20, 703–726. doi:10.1080/13658810600661508

Malczewski, J. (2011). Local Weighted Linear Combination. *Transactions in GIS*, 15(4), 439–455. DOI

Malczewski, J. (2018). Multi-Criteria Analysis. In *Comprehensive Geographic Information Systems*. (Pages 197 – 217). Elsevier, ISBN 9780128047934. DOI

Mandych, A.F. (2011). Classification of floods. *Natural Disasters – Vol II*. Department of Physical Geography and Land use, Institute of Geography, Moscow, Russia.

Manfreda, S., Sole, A. and Fiorentino, M. (2008). Can the basin morphology alone provide insight into floodplain delineation? *WIT Transactions on Ecology and the Environment*, 118, 47–56. DOI

- Mark, D. M. (2000). Geographic Information Science: Critical Issues in an Emerging Cross-Disciplinary Research Domain. *Journal of the Urban and Regional Information Systems Association*, 12(1), 45–54.
- Martini, F., and Loat, R. (2007), *Handbook on good practices for flood mapping in Europe*. Paris/Bern: European exchange circle on flood mapping (EXCIMAP), 2007.
- Maryati, S. (2018). Identification of flood-prone areas for natural disaster mitigation using geospatial approach (A case study in Bone Bolango Regency, Gorontalo Province). *IOP Conference series: Earth and Environmental science*, 145, The 1st UPI International Geography Seminar 2017, Indonesia.
- Mashao, F. M., Mothapo, M. C., Munyai, R. B., Letsoalo, J. M., Mbokodo, I. L., Muofhe, T. P., Matsane, W., et al. (2022). Extreme Rainfall and Flood Risk Prediction over the East Coast of South Africa. *Water*, 15(1), 50. MDPI AG
- Mason, T. R. (1998). The problem of flooding in Ladysmith, Natal, South Africa. *Geological Society London, Engineering Geology Special Publications*.
- Mays, C. R. (2018). Using GIS and historical flood data to analyze the risk and vulnerability of a rural community, past and present: The Neosho River in Coffey County, Kansas. *Geography and the Graduate Faculty of the University of Kansas*. MA Thesis.
- Merz, B., Kreibich, H., Schwarze, R., and Thieken, A. (2010). Assessment of economic flood damage. *Natural Hazards and Earth Systems Sciences*, 10, 1697-1724. doi:10.5194/nhess-10-1697-2010.
- Messner, F., Penning-Roswell, E., Greener, C., Meyer, V., Tunstall, S., van der Veen, A. (2007). *Evaluating flood damages. Guidance and recommendations on principles and methods*, Flood site Consortium, Wallingford, 179.
- Meyer, V., Haase, D., Scheuer, S. (2007). GIS-based multicriteria analysis as decision support in flood risk management, *UFZ Discussion Paper*, No. 6/2007, Helmholtz-Zentrum für Umweltforschung (UFZ), Leipzig.
- Midgley, G.F., Chapman, R.A., Hewitson, B., Johnston, P., de Wit, M., Ziervogel, G., Mukheibir, P., van Niekerk, L., Tadross, M., van Wilgen, B.W., Kgope, B., Morant, P.D., Theron, A., Scholes, R.J., Forsyth, G.G. (2005). *A Status Quo, Vulnerability and Adaptation Assessment of the Physical and Socio-Economic Effects of Climate Change in the Western Cape*. Publication No ENV-S-C, Stellenbosch: CSIR, 2005-073.

- Milly, P.C.D., Wetherald, R.T., Dunne, K., and Delworth, T.L. (2002). Increasing risk of great floods in a changing climate. *Nature*, 415(6871), 514–517. <https://doi.org/10.1038/415514a>
- Moglen, G. E., and Maidment, D.R. (2005). Digital elevation model analysis and geographic information systems: in *Encyclopedia of Hydrological Sciences*, John Wiley and Sons, Ltd.
- Mohsen, O., and Fereshteh, N. (2017). An extended VIKOR method based on entropy measure for the failure modes risk assessment—A case study of the geothermal power plant (GPP). *Safety Science*, 92, 160–72.
- Mokhtari, E., Mezali, F., Abdelkebir, B., Engel, B. (2023). Flood risk assessment using analytical hierarchy process: A case study from the Cheliff-Ghrib watershed, Algeria. *Journal of Water and Climate Change*; 14(3), 694–711. doi: <https://doi.org/10.2166/wcc.2023.316>
- Mostafazadeh, R., Sadoddin, A., Bahremand, A., Sheikh, V., and Garizi, A. Z. (2017). Scenario analysis of flood control structures using a multi-criteria decision-making technique in Northeast Iran. *Natural Hazards*, 87. 10.1007/s11069-017-2851-1.
- Mothapo, M. C. (2019). Vulnerability assessment of settlements to floods: a case study of ward 7 and 9, in Lephalale Local Municipality, Limpopo Province, South Africa. MSc. Thesis, Department of Geography and Environmental Studies, University of Limpopo.
- Mucina, L., and Rutherford, M.C. (2006). The vegetation of South Africa, Lesotho, and Swaziland. Pretoria, South Africa: South African National Biodiversity Institute.
- Mulligan, J., Bukachi, V., Clause, J. C., Jewell, R., Kirimi, F., and Odbert, C. (2020). Hybrid infrastructures, hybrid governance: New evidence from Nairobi (Kenya) on green-blue-grey infrastructure in informal settlements. *Anthropocene*, 29, 100227. doi:10.1016/j.ancene.2019.100227
- Munier, N., and Hontoria, E. (2021). Shortcomings of the AHP Method. In: *Uses and Limitations of the AHP Method. Management for Professionals*. Springer, Cham. https://doi.org/10.1007/978-3-030-60392-2_5
- Munier, N., and Hontoria, E. (2021). Shortcomings of the AHP Method. In: *Uses and Limitations of the AHP Method. Management for Professionals*. Springer, Cham. https://doi.org/10.1007/978-3-030-60392-2_5
- Munier, N., and Hontoria, E. (2021). Uses and Limitations of the AHP Method. A Non-Mathematical and Rational Analysis. In *Management for Professionals*; Springer: Berlin, Germany.

Munoz, B., Romana, M. G., Ordonez, J. (2016). Sensitivity analysis of Multi-criteria Decision-Making Methodology for the selection of typologies of Earth-retaining walls in an Urban Highway. *Transportation Research Procedia*, 18, 135-139. ISSN 2352-1465, <https://doi.org/10.1016/j.trpro.2016.12.019>.

Munsaka, E., and Mutasa, S. (2020). Flooding and Its Impact on Education. In (Ed.). *Natural Hazards – Impacts, Adjustments, and Resilience*, IntechOpen. <https://doi.org/10.5772/intechopen.94368>.

Munyai, R.B. (2016). An assessment of community flood vulnerability and adaptation: A case study of Greater Tzaneen Local municipality, South Africa. Department of Geography and Geo-Information systems. University of Venda.

Muofhe, T.P.; Chikoore, H.; Bopape, M.M.; Nethengwe, N.S.; Ndarana, T.; Rambuwani, G.T. (2020). Forecasting intense cut-off lows in South Africa using the 4.4 km Unified Model. *Climate*, 8, 129.

Musa, S.D., and Shabu, T. (2019). Using geographic information system to evaluate land use and land cover affected by flooding in Adamawa State, Nigeria. *Jamba J. Dis. Risk Stud.* 11(1), 1–11.

Musungu, K., Drivdal, L., and Smit, J. (2016). Collecting flooding and vulnerability information in informal settlements: The governance of knowledge production. *South African Geographical Journal*, 98(1), 84–103. <https://doi.org/10.1080/03736245.2015.1117013>

Musyoki, A., Thifhufhelwi, R., and Murungweni, F.M. (2016). The impact of and responses to flooding in Thulamela Municipality, Limpopo Province, South Africa. *Jàmbá: Journal of Disaster Risk Studies*, 8(2), Art. #166, 10 pages.

Mwape, Y.P. (2009). An impact of floods on the socio-economic livelihoods of people: A case study of Sikaunzwe community in Kazungula district of Zambia. Master's degree mini-dissertation. University of the Free State faculty of Natural and Agricultural sciences.

Naghibi S, Pourghasemi H, Pourtaghi Z, Rezaei A. (2015). Groundwater qanat potential mapping using frequency ratio and Shannon's entropy models in the Moghan watershed, Iran. *Earth Sci Inform*, 8(1), 171–186.

Ncube, S., and Arthur, S. (2021). Influence of Blue-Green and Grey Infrastructure Combinations on Natural and Human-Derived Capital in Urban Drainage Planning. *Sustainability*, 13(5), 2571. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/su13052571>

Nicholls, R.J., Hanson, S., Herweijer, C., Patmore, N., Hallegatte, S., and Muir-Wood, R. (2007). Ranking of the world's cities most exposed to coastal flooding today and in the future. School of Civil Engineering and Environment and the Tyndall Centre for Climate change research, University of Southampton, UK.

Ntanganedzeni, B., and Nobert, J. (2021). Flood risk assessment in Luvuvhu river, Limpopo province, South Africa. Department of Water Resources Engineering, University of Dar es Salaam, P.O Box 35131, Dar es Salaam, Tanzania.

O'Brien, K., Pelling, M., Patwardhan, A., Hallegatte, S., Maskrey, A., Oki, T., Oswald-Spring, U., Wilbanks, T., and Yanda, P. Z. (2012). Toward a sustainable and resilient future. In C.B. Field, V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (Eds.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (pp. 437-486). Cambridge University Press.

Odu, G. (2019). Weighting methods for multi-criteria decision-making technique. *Journal of Applied Sciences and Environmental Management*, 23, 1449. 10.4314/jasem.v23i8.7.

Oguztimur, S. (2023). WHY FUZZY ANALYTIC HIERARCHY PROCESS APPROACH FOR TRANSPORT PROBLEMS?. Yıldız Technical University Department of City and Regional Planning Beşiktaş/İstanbul – Turkey.

Olusina, J., and Okolie, C. (2018). Visualisation of Uncertainty in 30m Resolution Global Digital Elevation Models: SRTM v3.0 and ASTER v2. *Nigerian Journal of Technological Development*, 15(3), 77. <https://doi.org/10.4314/njtd.v15i3.2>

Okaka, F.O, and Odhiambo B.D.O. (2018). Relationship between Flooding and Outbreak of Infectious Diseases in Kenya: A Review of the Literature. *J Environ Public Health*, 2018, 5452938. doi: 10.1155/2018/5452938. PMID: 30416526; PMCID: PMC6207902.

Ongdas, N., Akiyanova, F., Karakulov, Y., Muratbayeva, A., Zinabdin., N. (2020). Application of HEC-RAS (2D) for Flood hazard maps generation for Yesil (Ishim) River in Kazakhstan. doi: 10.3390/w1202672, <https://www.mdpi.com/2073-4441/12/10/2672>

Onifade, O.A., Ruth, A., Adigun, J.O., Oguntunji, I.O., and Ogunboye, R.O. (2014). Impacts of Flood Disaster on Sustainable National Development in Ibadan North Local Government, Oyo State. *Arabian Journal of Business and Management Review (OMAN Chapter)*, 4(2), 139-147.

Oosterom, P., Zlatanova, S, and Fendel E.M. (2005). *Geo-Information for disaster management*. Dordrecht: Springer.

Osei, B. K., Ahenkorah, I., Ewusi, A., and Fiadonu, E. B. (2021). Assessment of flood-prone zones in the Tarkwa mining area of Ghana using a GIS-based approach. University of Mines and Technology, UMaT, Box 237, Tarkwa, W/R, Ghana.

Ouma YO, Tateishi R. (2014). Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: methodological overview and case study assessment. *Water*, 6(6), 1515–1545.

Pallard, B., Castellarin, A., and Montanari, A. (2009). A look at the links between drainage density and flood statistics, *Hydrol. Earth Syst. Sci.*, 13, 1019–1029, <https://doi.org/10.5194/hess-13-1019-2009>.

Pandey, V.P., Manandhar, S., and Kazama, F. (2014). 'Climate change vulnerability assessment', in S. Shrestha, M.S. Babel and V.P. Pandey (eds.), *Climate change and water resources*, pp. 183–206, CRC Press, London.

Papaioannou, G., Vasiliades, L., and Loukas, A. (2015). Multi-criteria analysis framework for potential flood-prone areas mapping. *Water Resources Management*, 29(2), 399–418.

Pappenberger, F., Beven, K.J., Ratto, M., and Matgen, P. (2007). Multi-method global sensitivity analysis of flood inundation models. Hydrology and Fluid Dynamics Group, Environmental Science, Lancaster University, Lancaster LA1 4YQ, UK. Joint Research Centre, The European Commission, Ispra, Italy.

Parker, D., Tapsell, S., and McCarthy, S. (2007). Enhancing the human benefits of flood warnings, *Natural Hazards*, 43, 397-414, DOI 10.1007/s11069-9137-y, 2007a.

Pathan, A.I., Girish Agnihotri, P., Said, S., et al. (2020). AHP and TOPSIS based flood risk assessment - a case study of the Navsari City, Gujarat, India. *Environ Monit Assess*, 194, 509. <https://doi.org/10.1007/s10661-022-10111-x>

Pathan, A.I., Girish Agnihotri, P., Said, S., et al. (2022). AHP and TOPSIS based flood risk assessment – a case study of the Navsari City, Gujarat, India. *Environ Monit Assess*, 194, 504. <https://doi.org/10.1007/s10661-022-10111-x>

Pelling, M., and Holloway, A. (2006). *Legislation for Mainstreaming Disaster Risk Reduction*. Teddington, United Kingdom: Tearfund.

Penning-Roswell, E. C., and Green, C. (2000a). New insights into the flood-alleviation benefits (2). *The broader context, water and environmental journal*, 14, 354-362, 10.1111/j.1747-6593.2000.tb00273.x.

Pharoah, R., Holloway, A., Fortune, G., Chapman, A., Schaber, E., Zweig, P. (2016). OFF the RADAR: Synthesis Report. High Impact Weather Events in the Western Cape, South Africa 2003 – 2014.

Perera, D., Agnihotri, J., Seidou, O., and Djalante, R. (2020). Identifying societal challenges in flood early warning systems. *International Journal of Disaster Risk Reduction*, 51, 101794.

Pianosi, F., Sarrazin, F., and Wagener, T. (2015). A Matlab toolbox for global sensitivity analysis. *Environmental Modelling and Software*, 70, 80-85. doi: <https://doi.org/10.1016/j.envsoft.2015.04.009>.

Pistrika, A., and Tsakiris, G. (2007). Flood Risk Assessment: A Methodological Framework. *European Water Resources Association*, 14-16.

Poolma, E., de Coning, E., Burger, E., Pegram, G., Sinclair, S. (2015). Improvement of Early Preparedness and Early Warning Systems for Extreme Climatic Events – Flood Warnings. Report to the Water Research Commission. Water Research Commission.

Poussin, J.K, Botzen, W.J.W., and Aerts, J.C.J.H. (2014). Factors of influence on flood damage mitigation behaviour by households. Institute for environmental Studies, VU University of Amsterdam.

Pyle, D.M., Jacobs, T.L. (2016). The Port Alfred floods of 17-23 October 2012: A case of disaster (mis)management? *Jàmbá J. Disaster Risk Stud*, 8, 8 pages.

Quigley, M., and Duffy, B. (2020). Effects of Earthquakes on Flood Hazards: A Case Study From Christchurch, New Zealand. *Geosciences*, 10(3), 114. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/geosciences10030114>

Radočaj, D., and Jurišić, M. (2022). GIS-Based Cropland Suitability Prediction Using Machine Learning: A Novel Approach to Sustainable Agricultural Production. *Agronomy*, 12(9), 2210. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/agronomy12092210>

Rafiei-Sardooi, E., Azareh, A., Choubin, B., Mosavi, A.H., and Clague, J.J. (2021). Evaluating urban flood risk using a hybrid method of TOPSIS and machine learning. *International Journal of Disaster Risk Reduction*, 66, 102614.

Rahmati O, Pourghasemi HR, Zeinivand H. (2016). Flood susceptibility mapping using frequency ratio and weights of-evidence models in the Golastan Province, Iran. *Geocarto Int.*, 31(1), 42–70.

- Rahmati, O., Zeinivand, H., and Besharat, M. (2016). Flood hazard zoning in Yasooj region, Iran, using GIS and multi-criteria decision analysis. *Geomatics, Natural Hazards and Risk*, 7(3), 1000-1017. DOI: 10.1080/19475705.2015.1045043
- Ran, J., and Nedovic-Budic, Z. (2016). Integrating spatial planning and flood risk management: A new conceptual framework for the spatially integrated policy infrastructure. *Computers, Environment and Urban Systems*, 57, 68-79. doi:10.1016/j.compenvurbsys.2016.01.008
- Rentschler, J., and Salhab, M. (2020). People in Harm's Way: Flood Exposure and Poverty in 189 Countries. Policy Research Working Paper; No. 9447. World Bank, Washington, DC. <https://openknowledge.worldbank.org/handle/10986/34655> License: CC BY 3.0 IGO.
- Rezaei, J., Ortt, R., and Scholten, V. (2013). An improved fuzzy preference programming to evaluate entrepreneurship orientation. *Applied Soft Computing Journal*, 13, 2749–2758.
- Rimbaud, L., Bruchou, C., Dallot, S., Pleydell, D. R. J., Jacquot, E., Soubeyrand, S., and Thébaud, G. (2018). Using sensitivity analysis to identify key factors for the propagation of a plant epidemic. *R Soc Open Sci.*, 5(1), 171435. doi: 10.1098/rsos.171435.
- Rincón, D., Khan, U., and Armenakis, C. (2018). Flood Risk Mapping Using GIS and Multi-Criteria Analysis: A Greater Toronto Area Case Study. *Geosciences*, 8(8), 275. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/geosciences8080275>
- Salami, R.O., Von Meding, J.K., and Giggins, H. (2017). Vulnerability of human settlements to flood risk in the core area of Ibadan metropolis, Nigeria. *Jàmbá: Journal of Disaster Risk Studies*, 9(1), a371. <https://doi.org/10.4102/jamba.v9i1.371>
- Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., Li, S., and Wu, Q. (2019). Why so many published sensitivity analyzes are false: a systematic review of sensitivity analysis practices. *Environ. Model. Softw.*, 114, 29–39. <https://doi.org/10.1016/j.envsoft.2019.01.012>.
- Sam U. Shamsi. (2002). GIS Applications in Floodplain Management. In: 22nd Annual ESRI International User Conference, July 8–12, San Diego, CA: ESRI.
- Samela, C., Manfreda, S., De Paola, F., Giugni, M., Sole, A., and Fiorentino, M. (2015). DEM-Based Approaches for the Delineation of Flood-Prone Areas in an Ungauged Basin in Africa. *Journal Hydrological Engineering*. DOI: 10.1061/(ASCE)HE.1943-5584.0001272.
- Santangelo, N., Santo, A., Di Crescenzo, G., Foscari, G., Liuzza, V., Sciarrotta, S., and Scorpio, V. (2011). Flood susceptibility assessment in a highly urbanized alluvial fan: The case study of Sala Consilina (southern Italy). *Nat. Hazards Earth Syst. Sci.*, 11, 2765–2780.

Sapkota, P. (2017). Sustainable Riverine Flood risk management: Potential Techniques and Challenges. Metropolia University of applied sciences.

Sauka, S. (2016). Flood risk assessment of the crocodile river, Mpumalanga. Department of Geography, Archaeology and Environmental Studies, Faculty of Science at the University of the Witwatersrand, Johannesburg.

SAWDIS. (n.d). The Lainsburg Flood Disaster: January 1981, from S.A Weather and Disaster Information Service, [online], Available at saweatherobserver.blogspot.com [Accessed: 20 November 2022]

Sayers, P., Li, Y., Galloway, G., Penning-Rowsell, E., Shen, F., Wen, K., Chen, Y., and Le Quesne, T. (2013). Flood Risk Management: A Strategic Approach. Paris, UNESCO.

Sayl, K., Adham, A., and Ritsema, C. J. (2020). A GIS-Based Multicriteria Analysis in Modeling Optimum Sites for Rainwater Harvesting. *Hydrology*, 7(3), 51. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/hydrology703005>

Schatz, J.J. (2008). Floods hamper health-care delivery in southern Africa. *The Lancet*, 371(9615), 799-800.

Seejata K, Yodying A, Wongthadam T, Mahavik N, Tantanee S. (2018). Assessment of flood hazard areas using Analytical Hierarchy Process over the Lower Yom Basin, Sukhothai Province. *Procedia Eng.*, 212, 340–347.

Sengani, F., Mashao, F. M., and Allopi, D. (2022). An integrated approach to developing a slope susceptibility map based on a GIS-based approach, soft computing technique, and finite element formulation of the bound theorems. *Transportation Geotechnics*, 36, 100818. <https://doi.org/10.1016/j.trgeo.2022.100818>

Sepehri, M., Malekinezhad, H., Jahanbakhshi, F., Rerza, A., and Javad, I. (2020). Integration of interval rough AHP and fuzzy logic for the assessment of flood-prone areas at the regional scale. *Acta Geophys.*, 1–17. <https://doi.org/10.1007/s11600-019-00398-9>.

Sepuru, T. (2018). A Dissertation Submitted in Fulfilment of the Degree of Master of Science in Geography in the Department of Geography and Environmental Studies, School of Agricultural and Environmental Sciences, Faculty of Science and Agriculture, University of Limpopo, South Africa.

Seyoum, S.D., Vojinovic, Z., Price, R.K., and Weesakul, S. (2011). Coupled 1D and noninertia 2D flood inundation model for the simulation of urban flooding. *Journal of Hydraulic Engineering*, 138(1), 23–34. [http://dx.doi.org/10.1061/\(ASCE\)HY.1943-7900.0000485](http://dx.doi.org/10.1061/(ASCE)HY.1943-7900.0000485)

Sharifi, A., and Dinpashoh, Y. (2014). Sensitivity Analysis of the Penman-Monteith reference Crop Evapotranspiration to Climatic Variables in Iran. *Water Resources Management*, 28(15), 5465–5476. <https://doi.org/10.1007/s11269-014-0813-x>.

Sharma, S. K., Kwak, Y. J., Kumar, R., and Sarma, B. (2018). Analysis of hydrological sensitivity for flood risk assessment. *ISPRS International Journal of Geo-Information*, 7(2), 51.

Sholihah et al. (2020). *IOP Conf. Ser.: Earth Environ. Sci.*, 437, 012056.

Siddayao, G. P., Valdez, S. E., and Fernandez, P. L. (2014). Analytic hierarchy process (AHP) in spatial modeling for floodplain risk assessment. *International Journal of Machine Learning and Computing*, 4(5), 450.

Singh, J. A., Thalheimer, L., van Aalst, M., Li, S., Sun, J., Vecchi, G., ... and Dipura, R. (2022). Climate change exacerbated rainfall causing devastating flooding in Eastern South Africa.

Singh, T., Singh, V., Ranakoti, L., and Kumar, S. (2023). Optimization of tribological properties of natural fiber reinforced brake friction composite materials: Effect of objective and subjective weighting methods. *Polymer Testing*, 117, 107873. doi:<https://doi-org.nwulib.idm.oclc.org/10.1016/j.polymertesting.2022.107873>

Sohl, T. L., Sleeter, B. M., Zhu, Z., Sayler, K. L., Bennett, K. L., Bouchard, M., Hawbaker, T., Wein, A., Liu, S., Kanengieter, R., and Acevedo, W. (2010). A land-use and land-cover modeling strategy to support a national assessment of carbon stocks and fluxes. *Applied Geography*, 34, 111-124.

Souissi, D., Zouhri, L., Hammami, S., Msaddek, M. H., Zghibi, A., Dlala, M. (2019). GIS-based MCDM - AHP modeling for flood susceptibility mapping of arid areas, southeastern Tunisia. *Geocarto International*, 35, 1-25. <https://doi.org/10.1080/10106049.2019.1566405>.

South Africa - Floods and severe weather, update (Floodlist, media, SAWS) (ECHO Daily Flash of 27 September 2023) - South Africa. (2023, September 27). Retrieved from <https://reliefweb.int/report/south-africa/south-africa-floods-and-severe-weather-update-floodlist-media-saws-echo-daily-flash-27-september-2023>

South Africa (Republic). (2003). Disaster Management Act, 2002 (Act 57 of 2002). Government Printer, Pretoria.

South African Weather Service Act 8 of 2001.

Spaliviero, M., and Dapper, M. (2014). Flood analysis in the Limpopo River basin through past evolution reconstruction and geomorphological approach. *Natural Hazards and Earth Systems Sciences*, 14. 10.5194/nhess-14-2027-2014.

Statistics South Africa. (2022). Statistics South Africa Annual Report 2022/23: Book 1 [PDF]. Retrieved from https://www.statssa.gov.za/publications/AnnualReport/StatisticsSouthAfricaAnnualReport202223_Book1.pdf

Strauss, M. (2019). A historical exposition of spatial injustice and segregated urban settlement in South Africa. *Fundamina*, 25(2), 135-168. <https://dx.doi.org/10.17159/2411-7870/2019/v25n2a6>

Su, M.D., Kang, J.L., Chang, L.F., and Chen, A. S. (2005). A Grid-Based GIS Approach to Regional Flood Damage Assessment. *Journal of Marine Science and Technology*, 184-192.

Suh Y, Park Y, Kang D. (2019). Evaluating mobile services using an integrated weighting approach and fuzzy VIKOR. *PLoS One*, 14(6): e0217786. doi: 10.1371/journal.pone.0217786.

Sun, C., Li, S., and Deng, Y. (2020). Determining Weights in Multi-Criteria Decision Making Based on the Negation of Probability Distribution under Uncertain Environment. *Mathematics*, 8(2), 191. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/math8020191>

Sutanta, H., Bishop, I., and Rajabifard, A. (2010). Integrating Spatial Planning and Disaster Risk Reduction at the Local Level in the Context of Spatially Enabled Government.

Swain, K. C., Singha, C., and Nayak, L. (2020). Flood Susceptibility Mapping through the GIS-AHP Technique Using the Cloud. *ISPRS International Journal of Geo-Information*, 9(12), 720. <https://doi.org/10.3390/ijgi9120720>

Swathy Krishna, P. S., Tiju, V. I., Sheela Nair, L., and Ramesh, M. (2023). Coastal flooding by wave, wind, tide interactions and related processes along the southern part of the SW coast of India. *Regional Studies in Marine Science*, 62, 102968. doi: 10.1016/j.rsma.2023.102968

Taguchi, R., Tanoue, M., Yamazaki, D., and Hirabayashi, Y. (2022). Global-Scale Assessment of Economic Losses Caused by Flood-Related Business Interruption. *Water*, 14, 967. <https://doi.org/10.3390/w14060967>

Talukdar, S., Ghose, B., Shahfahad, Salam, R., Mahato, S., Pham, Q.B., Linh, N.T.T., Costache, R., Avand, M. (2020). Flood susceptibility modeling in Teesta River basin, Bangladesh using novel ensembles of bagging algorithms. *Stoch. Environ.*

Tang, Z., Zhang, H., Yi, S., Xiao, Y. (2018). Assessment of flood susceptible areas using spatially explicit, probabilistic multi-criteria decision analysis. *J. Hydrol.*, 558, 144–158. <https://doi.org/10.1016/j.jhydrol.2018.01.033>

Tariq, A., Yan, J., Ghaffar, B., Qin, S., Mousa, B. G., Sharifi, A., Huq, Md. E., et al. (2022). Flash Flood Susceptibility Assessment and Zonation by Integrating Analytic Hierarchy Process and Frequency.

Tariq, M. I., Ahmed, S., Memon, N. A., Tayyaba, S., Ashraf, M. W., Nazir, M., Hussain, A., Balas, V. E., and Balas, M. M. (2020). Prioritization of Information Security Controls through FAHP for Cloud Computing Networks and Wireless Sensor Networks. *Sensors* (Basel, Switzerland), 20(5). <https://doi.org/10.3390/s20051310>

Taylor, A. and Davies, H. (2019). An overview of climate change and urban development in Cape Town. *Climate change and urban development: lessons from Cape Town*. Cape Town: UCT Press.

Tehrany, M.S., Lee, M., Pradhan, B., Jebur, M.N., Lee, S. (2014). Flood susceptibility mapping using integrated bivariate and multivariate statistical models. *Environ. Earth Sci.*, 72, 4001–4015.

Tehrany, M.S., Pradhan, B., Jebur, M.N. (2014). Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. *J. Hydrol* 512, 332–343, <https://doi.org/10.1016/j.jhydrol.2014.03.008>.

Thakur, B.; Parajuli, R.; Kalra, A.; Ahmad, S.; Gupta, R. Coupling HEC-RAS and HEC-HMS in precipitation runoff modelling and evaluating flood plain inundation map. In *Proceedings of the World Environmental and Water Resources Congress 2017*, Sacramento, CA, USA, 21–25 May 2017; pp. 240–251.

The 1988 Orange River flood, Upington Region, Northwestern Cape Province, RSA. P.K. Zawada, A.M. Smith. (1991)

The United States Agency for International Development. (2015). A GUIDE FOR USAID PROJECT MANAGERS FLOOD MANAGEMENT.

The World Bank (2015). *Disaster Risk Management in the Transport Sector: A Review of Concepts and International Case Studies*.

Topalovic, Z., and Marković, Đ. (2018). Integrated approach to flood management. In *Integrated urban planning: directions, resources, and territories* (pp. 143-169). Edition: Reviews of sustainability and resilience of the built environment for education, research and design Publisher: TU Delft Open.

Torterotot, J. P. (1993). *Le cout des dommages dus aux inondations: Estimation et analyse incertitudes*, Cergrene, Ecole Nationale des Ponts et Chausees, Paris, 634, pp.

Tran, P., and Shaw, R., Chantry, G., Norton, J. (2008). GIS and local knowledge in disaster management: A case study of flood risk mapping in Viet Nam. *Disasters.*, 33, 152-69. 10.1111/j.1467-7717.2008.01067.x.

Tripathi, A.K., Agrawal, S., and Gupta, R.D. (2022). Comparison of GIS-based AHP and FAHP methods for hospital site selection: A case study for Prayagraj City, India. *GeoJournal*, 87, 3507-3528. <https://doi.org/10.1007/s10708-021-10445-y>.

Tsai, H., Chang, C, and Lin, H. (2010). Fuzzy hierarchy sensitive with Delphi method to evaluate hospital organization performance. Graduate Institute of Business Management, Yuanpei University, 306 Yuanpei St. Hsin Chu 30015, Taiwan, ROC.

Tsenkova, S. (2010). Informal settlements in post-communist cities: diversity factors and patterns. *Urbani Izziv*, 21(2), 73–84. <https://doi.org/10.5379/urbani-izziv-en-2010-21-02-001>.

Twumasi, Y. A. a. A.-B., R. (2002). Mapping seasonal hazards for flood management in Accra, Ghana using GIS. Paper presented at the Geoscience and Remote Sensing Symposium 2002 IEEE International, Canada.

Ugwuibe, C. O., Onah, F. N., and Olise, C. N. (2021). Chapter 23 - flood disasters in aba north local government area of abia state, nigeria: Policy options. In T. Chaiechi (Ed.), *Economic effects of natural disasters* (pp. 373-380) Academic Press. doi:10.1016/B978-0-12-817465-4.00023-6 Retrieved from <https://www.sciencedirect.com/science/article/pii/B9780128174654000236>

UNESCO-IHE, Institute for Water Education. Flood Vulnerability Indices (FVI). (Retrieved: 2022/10/17)

United Nations Economic Commission for Europe. (2017). Agreement concerning the International Carriage of Dangerous Goods by Road (ADR 2017). Retrieved from https://unece.org/fileadmin/DAM/trans/danger/publi/adr/adr2017/ADR2017e_web.pdf

United Nations NY (1982). Proceedings of the seminars on flood vulnerability analysis and on the principles of floodplain management for flood loss prevention. Bangkok.

United Nations Office for Disaster Risk Reduction. (2015). COP21 Weather-Related Disasters Report 2015: The Human Cost of Weather-Related Disasters 1995-2015. https://www.unisdr.org/files/46796_cop21weatherdisastersreport2015.pdf

United Nations Office for the Coordination of Humanitarian Affairs. (2021). SOUTHERN AFRICA – TROPICAL CYCLONE ELOISE Flash Update No.7 As of 24 January 2021.

Use of GIS Technology in Disaster Management | GIS for Disaster Management. (2022, April 26). Retrieved January 9, 2023, from <https://www.sgligis.com/gis-in-disaster-management/>

Uys, D. (2014). Climate Change Risks Require Combined Effort [Homepage of RISKSA], [Online]. Available: <http://www.risksa.com/urgent-forum-on-climate-change-called/> [2015, 03/02].

Van der Berg, A. (2018). Municipal flood management in South Africa: a critical reading of recent case law. *South African Journal of Environmental Law and Policy*. ISSN 1023-1765 <https://doi.org/10.10520/EJC-1a709ae691>

Van Niekerk, D., Murphree, M., Prinsloo, V., Lunga, W., Kruger, L., Bredenkamp, P.W., Nemaakonde, L., Coetzee, C., (2016). Regional Assessment on Ecosystem-based Disaster Risk Reduction and Biodiversity in South Africa. Eastern and Southern Africa Regional Office, IUCN, Nairobi.

Vazhuthi, H, I, N., and Kumar, A. (2020). Causes and Impacts of Urban Floods in Indian Cities: A Review. *International Journal on Emerging Technologies*, 11(4), 140-147. ISSN No. (Online): 2249-3255.

Veerappan, Ramesh and Sayed, Sumaira. (2020). Urban flood susceptibility zonation mapping using evidential belief function, frequency ratio and fuzzy gamma operator models in GIS: a case study of Greater Mumbai, Maharashtra, India. *Geocarto International*. 10.1080/10106049.2020.1730448.

Verma, P., Raghubanshi, A., Srivastava, P., and Raghubanshi, A. (2020). Appraisal of kappa-based metrics and disagreement indices of accuracy assessment for parametric and nonparametric techniques used in LULC classification and change detection. *Modeling Earth Systems and Environment*. <https://doi.org/10.1007/s40808-020-00740-x>

Vermaak, J. and D. van Niekerk (2004). 'Disaster Risk Reduction Initiatives in South Africa'. *Development Southern Africa*, 21(3), pp. 555–74.

Vojinović, Z. (2015). *Flood risk: The holistic perspective: From integrated to interactive planning for flood resilience*, IWA Publishing, London.

Vojinović, Z. and Abbott, M.B., 2012. *Flood risk and social justice: From quantitative to qualitative flood risk assessment and mitigation*, Vol. 2, IWA Publishing, London.

Vozinaki, A.-E.K.; Morianou, G.G.; Alexakis, D.D.; Tsanis, I.K. Comparing 1D and combined 1D/2D hydraulic simulations using high-resolution topographic data: A case study of the Koiliaris basin, Greece. *Hydrol. Sci. J.* 2017, 62, 642–656

Wang, L., Cui, S., Li, Y., Huang, H., Manandhar, B., Nitivattananon, V., Fang, X., and Huang, W. (2022). A review of the flood management: from flood control to flood resilience. *Heliyon*, 8(11), e11763. <https://doi.org/10.1016/j.heliyon.2022.e11763>

Wang, X., Wu, F., Hu, T., Zeng, X., Li, X., and Huang, J. (2023). Modeling competitive-cooperative relationship between flood control and hydropower generation within hierarchical gaming structure of reservoir operation. *Journal of Hydrology*, 620, 129429. doi:<https://doi-org.nwulib.idm.oclc.org/10.1016/j.jhydrol.2023.129429>

Washington Coastal Hazards Resilience Network. (2022). Washington State Department of Ecology and Washington Sea Grant. <https://wacoastalnetwork.com/chrn/coastal-hazards/coastal-flooding/> (last accessed: 03/12/2022)

Weighted Overlay (Spatial Analyst)—ArcGIS Pro | Documentation. (n.d.). Retrieved from [https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/weighted-overlay.htm#:~:text=Each%20raster%20is%20assigned%20a,3%20*%200.25\)%20%3D%200.75](https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/weighted-overlay.htm#:~:text=Each%20raster%20is%20assigned%20a,3%20*%200.25)%20%3D%200.75)

Western Cape Government, (2004). Upgrade of Cemetery, from Western Cape Government, 24 March [online], Available at www.westerncape.gov.za [Accessed: 20 January, 2009]

Wiles, J.J., and Levine, N. S. (2002). “A combined GIS and HEC model for the analysis of the effect of urbanization on flooding; the Swan Creek watershed, Ohio,” *Environmental and Engineering Geoscience*, vol. 8, no. 1, pp. 47–61.

Williams, D, S., Costa, M.M., Celliers, L., Sutherland, C. (2018). Informal Settlements and Flooding: Identifying Strengths and Weaknesses in Local Governance for Water Management. *Water.*, 10. 871. [10.3390/w10070871](https://doi.org/10.3390/w10070871).

Wisner B, Blaikie P, Cannon T and Davis I 2004. At risk: Natural hazards, people’s vulnerability and disasters. New York: Routledge.

Wisner, B., Blaikie, P., Cannon, T. and Davis, I., 2004. At risk: Natural hazards, people’s vulnerability and disasters, Routledge, London.

Wisner, B., Blaki, P., Cannon, T., and Davis, I. (2003). At Risk: Natural hazards, people's vulnerability, and disasters, Second Edition, Routledge, London and New York, 45.

Wondim, Y. K. (2016). Flood Hazard and Risk Assessment Using GIS and Remote Sensing in Lower Awash Sub-basin, Ethiopia. *Journal of Environment and Earth Science*, 06(09).

World Meteorological Organization. (2013). Integrated Flood Management Tools Series No.19.

World Meteorological Organization. (2022). WMO-No. 1290.

Wright JM 2008. Floodplain management: Principles and current practices. Knoxville: University of Tennessee.

Wu, D., Yang, Z., Wang, N., Li, C., and Yang, Y. (2018). An Integrated Multi-Criteria Decision Making Model and AHP Weighting Uncertainty Analysis for Sustainability Assessment of Coal-Fired Power Units. *Sustainability*, 10(6), 1700. MDPI AG. Retrieved from <http://dx.doi.org/10.3390/su10061700>.

Xiao, Y., Yi, S., and Tang, Z. (2017). Integrated flood hazard assessment based on spatial ordered weighted averaging method considering spatial heterogeneity of risk preference. *Science of the Total Environment*, 599-600, 1034-1046. doi:10.1016/j.scitotenv.2017.04.218.

Xiao, Y., Yi, S., Tang, Z. (2017). Integrated flood hazard assessment based on spatial ordered weighted averaging method considering spatial heterogeneity of risk preference. *Sci. Total Environ.* 599, 1034–1046.

Xu, Q., Zhang, Y., Zhang, J., and Lv, X. (2015). Improved TOPSIS Model and its Application in the Evaluation of NCAA Basketball Coaches | Xu | *Modern Applied Science* | CCSE. <https://doi.org/10.5539/mas.v9n2p259>.

Yahaya S, Ahmad N, Abdalla RF. (2010). Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are River Basin, Nigeria. *Eur J Sci Res.*, 42 (1):71–83.

Yang, XI., Ding, JH and Hou, H. (2013). Application of a triangular FAHP approach for flood risk evaluation and response measures analysis. *Nat. Hazards* 68, 657-674.

Yankson, P.W.K., Owusu, A.B., Owusu, G. et al. (2017). Assessment of coastal communities' vulnerability of floods using indicator-based approach: A case study of Greater Accra Metropolitan Area, Ghana. *Nat Hazards* 89, 661-689 (2017).

Yen, B.C. (1999). *Hydraulics and effectiveness of levees for flood control*. University of Illinois at Urbana-Champaign Urbana, Illinois 61801, USA.

Yerramilli, S. (2012). A Hybrid Approach of Integrating HEC-RAS and GIS Towards the Identification and Assessment of Flood Risk Vulnerability in the City of Jackson, MS, *American Journal of Geographic Information System*, Vol. 1 No. 1, 2012, pp. 7-16. doi: 10.5923/j.ajgis.20120101.02.

Yodyin, A., Seejata, K., Chatsudarat, S., Chidburee., P., Mahavik., N., Kongmuang., C., Tantanee, S. (2019). Flood hazard assessment using fuzzy analytical hierarchy process: a

case study of bang rakam model in Thailand. Department of civil engineering, faculty of engineering, Naresuan university, phitsanulok, 65000, Thailand.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338-353.

Zavadskas, E.K., Vilutienė, T., Turskis, Z. et al. (2014). Multi-criteria analysis of Projects' performance in construction. *Archiv.Civ.Mech.Eng* 14, 114–121. <https://doi.org/10.1016/j.acme.2013.07.006>.

Zehtabiyani Gh, Ghoddusi J, Ahmadi H, Khalilizadeh M (2011). Assessment of the efficiency of check dams in the control of stream suspended load (case study: Marmeh Watershed in southern Iran). *J Environ Hydrol* 19, 1–10.

Zhang, K., Shalehy, H, M., Ezaz, T., Chakraborty, A., Mohib, M. K., Liu, L. (2022). An integrated flood risk assessment approach based on coupled hydrological – hydraulic modelling and bottom-up hazard vulnerability analysis, *Environmnetal Modelling and Software*, Volume 148.

Zhen, Y., Liu, S., Zhong, G., Zhou, Z., Liang, J., Zheng, W., and Fang, Q. (2022). Risk assessment of flash flood to buildings using indicator-based methodology: A case study of mountainous rural settlements in South West, China. *Front. Environ. Sci.* 10: 931029.doi: 10.3389/fenvs.2022.931029.

Zimmer, K., Fröhling, M., Breun, P., and Schultmann, F. (2017). Assessing social risks of global supply chains: A quantitative analytical approach and its application to supplier selection in the German automotive industry. *Journal of Cleaner Production*, 149, 96–109.

Zoraghi, N., Amiri, M., Talebi, G. et al. (2013). A fuzzy MCDM model with objective and subjective weights for evaluating service quality in hotel industries. *J Ind Eng Int* 9, 38.

Zozaya, N., Oliva-Moreno, J., Hidalgo-Vega, A., Ruiz, A., Soler, N., Puig-Junoy, J., Espín, J., Saborido, M., Bertran, T., Mar, J., Campillo-Artero, C. Llach, X., Gilabert-Perramón, A., Revilla, B. (2018). Multi-Criteria decision analysis in healthcare its usefulness and limitations for decision making. DOI: 10.37666/L5-2018.

Zungu, M. M., Maseko M., Kalle, R., and Ramesh, T. (2018). Fragment and life-history correlates of extinction vulnerability of forest mammals in an urban-forest mosaic in EThekweni Municipality, Durban, South Africa. *University of KwaZulu-Natal*