A Multi-Scale Assessment and Modeling of Water and Land Resources for Sustainability in the Lower Okavango River Basin: Integrating Climate Change, Land Use, and Hydrological Dynamics

Dissertation

for the award of the degree

"Doctor rerum naturalium" (Dr. rer. Nat.)

of the Georg-August-Universität Göttingen

within the doctoral program Geography

of the Georg-August University School of Science (GAUSS)

submitted by

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Göttingen 2025

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Date of the oral examination: **3rd July 2025**

Dedication

To my father and mother, who laid the foundation for my education; to my wife, who walked every step of this journey with me; and to my daughter, whose smile gave me strength every day.

Acknowledgements

I am indebted to the many individuals who have played a significant role in making this research possible. Their support, guidance, and encouragement have been invaluable throughout this journey.

First and foremost, I extend my deepest gratitude to my supervisor(s), Prof. Dr. Martin Kappas and Prof. Dr. Daniela Sauer. Their insightful guidance, unwavering support, flexibility, encouragement, technical expertise, and open-door policy as well as constructive feedback were critical to the completion of this thesis and my broader academic pursuits.

A very special and heartfelt thank you goes to Dr. Daniel Wyss. He was an amazing source of support and encouragement from the very beginning. He consistently cheered me on, provided invaluable constructive feedback, and was always there to pick me up when I was down. His belief in me, his willingness to review my work, his flexibility, technical insights, open-door policy, and unwavering encouragement were profoundly important to me, and I am incredibly grateful for the time and care he invested.

My appreciation also goes to the members of my doctoral committee, Prof. Dr. Heiko Faust, Dr. Stephen Boahen Asabere, Dr. Michael Dietze, Dr. Birgitta Putzenlechner, and Dr. Daniel Wyss, who consented to be part of this process and offered valuable insights.

I am deeply indebted to Dr Bisrat Haile Gebrekidan, Dr Miguel Vallejo Orti and Dr Eva Corral for their genuine friendship and generously sharing their programming experience, methodological knowledge, engaging in many useful scientific discussions, and for their friendly conversations, nurturing support. The completion of my dissertation would not have been possible without their consistent support and critical feedback, and I am particularly grateful for the time they took to read all my drafts, provide feedback, it was a pleasure having you in this journey and in my life. I also want to thank Dr Nichola Knox, for the technical feedback and personal support on early ideas.

I want to thank the staff and colleagues at the Department of Land and Spatial Sciences in Namibia University of Science and Technology. The friendly atmosphere and collaborative spirit provided an enjoyable and stimulating environment to work in. Specifically, I would like to thank Celeste Espach, for her unwavering support in the last five years, and Dr Oluibukun Ajayi, for his wise words and support in the final stages of my thesis. A special thank you to David Varges for supporting me with my specific requests and lending his ear for my never-ending complaints.

To the good friends and family, particularly in Ethiopia, Namibia, Germany and South Africa, who provided immense support, valuable advice, engaging discussions, and true friendship and love: thank you. Special mentions to Melaku Mekuriaw, Bruh Ayele, Solomon Feleke, Mikiyas Bashah, Meron, Eyasu, Yordanos, Paul Bantelmann, Hirut Astatke and her family, Eldana and her family, Emebet and her family and Betsegaw and his family who gave me a good hand when it was most needed, kept me going.

Finally, and most importantly, I wish to acknowledge the unwavering support, endless patience, huge generosity, and great love and sacrifice of my family: my wife and daughter, Kalkidan

(Echuye) and Luladey (Yoyi); my parents, Tsehay and Gizaw (Gashe); my brothers, Menelik (Mila) and Henock (Hena); and my sister, Fanta. Special thanks also go to my other family Asnakech (Enanye), Fiker (Fiki) and his family, Tsehay (Tsihu) and her family, Asnakech Negussie (Kankaye) and her whole family; your belief in me kept me going, and this work would not have been possible without your constant support and understanding.

I have been very fortunate to come across so many wonderful people. I am thankful to all who provided me with valuable advice, stimulating discussions, cooperation, and friendship throughout this journey.

Above all, I offer my deepest and most humble gratitude to God Almighty. For the strength, guidance, and unwavering presence that made this entire journey possible. Through every challenge and triumph, your grace has been my constant, and for this, I am eternally thankful.

Abstract

This dissertation provides a multi-scale assessment and modeling of water and land resources within the Lower Okavango River Basin, aiming to foster sustainability by integrating the complex dynamics of climate change, land use changes, and hydrological responses. Water scarcity, climate change and food insecurity are some of the challenges the world faces, which demand quick action and concerted efforts to achieve sustainable resource management, particularly in the arid and semi-arid environments of sub-Saharan Africa like the Okavango. The transboundary Okavango River basin located in the drylands of southern Angola, northeastern Namibia and northwestern Botswana, epitomizes the complex challenges of managing shared resources amongst pressures from climate extremes, rapid population growth, adverse land use practices.

The research addresses critical knowledge gaps by sequentially evaluating hydrological model performance, projecting future hydro-climatic scenarios, and assessing land suitability for climate-resilient agriculture. This study emanated from limited comprehensive assessments exploring this catchment (Mendelsohn et al., 2002; Strohbach, 2008), and its dynamic response to different variables.

Firstly, the Soil and Water Assessment Tool (SWAT) model's performance was evaluated for streamflow estimation in the semi-arid Okavango-Omatako catchment using high-resolution TanDEM-X DEM. The model was configured for a 31-year period from 1985 to 2015. Subsequently, calibration and validation processes followed using the SUFI-2 algorithm. SWAT demonstrated reasonable results in modelling semi-arid streamflow with high and low flows adequately captured, establishing its applicability for this data-scarce, flat terrain. The semi-arid characteristics together with relatively flat terrain features justified the need for the evaluation of model performance using discharge data in our study region.

Secondly, the SWAT+ model was employed to assess the projected streamflow response of the lower Okavango River Basin under combined climate and LULC change scenarios. Integrating CMIP6 GCMs and Shared Socioeconomic Pathways (SSPs), projections indicate a 5-20% decrease in precipitation, with a more substantial decline, reaching up to 60%, anticipated in streamflow by the year 2100. Projections indicate that dry season flows will nearly cease, thereby confirming the "dry gets drier" paradigm. Furthermore, it is projected that the water yield will be increasingly concentrated along river corridors, with the majority of the basin experiencing an annual water volume of less than 129 mm by the end of the century. Projections indicate that the expansion of cropland will exceed 65% of the basin area, replacing wetlands and natural vegetation.

Thirdly, to explore adaptation strategies, land suitability for drought-tolerant leguminous crops (sunn hemp and pigeon pea) was assessed in the Rundu sub-basins. This study proposed an innovative approach through the integration of subjective and objective analytical methods, which are independent of one another. The subjective component of the analysis employed a Multi-Criteria Decision Making-Analytic Hierarchy Process (MCDM-AHP), while the objective component used a data-driven multivariate approach supported by tree-based learning algorithms, including Random Forest and XGBoost. The MCDM-AHP method utilised expert evaluations to rank the importance of variables, identifying water sources, slope, and soil properties as key

factors. A suitability mapping analysis revealed that 17.63% of the area was highly suitable and 62.77% moderately suitable for these legumes. Conversely, according to the data driven methodology, soil fertility and nitrogen content emerged as key determinants for land suitability.

This integrated research underscores the sensitivity of streamflow to both precipitation and land cover dynamics in semi-arid regions and highlights the urgent need for nature-based adaptation strategies and an improved regulatory framework for climate resilient water management in the Okavango Basin. The findings aim to provide reference materials for water and land resource managers, policymakers and concerned professionals to make informed decision and improve resource management and planning contributing in development of future adaptation strategies. Ultimately, this work contributes to a deeper understanding of the Okavango's hydrological system and its vulnerabilities, offering scientific evidence to support sustainable development, transboundary cooperation through entities like OKACOM, and alignment with SDGs in this critical basin.

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List of Abbreviations

AHP: Analytic Hierarchy Process

CIMMYT: International Maize and Wheat Improvement Center

CMIP6: Coupled Model Intercomparison Project Phase 6

CR: Consistency Ratio

DEM: Digital Elevation Model

EOSA-RTC: Earth Observation and Satellite Application Research and Training Centre

EPSMO: Every River Has Its People - an OKACOM project

FAO: Food and Agriculture Organization

GCM: General Circulation Model

GEOGLAM: Group on Earth Observations Global Agricultural Monitoring Initiative

GIS: Geographic Information System

HRU: Hydrologic Response Unit

IWRM: Integrated Water Resources Management

IAM: Integrated Assessment Model

IPCC: Intergovernmental Panel on Climate Change

LUH2: Land-Use Harmonization version 2

LULC: Land Use/Land Cover

MCDM: Multi-Criteria Decision Making

NDVI: Normalized Difference Vegetation Index

NSA: Namibia Statistics Agency

NSE: Nash-Sutcliffe Efficiency

OKACOM: Permanent Okavango River Basin Water Commission

PBIAS: Percent Bias

RCP: Representative Concentration Pathway

RMSE: Root Mean Square Error

RSR: RMSE-observations standard deviation ratio

R^2: Coefficient of Determination

SCS: Soil Conservation Service

SDG: Sustainable Development Goal

SSP: Shared Socioeconomic Pathway

SUFI-2: Sequential Uncertainty Fitting version 2

SWAT: Soil and Water Assessment Tool

SWAT+: Enhanced Soil and Water Assessment Tool

UN: United Nations

USDA: United States Department of Agriculture

Chapter 1: Overview of the thesis

1.1. Background and Motivation

Water scarcity, climate change and food insecurity are some of the challenges the world faces, which demand quick action and concerted efforts to achieve sustainable resource management. This is evident, especially in arid and semi-arid environments of sub-Saharan Africa, where increased vulnerability is observed due to variable climate and changing socio-economic conditions (Field et al., 2014). The transboundary Okavango River basin located in the drylands of southern Angola, northeastern Namibia and northwestern Botswana, epitomizes the complex challenges of managing shared resources amongst pressures from climate extremes, rapid population growth, adverse land use practices. A significant proportion of the population relies on activities like agriculture, tourism and other livelihoods that depend on water and land resources along the basin. Therefore, the region holds essential ecological value, supporting unique biodiversity and ecosystems like the Okavango Delta. The basin's delicate hydrological balance is gradually threatened by climate change, evolving land use practices and rapid population growth (Murray-Hudson et al., 2006). Given this, the need to negotiate for sustainable use of shared water resources with other riparian states has become increasingly important. One way to address these interconnected challenges is through the adoption of UN Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), SDG 13 (Climate Action), and SDG 15 (Life on Land).

Transboundary water resources management demands effective and efficient cooperation among riparian states as well as scientifically informed strategies. The Permanent Okavango River Basin Water Commission (OKACOM) is instrumental to implement these critical functions. OKACOM could facilitate and organize platforms for these states to coordinate efforts for balanced and sustainable use of the water and land resources along the basin (OKACOM, 2021). Moreover, the use of earth observation technologies to enhance agricultural productivity and monitoring food security is highlighted by global initiatives like the Group on Earth Observations Global Agricultural Monitoring Initiative (GEOGLAM), which are vital for the sustainable management of the basin's land and water (GEOGLAM, 2021).

Remote sensing has emerged as essential technology in environmental modelling, especially for data scarce environments much like the Okavango basin and similar regions around the globe. Its ability to monitor large inaccessible regions by providing alternative data inputs for determining environmental processes and support projection model developments makes it indispensable. Hydrological models represent the real-world system in a simplified manner through simulations of water resources. Such models follow complex processes to integrate different spatial and temporal variables to better understand catchment heterogeneity. The significance of these models is invaluable for assessing impacts of climate and land use changes on hydrological responses and for development of adaptive management strategies (Akhtar et al., 2021). Adaptive measures and resilience of vulnerable regions are dependant on accurate modelling of streamflow, projection of future water availability under changing climate and land use conditions, and identification of sustainable land management practices.

Namibia is the driest country in Sub-Saharan Africa, and its northern regions include the Kavango East and West where the Okavango River flows. This semi-arid environment is characterized as vulnerable to drought and food insecurity. Therefore, it is crucial to provide scientific insights that can help mitigate these vulnerabilities through improved water resource management and promotion of climate-resilient agriculture. The need for a multidisciplinary research stem from the urgency to address pressing environmental and socio-economic challenges in the Okavango River Basin and to contribute to sustainable development in Namibia especially by tackling water scarcity and food insecurity. The findings from this research intends to directly support Namibian national policies, such as the National Climate Change Strategy and Action Plan, by providing evidence-based assessments of climate impacts and adaptation options (Ministry of Environment and Tourism, 2013). Furthermore, the aim is to contribute to regional initiatives spearheaded by OKACOM for the sustainable and equitable management of the transboundary Okavango River Basin and align with global targets like the SDGs.

The application of integrated remote sensing technologies and complex modelling techniques (i.e., SWAT, MCDM-AHP, Tree-based ensemble learning models) in data-scarce environments demonstrate advance methodological approaches to overcome data limitations and provide valuable insights for environmental assessment and management in similar regions worldwide. There is a critical need for robust and state-of-the-art scientific information to guide policymakers, water resource managers, agricultural extension officers, and local communities in making informed decisions regarding land and water use. This research seeks to generate such actionable knowledge, translating complex model outputs into practical recommendations.

The projected intensification of aridity in semi-arid regions under climate change (the "dry gets drier" phenomenon) poses a severe threat (Xiong et al., 2022). Consequently, this motivates for the need to understand the local implications of this paradigm in the Okavango Basin and to explore practical adaptation strategies, such as conservation agriculture with drought-tolerant farming practices, that can help communities build resilience. The multifaceted nature of the challenges experienced in the Okavango Basin requires a cross-disciplinary approach. It is therefore, significant to create a nexus between hydrology, climate science, agriculture, and socio-economic factors to provide a comprehensive perspective that can inform more effective and integrated solutions. Ultimately, the study is motivated by the commitment to contribute to a more sustainable and resilient future for the people and ecosystems of the Okavango River Basin, a semi-arid environment where water is a critical limiting factor for development and livelihoods. Based on the above assertions, the primary focus of this thesis is to contribute to a deeper understanding of its hydrological system, assess its vulnerability to future changes, and explore sustainable adaptation pathways, particularly within the agricultural sector, by harnessing the power of integrated remote sensing and advanced modelling techniques.

1.2. Problem Statement and Research Gaps

Despite of the socio-economic and ecological importance of the Okavango River Basin, significant knowledge gaps persist, particularly concerning the detailed hydrological dynamics of its sub-catchments and its response to anthropogenic and climatic pressures. Specifically for the Namibian context, we identified several research deficiencies that this thesis seeks to address. While some studies have addressed the broader Okavango Basin, this study emanated from limited comprehensive assessments exploring this catchment (Mendelsohn et al., 2002; Strohbach, 2008), and its dynamic response to different variables. This limits the understanding of local streamflow generation mechanisms and water balance components, crucial for targeted water resource management.

Although advanced hydrological models are widely used, previous research has not attempted the use of SWAT model in the Okavango basin in Namibia, denoting a general lack of knowledge on hydrological processes in this relatively semi-arid flat terrain (Strohbach, 2008). Moreover, the coarse resolution from freely available Digital Elevation Models (DEM) supplemented with lack of streamflow gauge station data has created a challenge to unpack Namibia's hydrological systems and realistically simulate catchment behaviour. The potential of high-resolution DEMs, such as TanDEM-X, has not been documented for the Okavango catchment.

There is a pressing need for studies that project future streamflow responses under the latest combined climate change (e.g., CMIP6 GCM outputs) and land use/land cover (LULC) change scenarios (e.g., Shared Socioeconomic Pathways - SSPs) for the lower Okavango River Basin in Namibia. Since this assumption has never been empirically validated in our study area, the present study is set to fill in that gap by applying SWAT+ as an upgraded version of SWAT to simulate future streamflow responses under combined climate and LULC scenarios. Understanding how these combined pressures will alter water availability is critical, particularly in a region already prone to water scarcity (Moses, 2024).

Although growing evidence reveals the impacts of climate change, significant efforts to address its effects on land use management and practices have been lacking. Knowledge based sustainable land adaptation strategies are required to adequately cope with the resulting effects. One such example is the lack of crop suitability studies in semi-arid lower Okavango basin, especially in communal small-scale farming areas. There is a need for comprehensive land suitability assessments focusing on climate-resilient agricultural practices, such as the cultivation of drought-tolerant legume-based crops. Consequently, an in-depth analysis of land use/land cover is essential for integrated land and water resource management within the Okavango River basin, especially given the significant land use changes driven by anthropogenic pressures such as agricultural expansion and urban growth (Fortunato and Enciso, 2023).

Existing research often addresses hydrological modelling, climate impact assessment, or land suitability in isolation. There is a need for integrated research approaches that sequentially links these components. We aim to fill this gap by adopting such an integrated framework in this dissertation. Addressing these gaps is crucial for providing the scientific underpinning required for sustainable water and land management in the Namibian Okavango River Basin and similar semi-arid, data-scarce regions globally.

1.3. Research Aim and Objectives

The overall aim of this thesis is to assess current and future hydrological regimes and evaluate sustainable land use adaptation strategies in the Namibian segment of the lower Okavango River Basin using integrated remote sensing and spatiotemporal modelling techniques to support informed water and agricultural resource management. This research framework comprises three primary interconnected objectives, corresponding to the three core studies conducted. By achieving these objectives, we provide a comprehensive assessment, from understanding current hydrological conditions to projecting future vulnerabilities and exploring viable adaptation solutions:

1. **Evaluating SWAT model for semi-arid streamflow estimation with High-Res DEM** to assess the performance of the SWAT model for streamflow estimation in the semi-arid Okavango catchment using TanDEM-X. A fundamental point is the establishment of a baseline understanding of the SWAT model's applicability and limitations for hydrological studies in the region.
2. **Modelling future streamflow under climate and LULC scenarios using SWAT+** to assess the projected impacts of future climate and land use/land cover change scenarios on streamflow response and water yield in the lower Okavango River Basin using the SWAT+ model. The results have the potential to analyse the combined effects of climate and LULC changes on the basin's hydrology and assess the implications for water resource availability.
3. **Land suitability assessment of leguminous crops using a multicriteria and machine learning approaches** to identify land-based adaptation strategies for LULC-driven streamflow and land use changes in the Okavango River Basin by comprehensively assessing land suitability for drought-tolerant leguminous crops, using and comparing expert-driven MCDM-AHP with data-driven machine learning approaches.

1.4. Research Questions

This dissertation seeks to answer the following key research questions, which we structured around the three core studies:

1. How accurately does the SWAT model simulate streamflow in the semi-arid Okavango catchment using high-resolution TanDEM-X DEM data?
2. What are the projected impacts of future climate and LULC changes on streamflow and water yield in the lower Okavango River Basin?
3. Which areas in the Okavango River Basin are most suitable for drought-tolerant leguminous crops, and what are the key determinants according to multicriteria and machine learning assessments for climate adaptation?

1.5. Study Site

Location: The study site as seen in Figure 1.1, encompasses significant portions of the Okavango River Basin, a vital transboundary freshwater ecosystem where the river flows from the wetter highlands of Southern Angola, passing through Namibia, and dissipates downstream in northwestern Botswana. Approximately ninety-five percent of the Okavango Basin's streamflow originates from Angola and passes through Namibia before reaching the Okavango Delta in Botswana. This transboundary river system is occupied by approximately 1 million inhabitants, who are predominantly engaged in small-scale farming (EPSMO-BIOKAVANGO Eflows Team, 2009). Research focuses on different scales within this system, including the expansive Okavango-Omatako catchment in Namibia, which extends from central to northeastern Namibia, bordering Botswana to the east and Angola to the north, and covers an area of approximately 74,700 km^2 (Strohbach, 2008). This catchment is comprised of the perennial Okavango and ephemeral Omuramba-Omatako rivers, as well as groundwater resources. More specifically, investigations also concentrate on the lower Okavango River Basin, an area that includes the Rundu townlands in northeastern Namibia and neighboring areas of southern Angola. Here, the area around Rundu is situated along the Okavango River, forming a natural border between the two countries. This focal zone includes seven sub-basins surrounding the Rundu municipality in the Kavango East region of northeastern Namibia, which are part of the greater Okavango basin. Rundu, the second most populated town in Namibia, had a population of 63,431 in the 2011 census; with an annual growth rate of 5.4%, its current population is 118,632 (NSA, 2024). Rundu is a potential market for agricultural products and is located along the Trans-Caprivi Corridor.

Climate: The Namibian section of the basin is predominantly semi-arid. In the broader Okavango-Omatako catchment, annual rainfall ranges between 300 mm in the southwest to over 600 mm in the northeast of the country (Mendelsohn et al., 2002). The rainy season in northeast Namibia near Rundu, receives an average annual rainfall of 450-550 mm, typically occurs between October and April; light rainfall is observed at the beginning of the rainy season in October and November and towards its end in April, while an increase in rainfall is recorded between December and March (The World Bank Group, 2021). It is notable that increased rainfall variability and intermittent drought occurrences can be observed in this semi-arid environment. The region also experiences a high average loss of water through evaporation, estimated between 2,600 and 3,200 mm per annum within the Okavango-Omatako catchment (Atlas of Namibia Team, 2022).

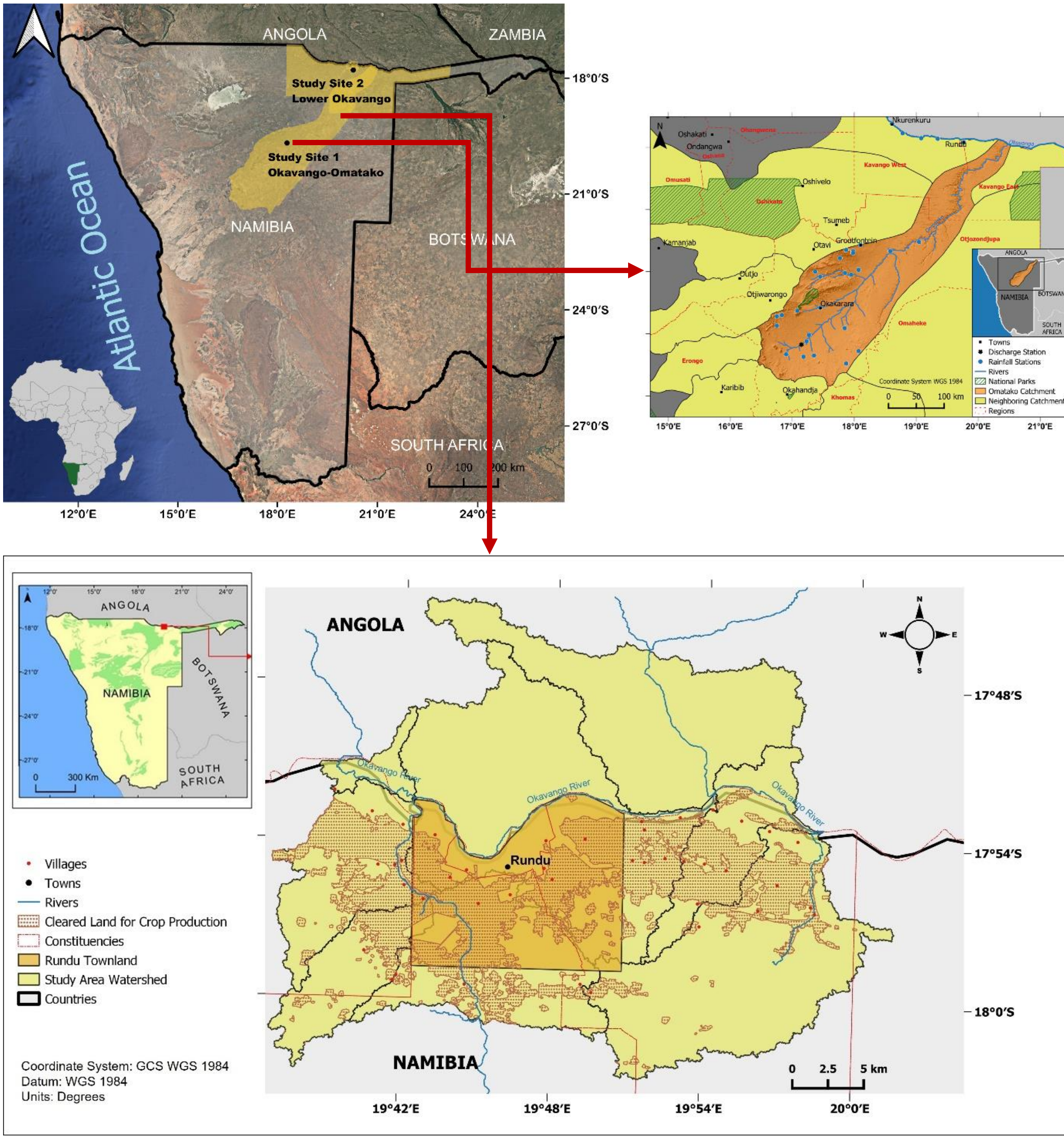

Figure 1.1: Location of study site

Hydrology: The main water inflow sources to this catchment are the perennial Cubango and Cuito rivers located in southern Angola. The Okavango-Omatako system includes the Omatako dam, which has been built on the Omuramba-Omatako ephemeral river. The Omatako River itself is a tributary to the Okavango; however, its contribution is minimal as the river originates from the dry central plateau of the Kalahari, with limited runoff either evaporating or draining into the sand along its course (IWRM, 2010). After heavy rains, other ephemeral streams such as Nhoma and Kaudom also join the drainage system of the river basin. Important groundwater resources, particularly those of the Tsumeb, Otavi, and Grootfontein Karstveld, are major water sources for central Namibia (Mendelsohn et al., 2002). Upstream precipitation from the Angolan highlands and LULC patterns are critical to regulate downstream flow regimes, making the downstream areas highly sensitive.

Topography: The topography of the Okavango-Omatako catchment is predominantly a flat sandy plateau, categorized as the Kalahari Sandveld landscape. Although known for its flat terrain, the sandy deposits form dunes in some areas. The landscape near Grootfontein is known as Karstveld and hosts Namibia's largest underground aquifers; its elevated terrain receives 550 to 600 mm of rainfall annually (Mendelsohn et al., 2002). Generally, the highest elevation is observed in the south-west of the catchment, with a gentle downward slope towards the northeast where it meets the Okavango valley. The area around Rundu has a uniform topography; elevation for this study site ranges between 1063 and 1152 m above sea level, whereas a dominant gentle slope is observed in most of the study region, between 2° to 5°. Soil types are diverse, soils further from the river corridor are mostly classed as low-nutrient arenosols, while river floodplains have nutrient-rich fluvisols and gleysols, supporting a higher degree of agricultural activity (Atlas of Namibia Team, 2022). The major constraints for farming inland away from the river are the poorly suited soil types, which are mostly characterized by low water and nutrient storing capacities. Along the river are the prevailing soil types; these soils consist mainly of silty clay loam and sandy clay loam, which contribute to their high nutrient content and water storage capacity. Within the broader Okavango-Omatako catchment, dominant soil groups include Cambisols, Regosols, Arenosols, Calcisols, Leptosols, and Fluvisols.

LULC: Natural vegetation in the Okavango-Omatako catchment varies from moderate-dense shrubland in the southwest, to a shrubland-woodland mosaic towards the center of the basin, and a dry woodland-grassland mosaic in the northeastern parts. Similar to other valleys found along rivers, the Okavango valley is dominated by floodplain grasslands and woodland vegetation (Mendelsohn and El Obeid, 2004). In terms of land use within the Okavango-Omatako catchment, large-scale irrigation for maize, sorghum, cotton, and wheat are predominant water consumers, followed by livestock and urban consumption. On the Namibian side of the lower Okavango River, the population along the basin mainly relies on farming pearl millet (known as mahangu in the local language), and to a lesser extent on sorghum, maize, and vegetables such as cabbages and tomatoes. The typical size of a crop farm along the study area varies between 2 and 5 ha and usually belongs to an individual household. In the Kavango East region, 53% of households are engaged in crop farming, which is higher than the national average of 32.8% (Mwinga et al., 2018). There has been a significant shift in land use with more cultivation and expansion of urban sprawl, primarily in and around Rundu. Consequently, much of this land has been cleared for accelerated crop production, resulting in soil degradation caused by erosion, which adversely affects the levels of organic matter and nutrients. Water extracted from the Okavango-Omatako catchment caters to approximately 15% of the Namibian population through livelihood activities such as irrigation, mining, tourism, and livestock (IWRM, 2010). The Okavango River basin is under constant pressure due to climate variability, fast population growth, and varying land use practices. Food security poses a significant challenge in Sub-Saharan Africa, and the state of food insecurity in Namibia mirrors the conditions found across this region.

1.6 Structure and Contributions

This thesis is a cumulative compilation of three studies. Each research question is answered in three self-contained chapters constituting the main chapters 2 to 4. This section summarizes the main chapters and contributions of the thesis. For each chapter, I provide the objective, approach, and main findings. Also, it will highlight how each chapter is related to the subsequent chapters.

The relevant thesis publications and contributions are summarized in the tables below (Table 1.1 to 1.3):

Table 1.1: Contributions to manuscript 1 (Chapter 2)

Title: Evaluating SWAT model for streamflow estimation in the semi-arid Okavango-Omatako catchment, Namibia	
Authors	**Contribution to study**
Kaleb Gizaw Negussie[1,2,5]	Conceptualization and design, data collection and analysis, visualization, manuscript writing, review & editing.
Daniel Wyss[2]	Supervision, reviewed draft manuscript.
Nichola Knox[1]	Supervision, reviewed draft manuscript.
Miguel Vallejo Orti[1,4]	Conceptualization, visualization, reviewed draft manuscript.
Eva Corral-Pazos-de-Provens[3]	Data Organization, supported manuscript structure.
Martin Kappas[2]	Conceptualization, supervision, reviewed draft manuscript.
Current Status: Published	**DOI:** **https://doi.org/10.5897/AJEST2022.3155**
Published in:	**African Journal of Environmental Science and Technology**

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Table 1.2: Contributions to manuscript 2 (Chapter 3)

Title: Modeling Future Streamflow under Climate and Land Use Scenarios in the Lower Okavango River Basin	
Authors	**Contribution to study**
Kaleb Gizaw Negussie[1,2,3]	Conceptualization and design, data collection and analysis, visualization, manuscript writing, review & editing.
Daniel Wyss[2]	Supervision, reviewed draft manuscript.
Martin Kappas[2]	Conceptualization, supervision, reviewed draft manuscript.
Current Status: Submitted	**Springer Nature – Regional Environmental Change**

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Table 1.3: Contributions to manuscript 3 (Chapter 4)

Title: Assessing land suitability for leguminous crops in the Okavango River basin: A multicriteria and machine learning approach	
Authors	**Contribution to study**
Kaleb Gizaw Negussie[1,2,4]	Conceptualization and design, data collection and analysis, visualization, manuscript writing, review & editing.
Bisrat Haile Gebrekidan[3]	Conceptualization, supported analysis, reviewed draft manuscript.
Daniel Wyss[2]	Supervision, reviewed draft manuscript.
Martin Kappas[2]	Conceptualization, supervision, reviewed draft manuscript.
Current Status: Published	**DOI:** **https://doi.org/10.1016/j.jag.2024.104284**
Published in:	**International Journal of Applied Earth Observation and Geoinformation**

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1.7. Summary of Key Findings

1.7.1. Evaluating SWAT model for streamflow estimation in a Semi-Arid Data-Scarce Environment using High-Res DEM

The second chapter of the thesis focused on evaluating the capability of the SWAT model to simulate streamflow in the Okavango-Omatako catchment, a region characterized by its semi-arid climate, relatively flat terrain, and scarcity of long-term, high-quality hydro-meteorological data. The SWAT and its enhanced version, SWAT+, are physically-based, semi-distributed, time-continuous river basin scale models developed to quantify and predict the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds (Arnold et al., 2012). SWAT divides a watershed into multiple sub-watersheds, which are then further subdivided into Hydrologic Response Units (HRUs) consisting of homogeneous land use, soil type, and slope characteristics. Hydrological components are simulated for each HRU, including surface runoff (typically using a modification of the SCS Curve Number method) (USDA, 1986), percolation, lateral subsurface flow, groundwater flow, evapotranspiration (e.g., Penman-Monteith method) (Allen et al., 1989), channel transmission losses, and water routing. Calibration and uncertainty analysis are integral to model application, often performed using tools like SWAT-CUP with algorithms such as SUFI-2 (Abbaspour, 2015). In this thesis, SWAT was used for the initial model evaluation in the Okavango-Omatako catchment, leveraging its capabilities to handle diverse environmental data and simulate complex hydrological interactions.

Results ranked "very good" according to Moriasi et al.'s (2007) performance evaluation criteria for streamflow simulation during calibration (1990-2003) and validation (2004-2008) periods on a monthly time step. Performance indicators such as Nash-Sutcliffe Efficiency (NSE) (0.82 cal, 0.80 val), Coefficient of Determination (R^2) (0.84 cal, 0.89 val), and RMSE-observations standard deviation ratio (RSR) (0.42 cal, 0.44 val) achieved very good ratings. Percent Bias (PBIAS) was -1.1 (calibration, very good) and -20.0 (validation, satisfactory). The model uncertainty analysis, using P-factor and R-factor, yielded 0.77 and 1.31 for calibration, and 0.68 and 1.82 for validation, respectively. While calibration metrics were within recommended ranges, the validation R-factor was slightly higher, a situation we attribute to the large catchment size and limited calibration data. Overall, we found that SWAT demonstrated its capability to reasonably model streamflow, capturing both high and low flow periods adequately in this challenging environment.

The findings underscored the critical role of high-resolution topographic data, specifically the TanDEM-X DEM (12m spatial resolution, 2m vertical accuracy), for accurate watershed delineation and Hydrologic Response Unit (HRU) definition in the catchment's characteristically flat terrain (Rizzoli et al., 2017; Wessel et al., 2018). This was essential for effective streamflow simulation, as coarser DEMs often fail to capture the subtle relief that governs hydrological pathways in such landscapes. Sensitivity analysis identified three parameters as highly influential on streamflow generation: the SCS runoff curve number (CN2), groundwater delay time (GW_DELAY), and baseflow alpha factor (ALPHA_BF). CN2, affecting surface runoff, was the most sensitive, which is consistent with findings in other arid and semi-arid watersheds. The sensitivity to GW_DELAY and ALPHA_BF highlighted the importance of groundwater processes in this semi-arid catchment's hydrology, similarly as (Desai et al., 2021; Mourad et al., 2019).

It was acknowledged that challenges inherent in modelling data-poor regions, including inconsistencies and missing observed discharge data, which restricted the calibration/validation period despite a longer simulation timeframe. Model uncertainty, particularly a higher R-factor during validation, was attributed to the large scale of the catchment and limited calibration data availability, consistent with Abbaspour et al.'s (2015) observations in continental-scale hydrology and water quality model for Europe. While the model performed well generally, we observed some overestimation during low flow periods and slight underestimation of peak flows, indicating areas for potential future model refinement. This foundational study confirmed that SWAT, when appropriately configured by us with high-resolution inputs, can be a valuable tool for understanding hydrological processes in the semi-arid Okavango basin, thereby paving the way for its application in assessing future climate and land use change impacts.

1.7.2. Modelling climate and LULC impacts on future streamflow and water yield using SWAT+

Enhanced SWAT+ model was used to project future hydrological responses in the lower Okavango River Basin (near Rundu). SWAT+ offers enhanced spatial representation of landscape processes and interactions within the watershed. To assess future hydrological impacts, we integrated outputs from General Circulation Models (GCMs) and LULC projection models. For climate change scenarios, we used downscaled and bias-corrected data from GCMs participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6). These GCMs simulate global climate responses to different greenhouse gas emission pathways, represented by Shared Socioeconomic Pathways (SSPs) combined with Representative Concentration Pathways (RCPs). Our study specifically used daily downscaled climate projections for variables like precipitation, temperature, solar radiation, humidity, and wind speed from selected CMIP6 GCMs (GFDL-ESM4, IPSL-CM6A-

LR, MPI-ESM1-2-HR, NorESM2-MM) under SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions) scenarios.

For LULC change scenarios, we employed global land use projection datasets, consistent with the SSPs. These datasets are often generated by Integrated Assessment Models (IAMs) that link socio-economic development trajectories with land use demands (Parson and Fisher-Vanden, 1997; Riahi et al., 2017). Our research utilized a 1 km resolution global land projection dataset (spanning 2015-2100) based on CMIP6-recommended LULC products from the Land-Use Harmonization (LUH2) project, which reconstructs historical land use and projects future patterns for various land cover types under different SSP-RCP scenarios (Hurtt et al., 2020). By forcing the SWAT+ model with these combined climate and LULC scenarios, we simulated future hydrological responses across different time horizons.

Projections from four CMIP6 GCMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, NorESM2_MM) consistently indicated a drying trend for the study area across three future periods (2025-2040, 2041-2070, and 2071-2100) under both SSP2-4.5 and SSP5-8.5 scenarios. Projections indicated a decrease in precipitation by 5-20% by 2100, with a more substantial decline in streamflow, potentially reaching up to 60%. Dry season flows were projected to nearly cease, particularly towards the end of the century under higher emission scenarios. Peak rainfall periods (January-March) showed notable decreases, with an even more significant and non-linear decrease in corresponding runoff. These findings are consistent with global hydrological assessments showing that arid and semi-arid regions are particularly vulnerable to future climate change impacts (Greve et al., 2014; Guo et al., 2020).

Spatially, we found that annual water yield was projected to become increasingly concentrated along river corridors, with the majority of the basin experiencing significantly reduced water yield (less than 129 mm/year) by the end of the century. Historically high-yield areas associated with wetlands and tree cover were projected to shrink dramatically. Mean annual surface runoff also showed a consistent decline across most GCMs and future periods under both SSPs, further indicating increasing aridity. The findings strongly supported the "dry gets drier" global paradigm for this semi-arid region (IPCC, 2022; Xiong et al., 2022). The disproportionately larger decline in streamflow compared to the reduction in precipitation highlighted the acute hydrological sensitivity of the Okavango Basin to climatic variability, a characteristic common to semi-arid southern African river systems (Aich et al., 2014; Conway et al., 2009; Goulden et al., 2009). This implies that even modest changes in upstream rainfall (originating from Angolan highlands) can have amplified impacts on downstream water availability in Namibia.

LULC projections which showed a dramatic expansion of cropland (projected to exceed 65% of the basin area by 2100) and urban areas, largely at the expense of wetlands and natural vegetation. As per the analysis, these land transformations indicates to worsen the climate-induced drying by reducing infiltration, increasing runoff concentration, and diminishing the ecosystem's natural buffering capacity. Scanlon et al., (2007), also found that conversions of natural ecosystem to agricultural land significantly impacts water resources, which aligns with our findings.

The projected declines in water availability pose serious risks to water security for domestic use, irrigated agriculture, and the ecological health of the Okavango River and its dependent ecosystems, including the downstream Okavango Delta. A concerning depiction of the future hydrological regime of the lower Okavango, emphasizing the combined pressures of climate change and adverse LULC transformations. These projections clearly signalled the necessity for proactive adaptation measures. It is vital to emphasize the urgent need for transboundary coordination (through OKACOM), integrated land and water management, and the development of robust climate adaptation strategies, as supported by (UN Water, 2020).

1.7.3. Land suitability assessment of leguminous crops using a multicriteria and machine learning approaches.

Given the projected increase in aridity and water stress, our fourth chapter focused on exploring an agricultural adaptation strategy to identify suitable land for cultivating drought-tolerant leguminous crops (sunn hemp and pigeon pea) in the sub-basins surrounding Rundu. Land suitability assessment evaluates the appropriateness of land for specific uses based on a range of biophysical and socio-economic factors (FAO, 1976). We adopted an innovative dual approach: i) a subjective Multi-Criteria Decision Making - Analytic Hierarchy Process (MCDM-AHP), developed by Saaty, (1987), which is a widely used MCDM technique that structures complex decisions into a hierarchy of criteria and alternatives. It involves pairwise comparisons of criteria by experts to derive their relative weights, which are then used in a weighted overlay analysis in a GIS environment to produce a final suitability map. The consistency of expert judgments is checked using a Consistency Ratio (CR) (Malczewski, 2006; Saaty, 1987). We used this method to subjectively assess land suitability for leguminous crops based on expert evaluations of various environmental criteria. ii) an objective data-driven machine learning technique to provide an objective counterpoint to AHP, we employed advanced tree-based ensemble machine learning models (Random Forest, Extra Trees, Gradient Boosting, XGBoost) and multivariate regression analyses. These models learn patterns directly from the data and have been found effective in spatial prediction and land suitability modelling (Belgiu and Drăguț, 2016; Sahragard and Chahouki, 2016). For classification (e.g., predicting cropland), models were trained on environmental variables to predict suitability classes. For regression (e.g., predicting NDVI as a proxy for vegetation health/suitability), models identified the strength and direction of relationships between predictors and the outcome. Feature importance analysis helped identify the most influential variables driving suitability according to the data itself. This approach, as we applied it, helps to mitigate the subjectivity inherent in expert-based systems.

MCDM-AHP used expert evaluations to rank the importance of 22 variables for climatic, hydro-geomorphologic, soil, vegetation, socio-economic categories. Key factors identified by experts as highly important for legume cultivation included distance to river (water source, 8.48% weight), precipitation (8.14%), and soil water content (8.02%), followed by slope, and various soil physical/chemical properties. Our AHP-based suitability map indicated that 17.63% of the area was suitable, 62.77% moderately suitable, 10% less suitable, and 9.59% unsuitable for these legumes. Suitable areas were often in proximity to the river and its tributaries, benefiting from higher soil moisture and favorable soil types (Fluvic Gleysols).

Advanced tree-based ensemble learning models (Random Forest and XGBoost performing best with accuracies of 0.97 and 0.96 respectively) and multivariate regression, driven purely by data (using NDVI as a proxy for crop health/suitability and cropland classification) were employed.

This data-driven methodology highlighted soil fertility capability classification (importance score 0.7884 for XGBoost regressor) and soil nitrogen content (importance score 0.0764) as the most crucial determinants for land suitability. Soil texture (sandy loam, loamy sand showing positive correlation with cropland) also emerged as significant.

The AHP method emphasized water availability and broader physical characteristics, while the data-driven machine learning approach, particularly when predicting existing cropland or high NDVI values, strongly prioritized intrinsic soil properties, especially fertility and nutrient status. Machine learning also offered the advantage of ranking individual categories within variables, whereas AHP assigned weights to variables as a whole.

The role of legume-based crops in conservation agriculture reiterated the benefits of sunn hemp and pigeon pea as drought-resistant, nitrogen-fixing cover crops that can improve soil organic matter, enhance soil moisture retention, reduce erosion, and suppress weeds (FAO, 2015; Ghosh et al., 2007). Their cultivation, especially intercropped with staple cereals like pearl millet and maize (dominant in the study area), presents a viable conservation agriculture practice to enhance food security and build soil resilience in the face of declining water resources and soil degradation. Results provided spatially explicit guidance on where to promote specific climate-resilient agricultural practices, offering a tangible adaptation pathway in response to the challenges we identified in the preceding hydrological and climate impact assessments.

1.8. Conclusion and Outlook

The Okavango River Basin is a complex environment both in terms of biophysical changes and socio-economic activities. The study investigated the hydrological dynamics, future environmental change impacts, and agricultural adaptation potential within the Namibian segment of the basin. Our primary projections indicate that the lower Okavango River Basin is set to experience a substantial reduction in future water availability. Under combined CMIP6 climate scenarios and SSP LULC pathways, we project that precipitation is expected to decrease, leading to a more severe decline in streamflow by 2100. Dry season flows are anticipated to nearly cease, validating the "dry gets drier" paradigm for this region. Projected LULC changes, particularly the expansion of cropland and urban areas at the expense of wetlands and natural vegetation, are expected to significantly worsen climate-induced water stress. Our analysis shows that these transformations, will likely reduce infiltration, increase surface runoff concentration, and diminish natural ecosystem buffering capacities.

The findings of this dissertation have direct and actionable implications for policy and management. The projected severe decline in streamflow necessitates strong transboundary water management through OKACOM. It is further recommended that scenario-based planning, incorporating climate and LULC projections such as those developed in our work, should be embedded in future water allocation protocols and basin management strategies. In addition, national and regional agricultural policies should actively promote conservation agriculture practices, including the cultivation of drought-tolerant, soil-enhancing legume-based crops in identified suitable areas. This effort requires targeted support for agricultural extension services and smallholder farmers. An improved regulatory framework for climate-resilient water management and sustainable land use is crucial. This includes measures to protect critical ecosystems like wetlands and riparian zones, and to manage the expansion of agriculture and urban areas sustainably. Policies should prioritize nature-based solutions, such as wetland protection, riparian buffer restoration, and sustainable land management, to enhance water retention, improve soil health, and build ecosystem resilience. While this research provides valuable insights, we acknowledge certain limitations:

- The inherent scarcity of long-term, high-quality ground-truthing data for model calibration/validation (especially discharge, detailed soil properties, and crop yield data) remains a constraint. Therefore, there is a critical need to enhance both ground and remote sensing based environmental monitoring systems for hydrology, climate, LULC, and agricultural performance to reduce uncertainties and improve model accuracy.

- A more dynamic and detailed integration of socio-economic drivers and impacts (e.g., farmer decision-making, market dynamics, policy implementation capacity) was beyond the scope of our current work but is important for holistic assessment.

In light of these findings, future research directions can be deduced, with the objective of further refining our understanding of the sustainable management of the Okavango region. A subsequent critical step entails addressing the limitations in data availability by implementing enhanced in-situ data collection methodologies through establishing a long-term ground measurement system to monitor microclimatic parameters. Some of these measurements are on Surface Soil Moisture (SSM) and Root Zone Soil Moisture (RZSM). It is imperative to recognize the significance of soil moisture, an Essential Climate Variable (ECV), in various disciplines. This encompasses its crucial role in agriculture, vegetation, and hydrological research. Soil moisture plays a significant role in calibrating and validating remote sensing products, facilitating the development of robust adaptation measures to address the intricate impacts of climate change.

Future research should be informed by the latest advancement in Earth observation technologies to ensure enhanced and more meaningful results. This includes exploring the potential of advanced hyperspectral imaging techniques, for instance, from new satellite missions like EnMAP, for detailed site-specific crop parameter assessment, crop health monitoring, and improved biomass estimations in the Okavango agricultural landscapes. The integration of sensors, including optical, thermal, and microwave, through data fusion methodologies can provide more comprehensive and consistent spatiotemporal datasets. Moreover, the use of Unmanned Aerial Vehicles (UAVs) equipped with multi and/or hyperspectral sensors provides a potentially viable ultra-high-resolution monitoring of critical sub-catchment areas, vegetation stress, and specific agricultural sites within the Okavango River Basin.

The assimilation of these enhanced datasets into future hydrological and crop models will facilitate further research and development in this area. The integration of these advancements has the potential to enhance the accuracy of future projections and the efficacy of decision-support tools. The knowledge that has been generated through these efforts has substantial value for global and regional initiatives. One such example is the GEOGLAM Crop Monitor. Our detailed suitability assessments and future impact scenarios could directly enhance such platforms by providing localized calibration data, or even form the basis for developing a dedicated Okavango crop modeling and food security monitoring system. This moves beyond general assessments to providing highly relevant, actionable information for the basin.

In addition to technological and modeling advancements, new research gaps have become apparent. While our work has laid a foundation, future studies should aim for a more dynamic and detailed integration of socio-economic drivers and impacts, explicitly modelling farmer decision-making processes, market access dynamics, and the implementation capacities for adaptation strategies. It is also extremely important to develop more deeply integrated models that explicitly incorporate socio-economic factors, farmer behavior, and policy feedbacks which would allow for a better assessment of the resilience of the coupled human-water system. A comprehensive strategy for climate adaptation must be established, including a range of initiatives beyond legume-based cropping systems, for example, water harvesting techniques, efficient small-scale irrigation, and alternative livelihood strategies. Further research is recommended into the governance structures and policy implementation frameworks necessary for effective transboundary water and land management in a changing climate.

Finally, this thesis has provided a comprehensive scientific assessment that enhances our understanding of the Okavango River Basin's complexities and vulnerabilities. The findings, as well as the proposed future research directions, especially the establishment of collaborative study on Soil Moisture investigation in Kavango east and west and the application of state-of-the-art remote sensing technologies underscore our continued commitment. Additionally, a long-term integrated monitoring programs has been suggested, with the objective of tracking environmental changes and evaluating the effectiveness of implemented adaptation strategies. It is through such sustained, integrated, and technologically advanced research that we can contribute to a more sustainable and resilient future for the people and unique ecosystems of the Okavango River Basin, ensuring that this vital life-source continues to thrive amidst contemporary and future challenges.

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Chapter 2: Evaluating SWAT Model for Streamflow Estimation in the Semi-Arid Okavango-Omatako Catchment, Namibia

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Abstract

A semi-distributed hydrological model was used for runoff estimation in the Okavango-Omatako catchment in Namibia. The model was configured for a 31-year period from 1985 to 2015. Subsequently, calibration and validation processes followed using the SUFI-2 algorithm. For evaluating catchment simulation, two methods were used: i. model prediction uncertainty measured by *P-factor* and *R-factor* and ii. model performance indicators, i.e., Nash-Sutcliffe Efficiency (NSE), Coefficient of determination (R^2), Percent bias (PBIAS), and Residual variation (RSR). The *P-factor* achieved 0.77 and 0.68 while *R-factor* attained 1.31 and 1.82 for calibration and validation, respectively. The following indicators were used to evaluate the model performance through calibration and validation results respectively; NSE with 0.82 and 0.80, R^2 with 0.84 and 0.89, PBIAS achieving $-20 \leq \text{PBIAS} \leq -1.1$ and RSR performing 0.42 and 0.44. All performance indices achieved very good ratings apart from PBIAS validation which rated as satisfactory. The semi-arid characteristics together with relatively flat terrain features justified the need for the evaluation of model performance using discharge data in our study region. SWAT demonstrated reasonable results in modelling semi-arid streamflow with high and low flows adequately captured. Consequently, this evaluation was necessary for further investigations into impacts of climate change on scarce water resources highlighting the challenges of SWAT model applications in our study area climatic regime and other similar regions globally for further model improvements.

Keywords: streamflow, catchment, semi-arid, SWAT, SUFI-2, calibration, TanDEM-X, Okavango, Namibia.

2.1. Introduction

Hydrological models represent the real-world system in a simplified manner through simulations of water resources (Sood & Smakhtin, 2015). Such models follow complex processes to integrate different spatial and temporal variables to better understand catchment heterogeneity (Mengistu *et al*., 2019). However, acquiring data that accurately represents these variables is a major challenge. Field data acquisition methods are expensive, time-consuming, tedious and error prone, causing limitations in the measurement of hydrological variables (Al-Sabhan *et al*., 2003). Over the years, traditional techniques for in-situ observations of precipitation, temperature, streamflow, geohydrology, soil moisture, dam levels, etc. have dominantly provided data for catchment monitoring worldwide (Essou *et al*., 2017). Such ground-based measurements create limitations based on the spatial distribution of the observing stations, which may insufficiently assess catchment evolution over a large area (Lai *et al*., 2019; Stehr *et al*., 2008). Considering these constraints, various hydrological investigations around the world explore the integration of satellite-based data and ground measurements to monitor large and complex catchment behavior (Abbaspour *et al*., 2015; Hashim *et al*., 2016; Thavhana *et al*., 2018). A model is a simplified real world representation of a certain phenomenon applied to predict system behavior and understand processes such as stream flow, droughts, floods, vegetation cover, etc. (Devi *et al*., 2015). The features of models are defined by the parameters used to represent the reality.

In places where natural disasters (e.g. droughts and floods) occur frequently, hydrological models are vital to characterize various processes in sustainable water resource management (Emam *et al*., 2017). The Soil and Water Assessment Tool (SWAT), is one of such model capable of simulating water balance in large geographical catchments and sub catchments using a time continuous semi-distributed hydrological model, integrating various parameters like land cover/land use, soil types, precipitation, temperature, topography and climate conditions (Arnold *et al*., 2012).

Namibia is an arid country located in Southwest Africa with regular occurrence of dry periods. Annual rainfall ranges between ~ 50 mm in the west to over 600 mm in the northeast of the country (Mendelsohn *et al*., 2006). Taking into account the low rainfall and variability of rainfall within the country, water management is vital to conserve the existing water resources (Palmer *et al*., 2008). According to the Integrated Water Resources Management report, the country is divided into eleven water management areas, each are further sub-divided into water basins (IWRM, 2010). These water management areas are defined by similar drainage systems of rivers, catchment areas, underground water, water supply lines and canals. One such area is the Okavango-Omatako catchment which extends from Central to the Northeastern regions of Namibia.

The Okavango-Omatako water management area also referred to as a "catchment" is comprised of the Omatako-Omuramba and Okavango catchments. The ephemeral Omatako is a tributary to the perennial Okavango. According to IWRM (2010) report, the catchment has indisputable socio- economic importance to activities in proximity to it. Water extracted from the catchment caters to approximately 15 % of the Namibian population through livelihood activities such as irrigation, mining, tourism, livestock, etc. Considering this, it is vital to monitor and explore the catchment's behavior to different variables influencing its dynamics. This study emanated from limited comprehensive assessments exploring this catchment (Mendelsohn *et al*., 2002; Strohbach, 2008), and its dynamic response to different variables.

Several studies have been conducted since the 1990's on catchments in Namibia; from investigations of large ephemeral catchments in Jacobson *et al.* (1995) to small-scale catchment analysis in O'Connor (2001), as well as more detailed work on various individual catchments (Manning & Seely, 2005; Marsh & Seely, 1992; Mendelsohn *et al*., 2000). Although considerable studies attempted to map catchments in Namibia, according to Strohbach (2008), many have methodological inaccuracies or non-repeatable methodological descriptions. Further, the coarse resolution from freely available Digital Elevation Models (DEM) supplemented with missing data due to atmospheric interference, shadow effects, etc., has created a challenge to unpack Namibia's hydrological systems and realistically simulate catchment behavior.

To understand streamflow processes, it is essential to evaluate the SWAT model performance (Meaurio *et al*., 2015), especially when considering large catchments as depicted in this study. To date, no peer reviewed studies have used the SWAT model in the Okavango-Omatako catchment, denoting a general lack of knowledge on hydrological processes in these semi-arid catchments (Strohbach, 2008). To fill the gap, this study evaluated the SWAT model for streamflow estimation using remotely sensed data supplemented by ground observation measurements. It is further imperative to evaluate hydrological models and uncertainty methods in areas with different climatic zones (i.e. tropical, arid, semi-arid, etc.) (Emam *et al*., 2018; Rafiei Emam *et al*., 2015). The semi-arid characteristics of our study site and its relatively flat terrain features justified the need for evaluation of the SWAT model performance using discharge data in an intermediate gauge. Krysanova and White (2015) highlighted the challenges of SWAT model applications in different climatic regimes and specific regions, globally, suggesting the need for several model evaluations and improvements. One such area are SWAT applications in regions where water management is crucial due to water scarcity. Estimation of streamflow using historical variables over the semi-arid water scarce environment of the Okavango-Omatako expose catchment behavior, which in turn can be used to prepare short term and long-term water management plans. SWAT depends on the basic units of sub-basins and Hydrological Response Units (HRUs) for streamflow estimation. Due to the study catchment flat terrain, the z-resolution of freely available DEM data is insufficient to generate accurate HRU's, this study therefore used state of the art, high resolution DEM - TanDEM-X (Rizzoli *et al*., 2017; Wessel *et al*., 2018). Enhanced knowledge on hydrological processes through modelling improves future investigations on impacts of climate conditions and LULC changes on water resources and management. The study thus supports Namibian National Climate Change Strategies and Action Plan with proposed strategies to counteract impacts of climate change. This includes understanding climate change and its related policy responses, using monitoring and data collection technologies for surface and ground water at the watershed level and promoting conservation and sustainable utilization of water resources.

2.2. Study Site

The Okavango-Omatako catchment (Figure 2.1) extends from central to North-eastern Namibia, bordering Botswana to the east and Angola to the north at approximately 74,700 km^2 (Strohbach, 2008). According to IWRM (2010), it is one of the eleven water management areas classified along shared drainage systems (i.e. aquifers, canals, rivers and pipelines). This catchment is comprised of perennial (Okavango) and ephemeral (Omuramba-Omatako) rivers as well as groundwater. The Omatako dam which has been built on the Omuramba-Omatako ephemeral river and the ground water of Tsumeb, Otavi and Grootfontein Karstveld are major water sources to central Namibia. The main water inflow sources to this catchment are the perennial Cubango and Cuito rivers located in southern Angola. After heavy rains, other ephemeral streams such as Nhoma and Kaudom also join the drainage system of the river basin. The Omatako river is similarly a tributary to the Okavango, however, the contribution is minimal as the river originates from the dry central plateau of the Kalahari with limited run off either evaporating or draining into the sand along its course (IWRM, 2010). The catchment's average annual rainfall varies between 300 mm in the west to 600 mm in the north-east with an average loss of water through evaporation between 2,600 and 3,200 mm per annum (Mendelsohn *et al*., 2002).

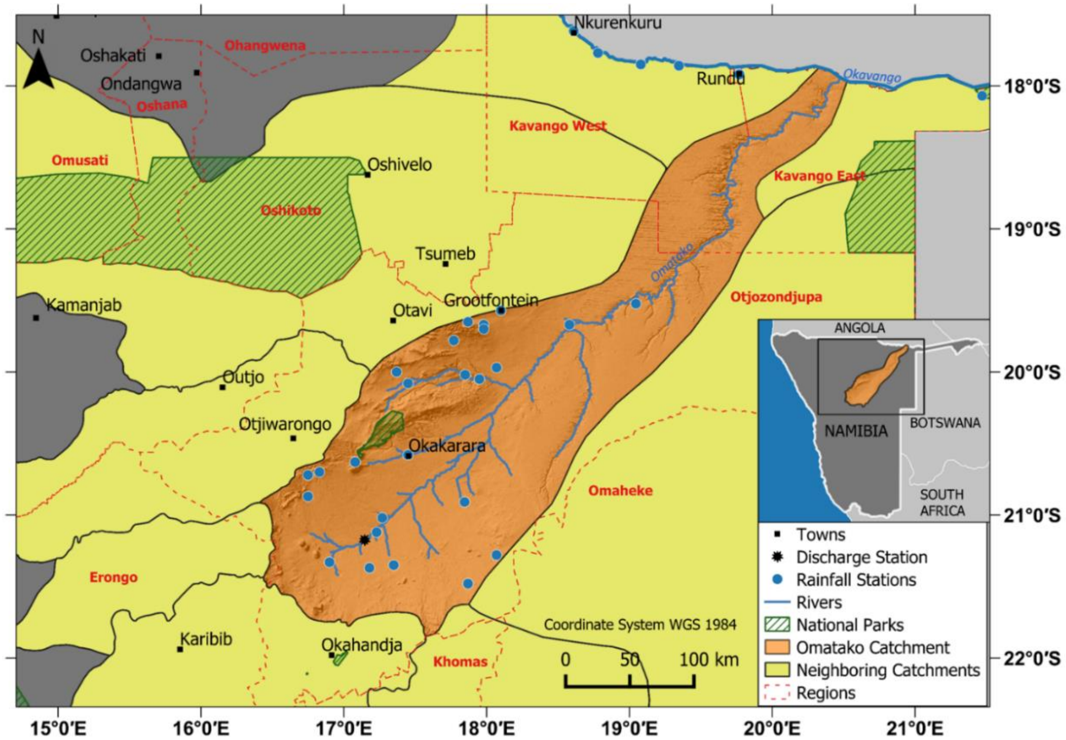


Figure 2.1: Location of the study area, Okavango-Omatako and neighboring catchments.

The Okavango-Omatako catchment is predominantly a flat sandy plateau categorized as the Kalahari Sandveld landscape (Mendelsohn *et al*., 2002). Although known for its flat terrain, the sandy deposits form dunes in some areas. The landscape near Grootfontein is known as Karstveld and is Namibia's largest underground aquifers, its elevated terrain receives 550 to 600 mm rainfall annually (Mendelsohn *et al*., 2002). The highest elevation is observed in the south-west of the catchment with a gentle downward slope towards the northeast where it meets the Okavango valley (Fig. 2). The vegetation varies from moderate-dense shrubland in the south west, a shrubland-woodland mosaic towards the center of the basin and a dry woodland-grassland mosaic in the north eastern parts (Mendelsohn *et al*., 2002).

According to IWRM (2010), the supply of water in Namibia is primarily allocated for domestic use such as livestock farming (communal and commercial). In the Okavango-Omatako catchment, large scale irrigation for, maize, sorghum, cotton and wheat are predominant water consumers, followed by livestock and urban consumption. To a lesser extent, rural domestic consumption, tourism and mining also utilize water from this catchment.

2.3 Materials and Methods

2.3.1. Data

The data used in this study includes climate data, elevation, soil characteristics, Land Use Land Cover (LULC) and streamflow data (Table 2.1). Daily in-situ measurements of precipitation and temperature from eight weather stations (Table 2.1), which cover the extent of the study area were identified and prepared for the period 1985-2015. While solar energy, relative humidity, and wind speed data were sourced from the Climate Forecast System Reanalysis (CFSR) of The National Centers for Environmental Prediction (NCEP, 2020). Moreover, the internal "weather generator" from SWAT generated missing weather data to fill the climatic gaps. The soil information over the river basin under study was sourced from an ongoing project to update the Soil Map of Namibia (Coetzee 2001, M. Coetzee, personal communication, December 6, 2019). Land use and land cover (LULC) information was derived from the Copernicus Sentinel-2 mission products supplemented by existing information from the Directorate of Survey and Mapping (DSM) in Namibia. The runoff discharge data measured by the Hydrological Services of Namibia at the Ministry of Agriculture, Water and Forestry was solicited for calibration/validation purposes. The following subsections will further discuss the datasets mentioned above in detail.

Table 2.1: Data used and sources.

	Data	Sources	Resolution
1.	Meteorological Variables: Precipitation(mm), temperature (°C), Solar radiation (MJ/m^2), Relative Humidity (%), and Wind Speed (m/s)	Namibia Meteorological Services (NMS) 1985-2015 and Climate Forecast System Reanalysis (CFSR) (Weather Stations: Awagobibtal, Grootfontein MET, Kalidona, Omambonde Tal, Otjikururume, Otjirukaku, Rundu and Simondeum)	Daily meteorological records
2.	Discharge of Omatako Dam (m^3/s)	Hydrological Services of Namibia	Monthly discharge from 1990 – 2008
3.	TanDEM-X Digital Elevation Model (DEM)	German Aerospace Center (DLR)	Relative vertical accuracy of 2 m and a Spatial resolution of 12 m
4.	Land use and land cover (LULC)	Sentinel-2 Products from European Space Agency (ESA) and Directorate of Survey and Mapping (DSM), Namibia	Spatial resolution 10 m

5.	Soil Information	SOTER (Soil and Terrain Database) (Coetzee 2001, M. Coetzee, personal communication, December 6, 2019, Batjes 2004) Updated Soil Map (from Agro-Ecological Zoning)	Scale 1:250 000

2.3.2. Digital Elevation Model

Streamflow simulation is a complex process with several uncertainties arising from input variables, missing assumptions in the model and lack of knowledge on the catchment being modeled (Abbaspour *et al*., 2007; Rostamian et al., 2008). Imperatively, while modelling a large and complex catchment as presented in this study, remote sensing plays a major role to successfully model streamflow. This is especially valid in data poor countries where lack of frequent high-resolution data is not accessible. For this reason and due to the flat terrain characteristics of the catchment in this study, a high-resolution TanDEM-X product was sourced to improve simulation capacity as recommended by (Archer *et al*., 2018). Thus, accurate watershed delineation (stream slopes and total length of streams) and HRU definition were achieved in this study catchment which were further used to simulate the streamflow effectively as established by Buakhao & Kangrang (2016) and Tan *et al*. (2015), where the accuracy of the DEM was sensitive to streamflow.

Due to the flat terrain characteristics of the Namibian Northern regions, elevation data of TanDEM-X from the TerraSAR-X DLR mission was used in the study with a relative vertical accuracy of 2 m and a spatial resolution of 12 m sourced from German Aerospace Center (DLR) (Wessel *et al*., 2018). According to Archer *et al*. (2018), Maharjan *et al*. (2013) and Rizzoli *et al*. (2017), without the High Resolution Terrain Information-3 (HRTI-3) from TanDEM-X, the study area of relatively flat terrain would not define an accurate watershed to create Hydrologic Response Units (HRUs), which are the smallest representation of the basin used in the simulation of streamflow in SWAT. In Figure 2.2, the elevation map of the river basin derived from TanDEM-X is displayed together with the generated sub-basins of the study area.

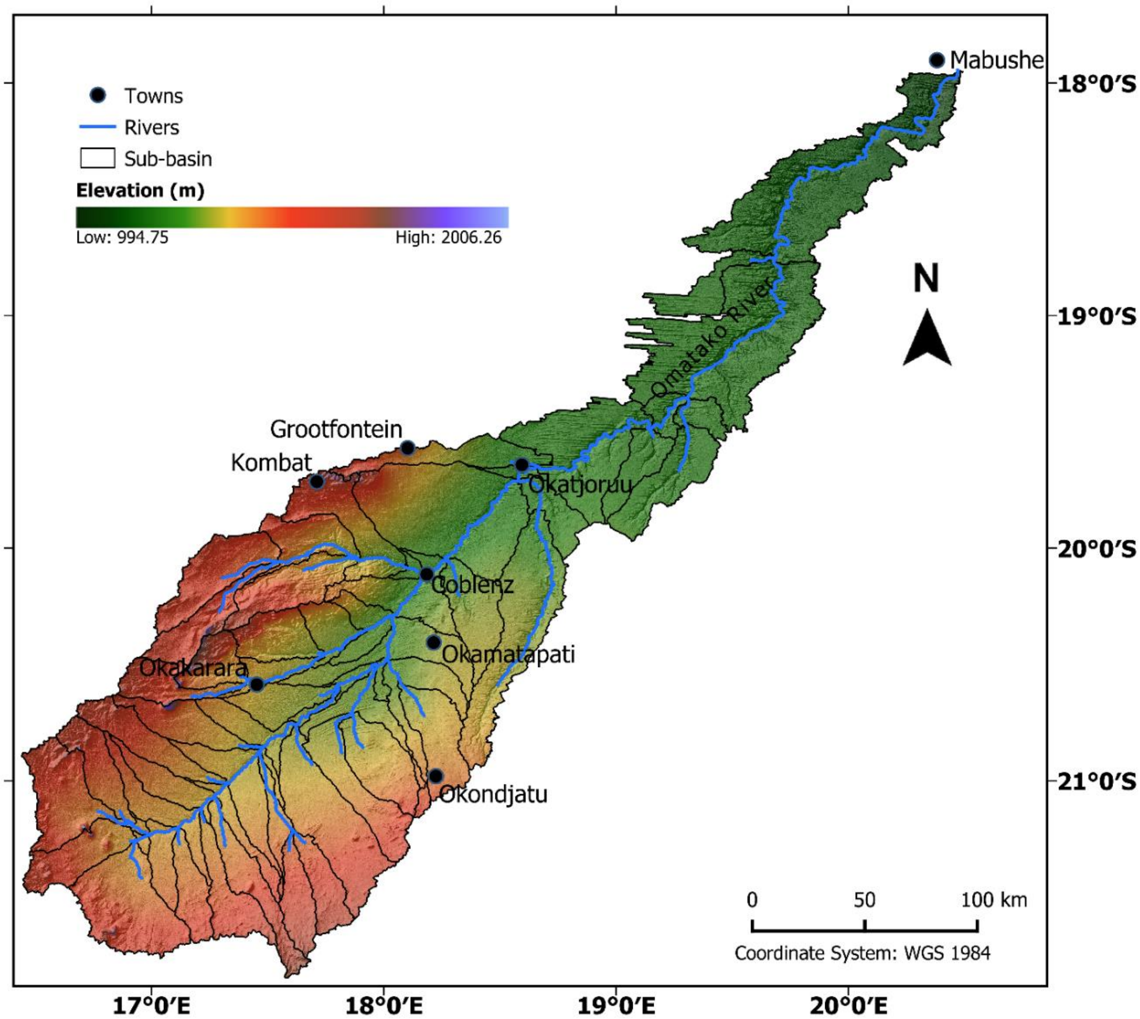


Figure 2.2: Elevation map showing the 60 sub-basins of the Okavango-Omatako catchment.

2.3.3. Land Use Land Cover Mapping

Land use land cover (LULC) is an essential input variable for simulation of streamflow in the SWAT model. An assessment of global LULC products indicated insufficient detail for runoff modelling purpose, therefore a LULC map was generated for the catchment. The LULC was generated using multiple scenes of Sentinel-2-A data of 2017 acquired and mosaicked from Copernicus Sentinel-2 mission (European Space Agency, 2020). This product further attained the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Normalized Difference Built-up Index (NDBI) indices to facilitate the differentiation of vegetation, water and built-up areas. Using high resolution topographic maps obtained from the Directorate of Survey and Mapping (DSM) for the same timeframe as the Sentinel-2 imagery, seven land cover classes (bare land, forest cover, cultivated land, grassland, built-up area, water bodies and bush/shrub) were visually identified. Using polygons of each landcover classes resultantly, a classification training and validation dataset was derived for these classes. Thanh Noi & Kappas (2017) compared and investigated performances of random forest, k-nearest neighbor, and support vector machine (SVM) classification methods for LULC classification with Sentinel-2 and achieved superior accuracy and consistency in their classification results using SVM. Consequently using ENVI 5.5.1 (Harris Geospatial Solutions Inc, 2020), the SVM algorithm was applied to compute the classification and generate a LULC map (see Figure 2.3) of the interest region. For the independent validation dataset, the classification was validated using a Cohen kappa (K) (Cohen, 1960) and overall accuracy assessment (Congalton, 1991). According to Nyeko *et al.* (2010) and Rani & Sreekesh (2019), approximately 80% and 0.8 is the overall accuracy and kappa for LULC to be suitable for input into the SWAT model. The classification for the catchment data was performed with an acceptable overall accuracy of 84% and a kappa coefficient 0.8.

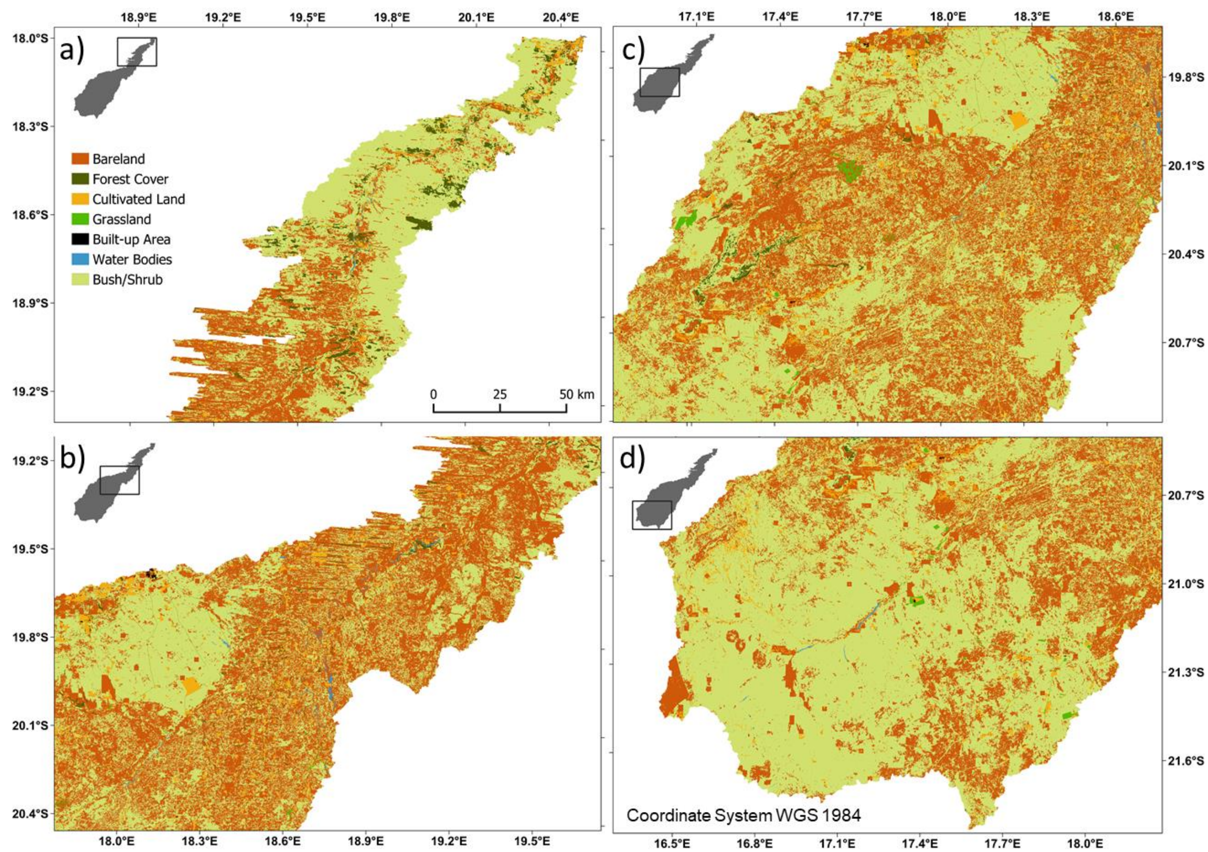


Figure 2.3: Land Use Land Cover (LULC) map of Okavango-Omatako catchment.

2.3.4. Soil Mapping

Soil type information plays a major role in runoff estimation. According to Yang *et al.* (2008), model variable inputs such as soil data and its resolution has an effect on modelling streamflow in SWAT. The Soil mapping of the study area was performed at the scale of 1:250 000 while most of the samples for the profile descriptions was taken along the study area as demonstrated in

(Coetzee, 2001). In this study, soil profile data for the catchment was acquired and significant information was extracted such as texture classes, profile depth, soil types, etc.

Once the watershed delineation of the study area was completed using the boundary of the delineated basin, sixteen soil classes were identified and further categorized into six dominant groups: Cambisols, Regosols, Arenosols, Calcisols, Leptosols and Fluvisols. The soil type distribution over the catchment was mapped as shown in Figure 2.4. Based on the available soil properties for different soil classes, all required information for the model input were calculated.

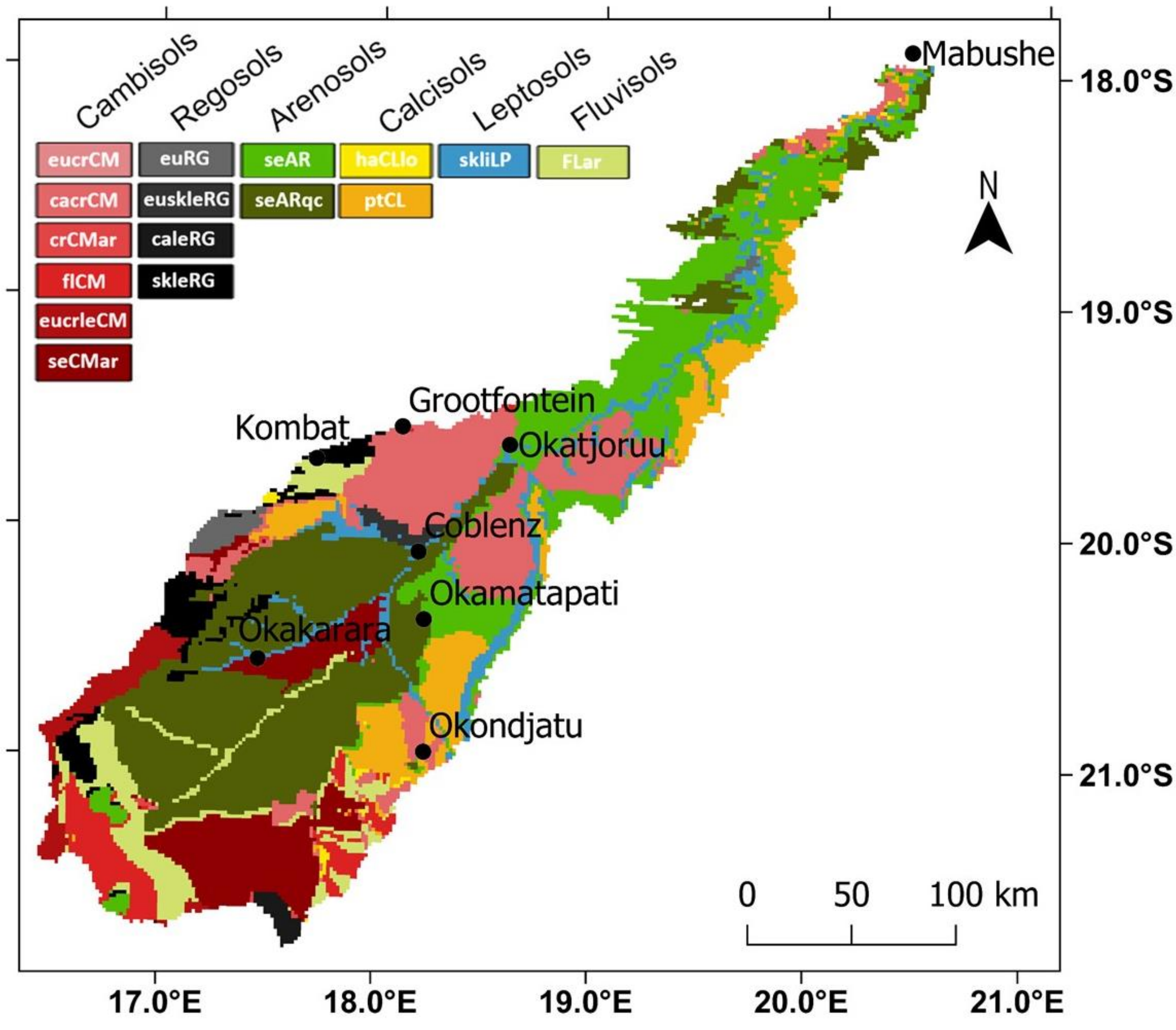


Figure 2.4: Soil classes of the study catchment.

2.3.5. Model Setup and Configuration

A hydrological SWAT model (see Figure 2.5) was employed to simulate the water balance components of different sub-basins in the catchment under study. To this end, the Okavango-Omatako catchment was delineated using the SWAT model. The spatial heterogeneity of the catchment was best modeled through sub-basins and was further divided into HRUs. HRUs represent the smallest spatial units of the catchment with homogenous slope class, soil characteristics and Land use and land cover (LULC) information. HRUs simulated the water balance components with the assumption that different HRUs have different hydrologic characteristics. To execute different SWAT scenarios, the various datasets outlined in Table 2.1 were utilized. These scenarios were thereafter used to simulate the quantity of water in each sub-basin, computed as the total water departing and arriving into the channel at each time step. Using this model, water balance was computed as shown in Equation (1) (Neitsch *et al*., 2011):

$$\boldsymbol{SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{Seep} - Q_{gw}\right)} \quad (1)$$

where SW_t refers to the soil water content at time t, the initial soil water content is denoted by SW_0, R_{day} is the amount of precipitation on day i, Q_{surf} indicates surface runoff on day i, E_a refers to the amount of evapotranspiration on day i, W_{seep} specifies the amount of percolation on day i and Q_{gw} denotes groundwater return flow on day i.

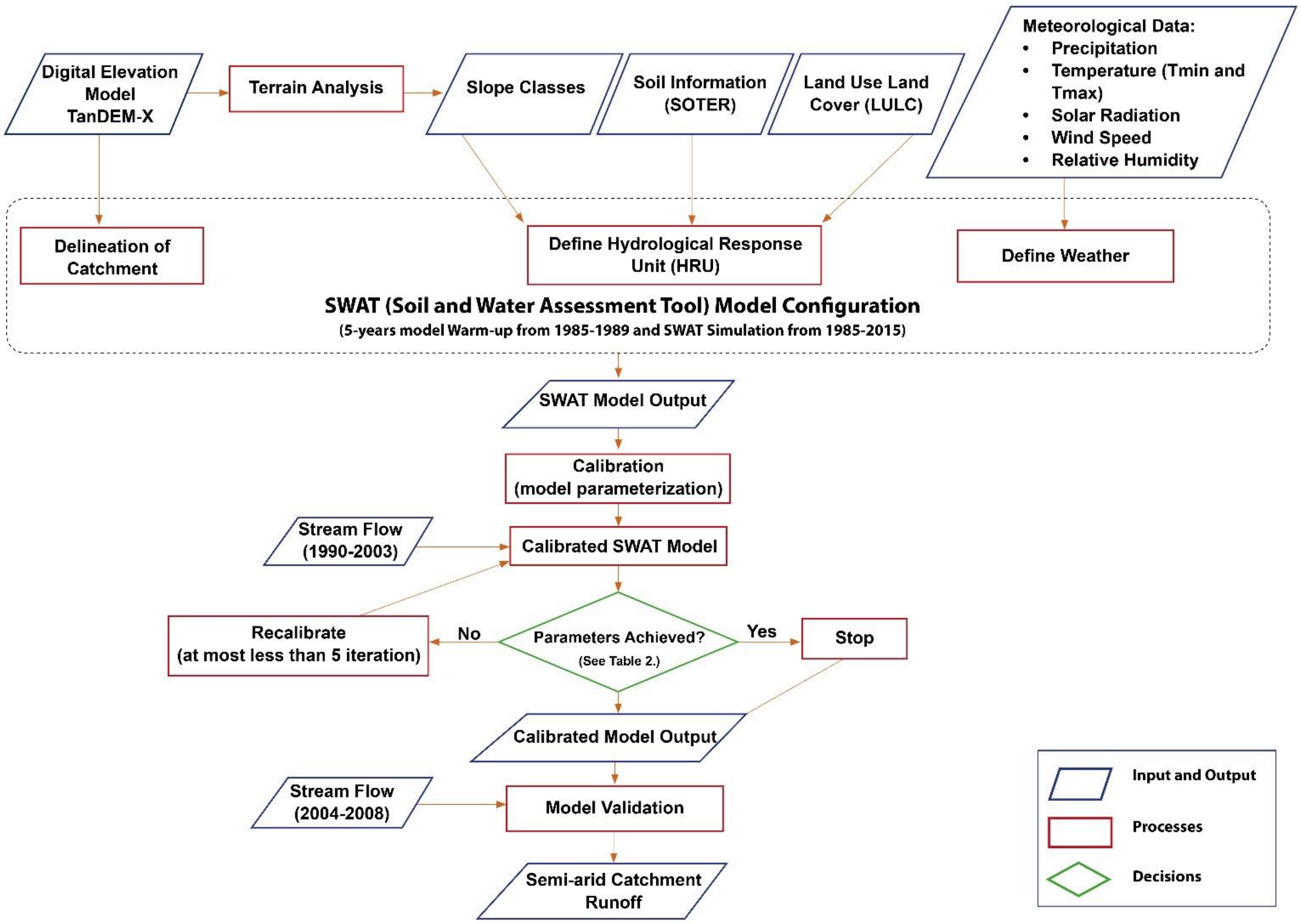


Figure 2.5: Framework of model setup and configuration using SWAT as well as calibration and validation processes in SUFI-2.

Surface runoff originates when precipitation received on the ground surface surpasses the rate of infiltration. The Soil Conservation Service Curve Number also referred to as SCS-CN is used in this study to simulate the surface runoff (USDA 1986). To determine surface runoff CN in a specific location of the catchment during a rain event, the method considers the soil hydrologic group, soil moisture conditions and LULC types. The Penman-Monteith approach (Allen *et al*., 1989; Howell & Evett, 2004) using solar energy, wind speed, humidity and temperature was used to estimate the potential evapotranspiration (PET) for the entire catchment area. Water flowing into the stream network of the basin is simulated using the variable storage routing method developed by (Williams, 1969). The SWAT model setup was adopted to delineate the Okavango-Omatako catchment into sub-basins using the high-resolution TanDEM-X digital elevation product due to its flat terrain characteristics. These processes were followed to fill DEM depressions, compute flow direction and accumulation, which are further used to apply thresholds for stream definition, subsequently determining stream networks and the number of sub basins. Thereafter, HRUs were created using unique combinations of LULC, Soil and Slope information within each sub basin. As discussed in Table 1.1, the precipitation and temperature (Tmin and Tmax) data for eight weather stations optimally distributed throughout the study area were defined and SWAT input tables were created. As a final step, the simulation was performed over 31-years (1985-2015), with a five-year warm-up period (1985-1989). The warm-up is an adjustment process used by the model to achieve a stable state (e.g. streamflow values), as initial conditions of a catchment are usually underestimated during simulation in SWAT (Kim *et al*., 2018). Consequently, the study simulated 26-years (non-inclusive warm-up period) of hydrological parameters of the catchment.

2.3.6. Parameter Sensitivity Analysis

Sensitivity analysis of parameters is the main driving force for a successful application of streamflow simulation (Mengistu *et al*., 2019; Thavhana *et al*., 2018). Sensitivities of parameters are computed through regression between parameters and the objective function. This process calculates the mean change in the objective function which results from changes in each parameter. Twelve parameters were selected through a careful review of related literatures and considering the semi-arid characteristics of the area under study. The parameters, i.e., CN2, OV_N, FFCB, ESCO, EPCO, CH_K2, CH_N2, ALPHA_BF, GW_DELAY, GWQMN, SURLAG and MSK_CO1 (abbreviations are explained in Table 2.3) were chosen based on their sensitive behavior to streamflow (Aqnouy *et al*., 2019; Desai *et al*., 2021; Mengistu *et al*., 2019). The list of parameters associated with streamflow was applied for further evaluation in a calibration process. Thereafter, a sensitivity analysis was performed by considering the changes in the objective function as a result of the sensitivity of one parameter to other parameters, which determines its influence on streamflow. The *t-stat* and *p-value* are used to quantify the sensitivity of a parameter and its significance. A higher *t-stat* value and a lower *p-value* demonstrates a more sensitive streamflow in the catchment (Abbaspour, 2015; Arnold *et al*., 2012).

2.3.7. Calibration, validation, and uncertainty analysis

Evaluation of hydrological models are performed, using performance criteria through comparison of simulated variables or processes in the basin against measured data. The model calibration and validation are the final vital step to assess the accuracy of the runoff simulation. Once the simulation process is completed in SWAT, the hydrological model undergoes calibration and uncertainty analysis as shown in Figure 2.5. SWAT Calibration and Uncertainty Procedures (SWAT-CUP) was employed for further processing, which is a program with five different algorithms commonly used in calibration and validation of simulated hydrological models. Large-scale and complex models usually make use of the Sequential Uncertainty Fitting also known as SUFI-2 due to its efficiency and reliability (Yang *et al*., 2008), especially when compared with deterministic approaches to calibration (Abbaspour, 2015). Given the scale and complexity of our catchment, the study therefore used this stochastic approach. In this algorithm, ranges associated with uncertainty of all variables convey the uncertainty of each parameter by considering the conceptual model, the data measured and its parameters. Uncertainties in parameters lead to uncertainty in model output which are commonly expressed in SUFI-2 by 95% probability distributions which are computed between 2.5% and 97.5% of cumulative distributions for an output variable. This is referred to as 95% prediction uncertainty or a confidence interval (95PPU). This output acquired from the stochastic calibration approach is the most suitable solution at 95% significance level, generated from specified parameter intervals and defined by the modeler.

The calibration and validation process in this study was performed using the split-sample approach with monthly streamflow data from Omatako gauge station used for the period 1990-2003 (calibration) and 2004-2008 (validation). This was performed to evaluate the efficiency of streamflow simulation compared to the observed data. The splitting of observed data based on time-period ensures data independence to assess the model performance. Moreover, the selected period for calibration and validation process was due to lack of in-situ data spanning the model duration. During calibration (1990-2003), four iterations each with no less than 500 simulations were executed to refine the model parameters (Abbaspour, 2015; Hajati *et al*., 2020). With each iteration performed, values of each parameter range become smaller approaching the best solution and achieving better models than previous iterations. According to Abbaspour (2015) the best solution is usually achieved within the above stated iteration. Thereafter, independent observed data can be used to validate the 2004-2008 period. During this process, the exact calibrated parameter ranges and same simulation quantity as defined in the final calibration was repeated, aimed to assess model performance. The calibration and validation results were both quantified using statistics known as *P-factor*, *R-factor*, and objective function value (Abbaspour, 2015; Abbaspour *et al*., 2004). As expressed by Abbaspour (2015), in SUFI-2, a good fit between observation and simulation results is conveyed using two indices '*P-factor*' and '*R-factor*'. *P-factor* refers to the observed data enveloped by 95% prediction uncertainty. While the *R-factor* refers to the thickness of the 95PPU. The *P-factor* is measured between 0 – 1 with 1 being the perfect result indicating 100 % of the observed data enveloped in the 95PPU, while 0 being the worst with none of the observed data represented within the envelope. In the case of *R-factor*, possible values range between zero and infinity. The recommended value for *R-factor* is less than 1.5 for streamflow, (Abbaspour *et al*., 2004, 2015), whereas *P-factor* is acceptable with values greater than 0.7. However, the former depends on the project scale, input data, etc. Hence, the above indices can evaluate the goodness of fit between our observed and simulated results in the calibration and validation process. Values slightly outside the acceptable range are still possible, as the recommended values are not necessarily fixed numbers, rather a quest to reach a balance between *R-factor* and *P-factor* (Abbaspour, 2015).

In this study the good agreement between the observed and simulated streamflow is evaluated through the objective function Nash-Sutcliffe coefficient (NSE) as shown in Equation (2),

$$\boldsymbol{NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{observed} - Q_{simulated})_i^2}{\sum_{i=1}^{n}(Q_{observed} - \bar{Q}_{Observed})^2}} \tag{2}$$

Coefficient of determination (R2) as shown in Equation (3),

$$\boldsymbol{R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{observed,i} - \bar{Q}_{observed})(Q_{simulated,i} - \bar{Q}_{simulated})\right]^2}{\sum_{i=1}^{n}(Q_{observed,i} - \bar{Q}_{Observed})^2 \sum_{i=1}^{n}(Q_{simulated,i} - \bar{Q}_{simulated})^2}} \tag{3}$$

Percent bias (PBIAS) as shown in Equation (4), and

$$P_{BIAS} = 100 * \frac{\sum_{i=1}^{n}(Q_{observed} - Q_{simulated})_i}{\sum_{i=1}^{n} Q_{observed,i}} \tag{4}$$

Ratio of RMSE to the Std. Dev. of observed data (RSR) as shown in Equation (5).

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}(Q_{observed} - Q_{simulated})_i^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_{observed,i} - \bar{Q}_{observed}\right)^2}} \tag{5}$$

Where Q is the variable under observation or simulation, i.e. discharge, $Q_{observed}$ and $Q_{simulated}$ are discharge data, which have been measured and simulated respectively, while n refers to the number of total records and $\bar{Q}_{observed}$ denotes the average measured data while i is the ith measured or simulated data. Similar to the *P-factor* and *R-factor*, there are no specific numbers to achieve, however, the recommended values for watershed scale (Gupta *et al*., 2009; Hajati *et al*., 2020; Moriasi *et al*., 2007, 2015) are as follows; $R^2 > 0.6$,$NSE > 0.5$ and $P_{BIAS} < \pm 25\%$. Hence, the model performance is evaluated as per the performance rating criteria listed in Table 2.2.

Table 2.2: Performance Rating for a Monthly Time Step adopted from (Koycegiz and Buyukyildiz, 2019; Moriasi D. N. et al., 2007)

Model Performance Rating	RSR	NSE	R^2	PBIAS
Very Good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	$0.75 < R^2 \leq 1.00$	$PBIAS < \pm 10$
Good	$0.50 < RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$0.60 < R^2 \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < NSE \leq 0.65$	$0.50 < R^2 \leq 0.60$	$\pm 15 \leq PBIAS < \pm 25$
Unsatisfactory	$RSR > 0.70$	$NSE \leq 0.50$	$R^2 \leq 0.50$	$PBIAS \geq \pm 25$

2.4. Results and Discussion

2.4.1. Results of SWAT

In the process of delineation, the catchment was divided into 60 sub-basins and further subdivided into 762 HRUs. The simulation was executed for a 31-year period between 1985 and 2015 with the initial five years from 1985-1989 used as model warm-up. The simulated results showed precipitation in the basin to be low and potential evapotranspiration being expectedly high for simulated timeframe. During the simulation, the ratio of surface runoff to total flow was very low at 0.27, the evapotranspiration to precipitation recorded was 0.57, and the baseflow to total flow ratio was a high 0.73. These results clearly show that the surface runoff was very low and most of the precipitation was lost to the shallow aquifer and the evapotranspiration process.

2.4.2. Sensitivity Analysis

Out of the twelve parameters discussed above (i.e., parameter sensitivity analysis), three parameters appeared to be highly sensitive to streamflow in the Okavango-Omatako catchment. The most sensitive appeared to be the runoff curve number controlling the surface runoff followed by ground water delay time and baseflow alpha factor influencing the baseflow of the semi-arid catchment during the period 1990-2003. Many of the studies performed in arid and semi-arid environments also confirmed these results with Esmali *et al*. (2021) observing runoff curve number (CN2) ranked the most sensitive in different climatic zones including semi-arid and arid, while ground water delay (GW_DELAY) was found to be most sensitive in arid and baseflow alpha factor (ALPHA_BF) in semi-arid environment. Additionally, Aqnouy *et al*. (2019) and Desai *et al*. (2021) noted that out of the three above parameters, two were the most significant in a semi-arid environment in Morocco and India. The sensitivity analysis as indicated by the *t-stat* and *p-value* in Table 2.3, showed CN2, GW_DELAY and ALPHA_BF as the most sensitive parameters in our catchment. The results agree with similar findings by Thavhana *et al*. (2018) and Koycegiz and Buyukyildiz (2019), Mengistu *et al*. (2019) and Leng *et al*. (2020) on frequently considered parameters which are amongst the most sensitive in the global sensitivity analysis for hydrological processes of semi-arid catchments. The remaining nine parameters were less sensitive with higher p-values and a lower t-stat.

Table 2.3: Parameters and range of values used in the calibration.

Parameter	Description	Parameter Range	Fitted Value	t-Stat	p-Value
CN2	**SCS runoff curve number f**	**-0.2 – 0.2**	**-0.1804**	**-11.697**	**0.000**
OV_N	Manning's "n" value for overland flow	-1.5 – 1.5	-0.273	1.496	0.135
FFCB	Initial soil water storage expressed as a fraction of field capacity water content	0.12 – 0.69	0.20037	-0.102	0.919
ESCO	Soil evaporation compensation factor	0 – 1	0.269	0.570	0.569
EPCO	Plant uptake compensation factor	0.3 – 1	0.9293	0.496	0.620
CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/h)	2 – 140	82.729996	-1.457	0.146
CH_N2	Manning's "n" value for the main channel	0.25 – 0.76	0.73807	0.453	0.651

ALPHA_BF	**Baseflow alpha factor (days)**	**0 – 1**	**0.135**	**-6.334**	**0.000**
GW_DELAY	**Groundwater delay time (days)**	**30 – 450**	**189.179993**	**7.923**	**0.000**
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).	0 – 2	0.142	-0.195	0.845
SURLAG	Surface runoff lag time	0 – 20	13.86	1.349	0.178
MSK_CO1	Calibration coefficient used to control impact of the storage time constant for normal flow	0 – 10	0.43	-0.274	0.785

The sensitivity analysis yielded *t-stat* and *p-value* for the model parameters as shown in Figure 2.6. The most dominant significance with the highest *t-stat* and a low *p-value* were seen in CN2, GW_DELAY and ALPHA_BF. The parameter CN2 also known as the SCS runoff curve number is used to determine runoff values for the catchment and are found to be the most sensitive parameter with a low *p-value* ($p < 0.05$) and a high *t-stat*. According to USDA (1986), this parameter has been used to characterize antecedent runoff conditions in arid and semi-arid watersheds. Following CN2, ALPHA_BF, a parameter affecting base flow, was classed to be sensitive to streamflow in the semi-arid catchment. The ALPHA_BF fitted value of 0.135 reveals a slow recharge response rate as discussed by Miskewitz (2007), constituting a slow baseflow in the catchment. The next sensitive parameter is GW_DELAY, which is highly influenced by the catchment area size under consideration. The parameter measures the time for water to percolate and reach the water table, being 189 days in this catchment. The remaining nine parameters (OV_N, FFCB, ESCO, EPCO, CH_K2, CH_N2, GMQMN, SURLAG and MSK_CO1) were found to be less sensitive to streamflow estimation causing increased model uncertainties in the study area. As part of this study, a further in-depth investigation which identifies parameter sensitivity to semi-arid environments similar to this study catchment will be valuable for better model performance in streamflow estimation.

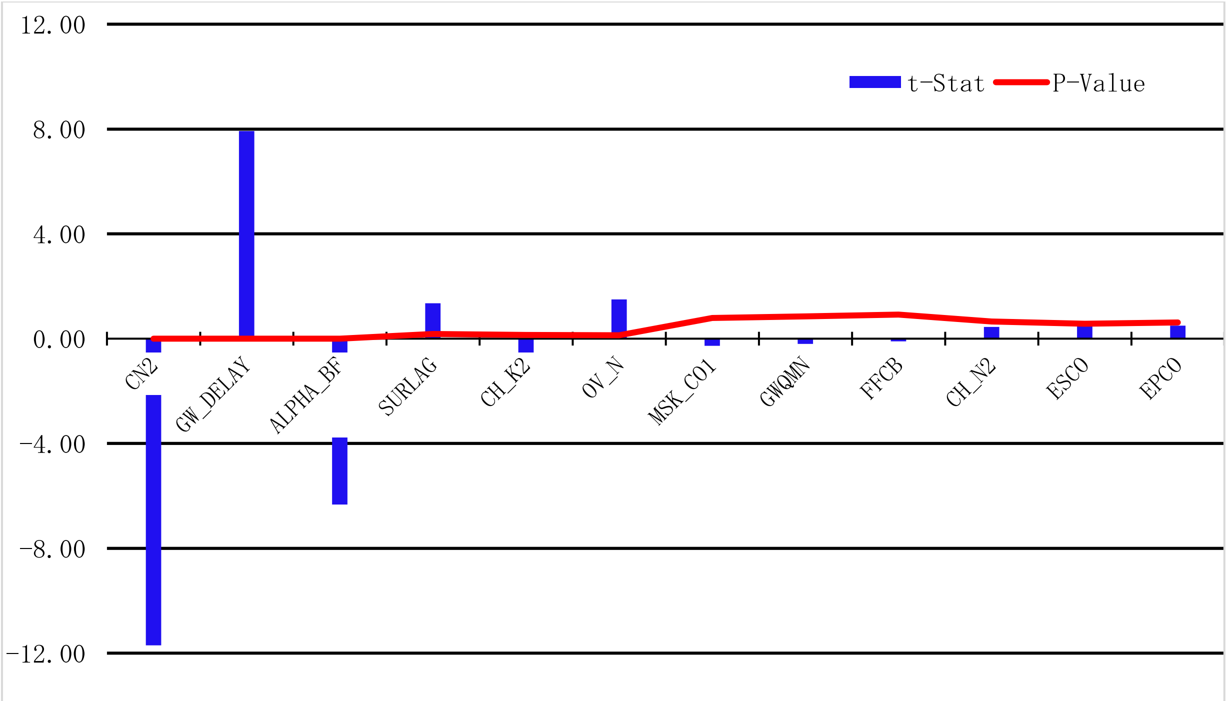


Figure 2.6: Parameters sensitivity analysis (t-stat and p-value) of SWAT simulation for the Okavango-Omatako catchment.

2.4.3. Model Calibration

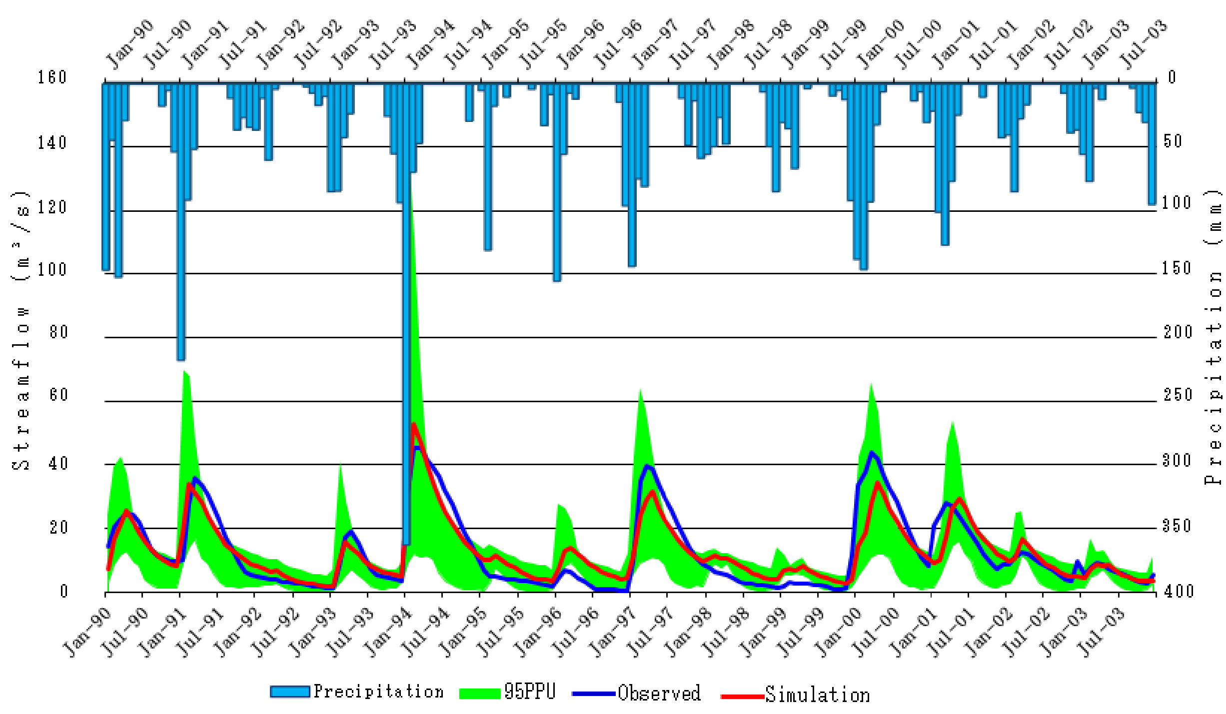
The output of the calibration illustrated the capacity of SWAT to simulate streamflow in this study catchment. The 95PPU illustrated in Figure 2.7(a), with green in the calibration processes displays the uncertainty of this model through computation of the *P-factor*, and *R-factor* indicators. As shown in Table 4, the *P-factor* estimate was 0.77, thus 77% of the observed discharge lies in the 95PPU bracket for the period of calibration, from 1990-2003. Whereas 95PPU bracket thickness was measured by the *R-factor*, which was 1.31, resulting in both indicators meeting the optimum value as determined by Abbaspour *et al*. (2015). During the calibration process, the study achieved the best model between observed and simulated streamflow. It is also apparent from Figure 2.7(a) that the observed mainly falls outside the 95PPU during the descent cycle of streamflow, demonstrating the start of the flow modelled very well as opposed to the end of the seasonal flow. In general, the model also performed well in simulating high and low flows between the observed and simulated streamflow.

In addition to the above model performance parameters, all other performance indicators for the model calibration (Table 2.4) scored between good to very good according to the evaluation criteria outlined in Table 2.2 (Koycegiz & Buyukyildiz, 2019; Moriasi *et al*., 2007). The model performance indices evaluated the agreement between simulation and observation of our catchment as presented in Table 2.4. The objective function used in this study to evaluate the model performance for the period 1990 to 2003 was Nash-Sutcliffe efficiency (NSE) with a calibration of 0.82. These results depict the model simulation success with good results produced according to the model performance evaluation criteria listed above in Table 2.2. Additionally, other performance indicators such as Coefficient of determination (R^2), Percent bias (PBIAS) and residual variation (RSR) were similarly used to evaluate the model. The calibration results as presented in Table 2.4, with R^2 (0.84) achieved very good performance rating for the recommended statistics on a monthly basis. The PBIAS scored (-1.1), ranking very good on the calibration while the RSR (0.42) also performed very well with values below 0.5 as recommended by (Arnold *et al*., 2012; Fernandez *et al*., 2005; Mengistu *et al*., 2019; Moriasi *et al*., 2015).

Table 2.4: Result from calibration and validation.

	Calibration	**Validation**
P-factor	0.77	0.68
R-factor	1.31	1.82
R^2	0.84	0.89
NSE	0.82	0.80
PBIAS	-1.1	-20.0
RSR	0.42	0.44

a)



b)

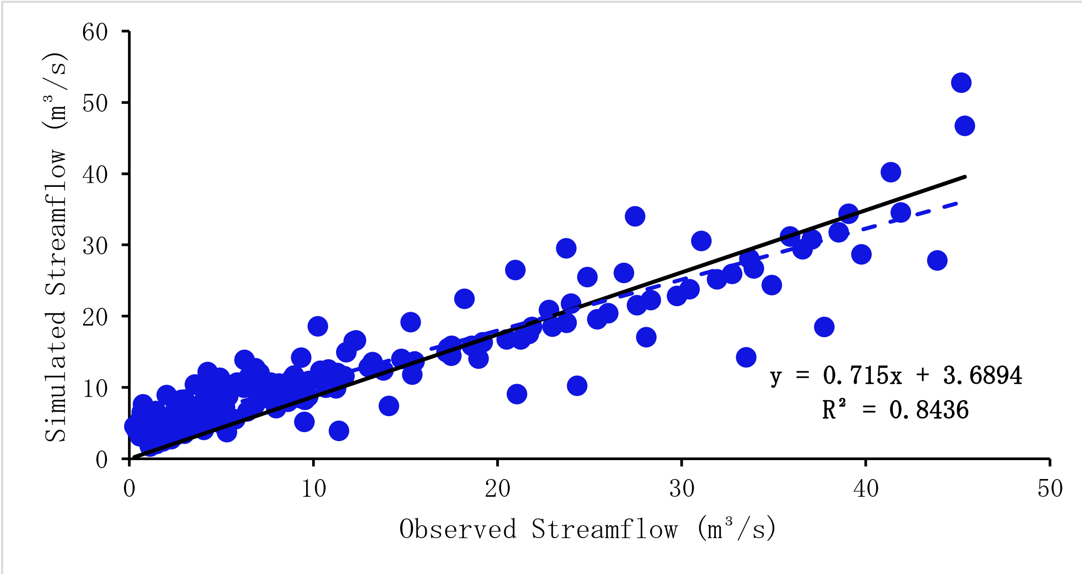


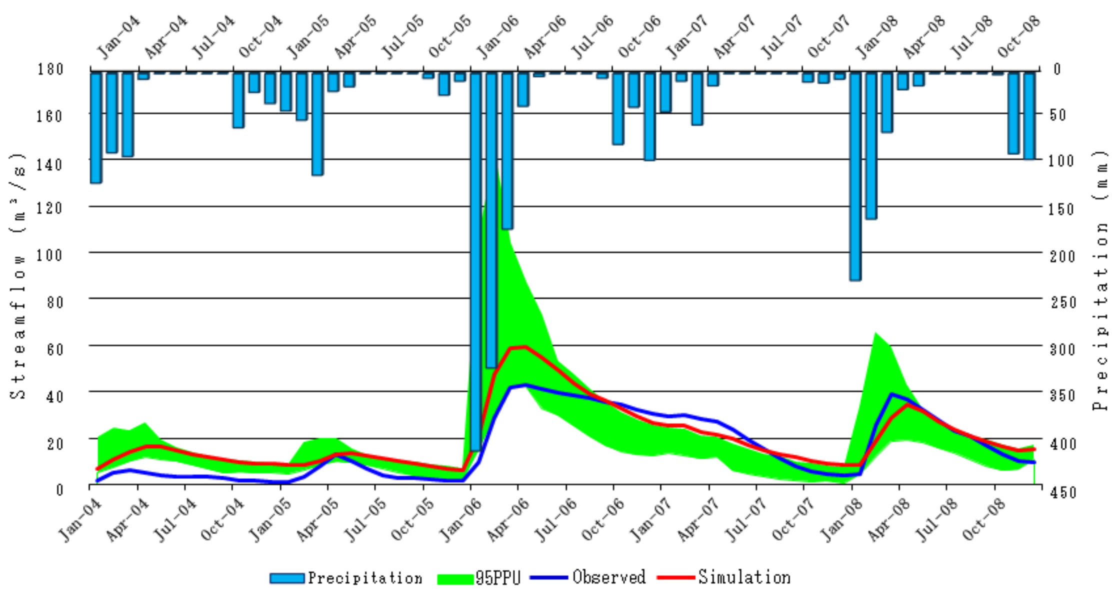
Figure 2.7: (a) Observed vs simulated monthly stream flow and (b) Scatter plot showing correlation between the observed and simulated for the calibration period (1990 - 2003)

According to Figure 2.7(b), the scatter plot representing measured vs simulated discharge, visualizes the success of the model performance. Coefficient of determination (R2) of the scatter plot shows 0.84 for calibration, indicating a higher correlation between observed and simulated data during the calibration period. However, in Figure 2.7(a) an overestimation during low flow periods were observed. While high flows were simulated satisfactorily, closely matching the observed values, excluding few cases of the peak flow estimations which were slightly underestimated. These findings agree with similar studies by (Koycegiz & Buyukyildiz, 2019; Thavhana *et al*., 2018; Vilaysane *et al*., 2015).

2.4.4. Model Validation

The validation process compared the simulated discharge of a selected outlet of a sub-basin with observed discharge measured at gauge station nearby, plotted in Figure 2.8(a) with corresponding precipitation data from the closest meteorological station. As outlined in the methods, the model validation was carried out using in-situ data from 2004 to 2008. The results were a *P-factor* of 0.68 (i.e., 68% of the observed discharge was bracketed by the modelling result of 95PPU), and *R-factor* of 1.82 (i.e., the 95PPU bracket thickness). In both cases, the results were unable to achieve the recommended values of (Abbaspour, 2015), which were set to be greater than 0.7 for *P-factor* and less than 1.5 for *R-factor*. These optimum values as endorsed by Abbaspour *et al*. (2015) act more of a guide rather than absolute numbers which must be achieved. The values are dependent on project scale and availability of input and calibration data as mentioned in (Abbaspour *et al*., 2015; Beharry *et al*., 2021; Musyoka *et al*., 2021; Pontes *et al*., 2021). In the validation process the *R-factor* recorded a value > 1.5, which was found to be satisfactory due to the large size of the study area under consideration and limited calibration data availability. Moreover, the recorded *R-factor* above the recommended value could be attributed to low flow during the years 2004-2005, especially when compared with peak-flow characteristics during the calibration period. Pontes *et* *al*. (2021) also recorded similar results during the evaluation of SWAT model to simulate monthly streamflow in a catchment in Brazil. Nonetheless, the objective function results in the validation process achieved NSE of 0.8, R^2 of 0.89 and RSR of 0.44 with all three scoring in the very good category as stipulated by (Moriasi *et al*., 2007). While the model indicated a PBIAS of -20.0 falling within a satisfactory range for validation as stated by (Koycegiz & Buyukyildiz, 2019; Moriasi *et al*., 2007). Similarly, the validation also demonstrated poor performance at the end of a streamflow season, but also at times during low flow by falling outside the 95PPU bracket.

a)



b)

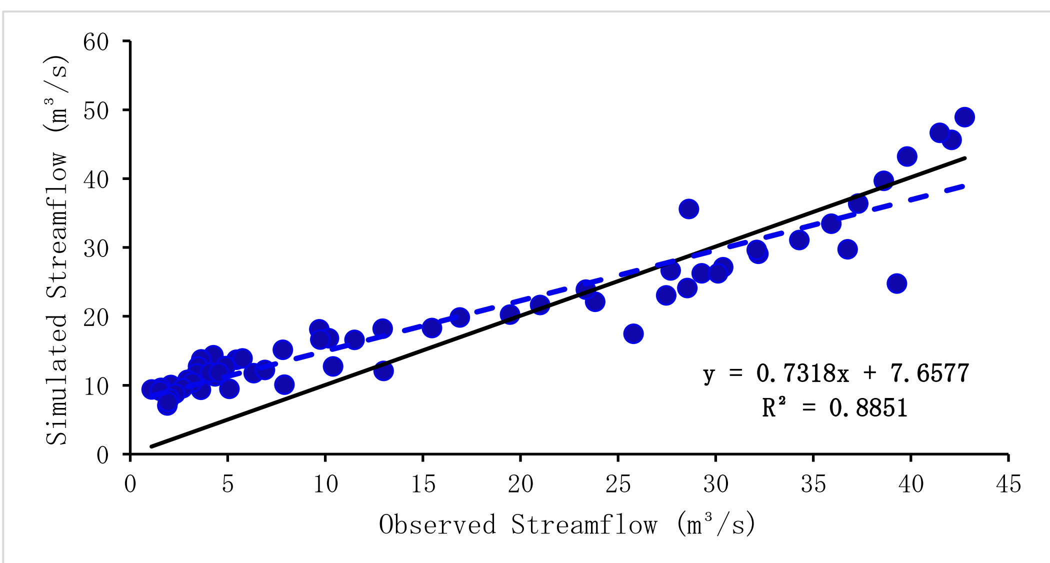


Figure 2.8: (a) Observed vs simulated monthly stream flow and (b) Scatter plot showing correlation between the observed and simulated for the validation period (2004 - 2008).

Coefficient of determination (R2) of the scatter plot in Figure 2.8(b) attained 0.88 indicating a positive correlation between observed and simulated data during the validation period. This result indicates the success of the model performance. However, in Figure 2.8(a) a high overestimation during low flow years were seen while closely matched results between simulated and measured streamflow during peak flow years were observed.

2.4.5. Model Performance Evaluation

A SWAT hydrological model was setup and implemented for a semi-arid catchment in Namibia to evaluate model performance for streamflow estimation. The model was calibrated using the limited available observed river discharge data. Despite the simulation for the study area carried out from 1985 to 2015, the calibration and the validation processes could only be implemented for the periods 1990 to 2008 due to inconsistencies and missing observed discharge data subsequent to this period. Such limitations were also observed by Terskii *et al*. (2019) in a similar study. Thus, reliable discharge observation stations collecting long term flow data could go a long way in modelling catchments similar to our study area.

The general performance of the model as indicated through the values achieved by the different indicators has a good agreement between the observed and simulated streamflow. 95PPU for the calibration and validation processes for the period of study with its corresponding rainfall records are shown in Figure 2.7(a) and 2.8(a). It is apparent that after intensive rain occurred, an increased streamflow was observed thereafter. However, this was not the case for all the years of calibration, which could be attributed to climate conditions such as high evapotranspiration, high percolation, abstraction, etc. Despite this, one can still observe the simulated data, predominantly falling within the confidence interval. Similar findings were observed by Koycegiz & Buyukyildiz (2019) and Mengistu *et al*. (2019), while modelling runoff in a semi-arid catchment, both studies observed an increased flow following a high rainfall event confirming the outcome of simulation in this study.

Prediction uncertainty is used to quantify the agreement between simulated and observed results. The *P-factor* value for calibration was adequate while the validation value was near the recommended value of 0.7 (Abbaspour *et al*., 2015). Similarly, the *R-factor* value of the calibration was within the acceptable range while the validation is slightly on the upper side of the recommended value of 1.5. This could be dependent to and highly attributed to the scale of the project as demonstrated in (Abbaspour *et al*., 2007, 2015). Hence, the results of this study can be considered to have lower uncertainty in the calibration and slightly higher uncertainty in the validation process. As stated by Abbaspour *et al*. (2015) while calibrating a continental scale hydrological system, a large-scale catchment as demonstrated in our study could attain slightly higher or lower results than the ranges of the recommended value. Abbaspour *et al*. (2015) and Beharry *et al*. (2021), Musyoka *et al*. (2021) and Pontes *et al*. (2021) demonstrated that a high *R-factor* could also occur due to lack of sufficient data for model calibration. To this end, the modelling of the Okavango-Omatako catchment has been challenging due to the quality of input and calibration data with uncertainties leading to a high *R-factor*.

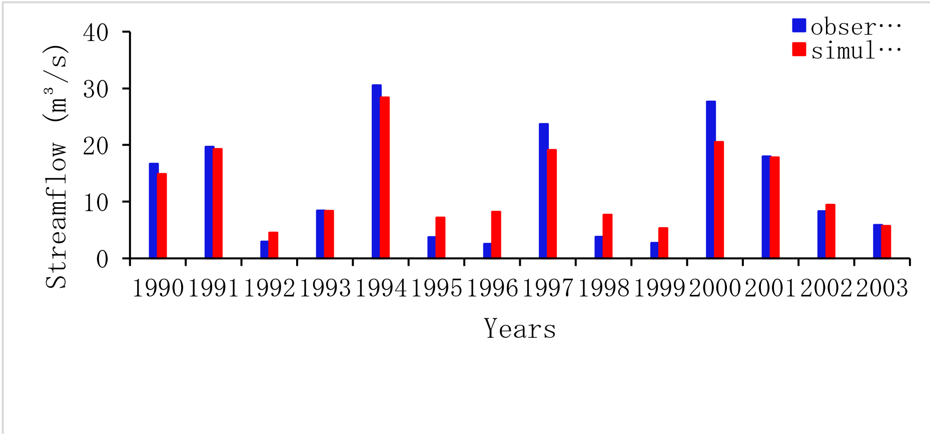
The model performance indicators used the NSE, R^2, PBIAS and RSR while results were ranked according to (Koycegiz & Buyukyildiz, 2019; Moriasi *et al*., 2007). All indicators achieved a very good performance rating with exception of PBIAS validation rated as satisfactory. Similar to

Abbaspour *et al*. (2015), Mengistu *et al*. (2019) and Moriasi *et al*. (2007), the results indicate a good overall achievement of model performance within the study area with a good level of agreement between observed and simulated streamflow. Taking a closer look, the PBIAS index reveals that the model underestimated streamflow in the process of simulation by 1.1% and 20% respectively for calibration and validation, when compared with observed data. Simulated and observed streamflow for both calibration and validation are demonstrated in Figure 2.7(a) and 2.8(a), respectively. The model is capable of simulating low and high flows satisfactorily, closely matched to the observed values. However, in some cases the peak flow estimation slightly falls short in the calibration period. These findings are cohesive to similar studies by (Koycegiz & Buyukyildiz, 2019; Thavhana *et al*., 2018; Vilaysane *et al*., 2015). Consequently, low flow might have caused an above limit *R-factor* in our catchment as supported by Musyoka *et al*. (2021) and Pontes *et al*. (2021), during the evaluation of SWAT model to estimate monthly streamflow in the dry season of their respective study areas.

After a careful assessment of the simulated versus observed results, the performance of SWAT to effectively model a large complex semi-arid catchment with scarce in-situ data was found to be satisfactory, demonstrating the potential of simulating future streamflow events. This indicates the effectiveness and further exploration of this model to assess impacts of climate change in similar catchments within the region. However, evident limitations are seen in overestimated low flows during calibration and validation timeframes, which are vital for extrapolation to forecast and assess climate change impacts. From a catchment management perspective, the model fairly estimated the peak flow in the calibration period verifying its capacity to be used as a water management tool, except in few cases where underestimations occurred. Further investigations into streamflow intensity and time lag between streamflow events are essential for water resource managers. Another relevant factor which must be considered as a potential impact on catchment flow characteristics are the changes in LULC. In this study, the temporal changes of LULC were not examined. However, the significance of a time-series analysis of the catchment's LULC cannot be refuted and could go a long way in understanding its impacts on streamflow behavior. This study thus proposes a subsequent investigation on this matter.

One of the limitations in this study is the inadequacy to evaluate parameter sensitivity in the entire catchment. The uncertainty analysis of our model estimation can only be quantified in locations of the sub-basin where calibration was performed. Therefore, results in areas further away from calibrated portions should be examined attentively. One of the reasons for such limitation is the lack of data for use in the calibration process. An alternative, which should be considered to overcome such limitation, is the calibration using other variables such as available remotely sensed evapotranspiration and soil moisture as successfully demonstrated by Emam *et al*. (2017) and Rajib *et al*. (2016), respectively. The sensitivity analysis found three parameters to have a dominant influence in the model parameterization for the catchment under investigation. Water resource managers in the area should collect these essential parameters (i.e., the runoff curve number, ground water delay time and baseflow alpha factor) to improve model performance.

a)



b)

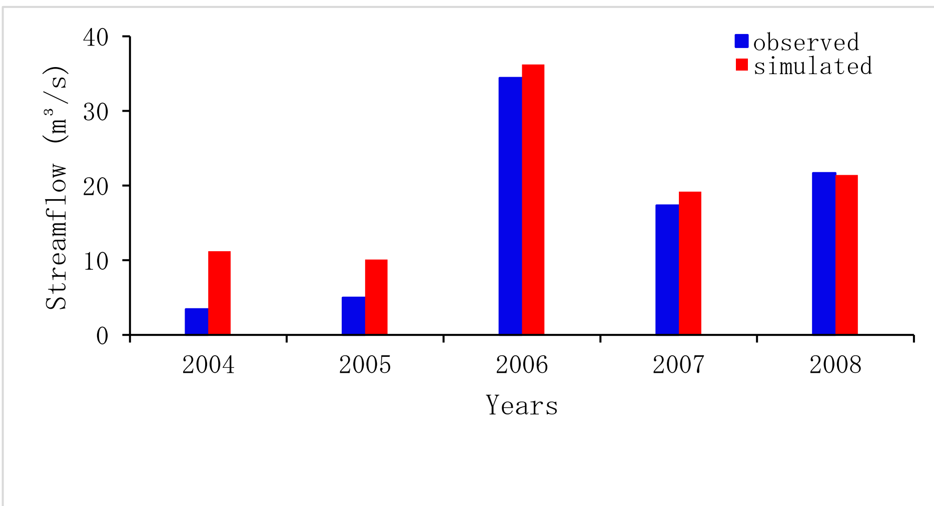


Figure 2.9: Annual monthly average streamflow of observed and simulated (a) during the calibration period (1990 - 2003) and (b) during the validation period (2004 - 2008).

Annual monthly average streamflow displayed in Figure 2.9(a) and 2.9(b), demonstrates variation of observed and simulated streamflow values with an average overestimation of 1.03% and 16.63% for the calibration and validation periods respectively. The model inclination to overestimate low flows is evident, especially for the periods of 1992, 1995, 1996, 1998, 1999, 2002, 2004 and 2005. The result is confirmed by similar investigations in Tegegne *et al. (2017),* Thavhana *et al*. (2018) and Turkmen *et al*. (2021), and is critical that the model is modified to handle low flows or adjoined with other models for improved estimates. The peak flows were estimated more reasonably and closely matched the observed values with slight underestimations. Bearing the adequate performance of the model estimation and results in mind, hydrological simulation in a semi-arid environment such as Okavango-Omatako catchment can be performed using modified SWAT and/or coupled with other models to manage scarce water resources in the region.

2.5. Conclusion

This study evaluated streamflow responses of selected parameters in the Okavango-Omatako catchment and recommends future work to explore the dynamics of the Okavango River basin starting from southern Angola through the northeastern part of Namibia and dissipating in the Okavango delta. Further, to understand the hydrological systems in this area, the link to climate systems such as El Nino/La Nina, Southern Oscillation (ENSO) and Sea Surface Temperature (SST) in the Atlantic and Indian Ocean should be investigated. These links are recommended by Landman & Mason (1999), Namibia Resource Consultants (1999) and Orti & Negussie (2019) to impact the management of water resources in this semi-arid environment, but have not been investigated to date.

It is paramount to understand hydrological systems and their characteristics as well as various parameters which influence these systems. A major part of this process is to recognize the spatial and temporal patterns of precipitation, evapotranspiration, LULC and soil moisture. The varying spatial distribution of these variables in the catchment creates a challenge in simulating streamflow. Serious deficiencies during the modelling process merged from the lack of knowledge on the catchment's physical environment. The need for more comprehensive research to better understand the hydrological processes on catchments in Namibia is obvious. This research is necessary to sustainably use water resources and support water resource managers for efficient planning and management of this scarce resource. This study further recommends the sensitivity of parameters in the catchment under study to be evaluated as familiarities could contribute to a better understanding of streamflow processes.

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Chapter 3: Modeling Future Streamflow under Climate and Land Use Scenarios in the Lower Okavango River Basin

Kaleb Gizaw Negussie, Daniel Wyss and Martin Kappas

Abstract

Among the most pressing drivers of hydrological change in data scarce regions are climate and land use/land cover (LULC) change. In this study, the SWAT+ hydrological model was used to assess the projected streamflow response of the lower Okavango River Basin under combined climate and LULC change scenarios. The model was calibrated and validated using long-term historical records (1981-2015) from guage station near Rundu. Downscaled climate projections from four CMIP6 GCMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, NorESM2-MM) and global land use simulations with a resolution of 1 km have been integrated under two scenarios: a regional climate model and a global land use model: SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions). Projections indicate a 5–20% decrease in precipitation, with a more substantial decline, reaching up to 60%, anticipated in streamflow by the year 2100. Projections indicate that dry season flows will nearly cease, thereby confirming the "dry gets drier" paradigm. It is projected that the water yield will be increasingly concentrated along river corridors, with the majority of the basin experiencing an annual water volume of less than 129 mm by the end of the century. Projections indicate that the expansion of cropland will exceed 65% of the basin area, replacing wetlands and natural vegetation. The results confirm that in semiarid regions, where evapotranspiration and infiltration processes are closely linked to vegetation and soil cover, the sensitivity of streamflow to both precipitation and land cover dynamics is particularly acute. The study highlights the need for transboundary coordination, especially between Namibia and Angola, and underscores the vulnerability of downstream dependent hydrological systems. It also provides support for integrated land and water management through scenario-based modelling and underlines the urgent need for nature-based adaptation strategies and an improved regulatory framework for climate resilient water management in the Okavango Basin.

Keywords: Climate change, Land use land cover change (LULCC), Streamflow simulation, SWAT+ model, Okavango River Basin, CMIP6, Water yield, SSP scenarios, Semi-arid hydrology

3.1. Introduction

Climate and land use/land cover (LULC) changes are both interrelated global environmental challenges. The beginning of industrial revolution in the mid-1800s is a major contributor to climate change, through rapidly increasing greenhouse gas emissions (IPCC, 2022). Climate change has adversely affected food security and terrestrial ecosystems through increasing frequency of extreme events globally. Temperature warming and precipitation patterns are prominent features of climate change, with direct impact on hydrological responses (Kaini et al., 2010). Recurrence of extreme rainfall and drought events are signs of climate change which in-turn influence hydrological responses. Similarly, LULC changes have impacts on streamflow, affecting evapotranspiration and infiltration, causing erosion and influencing the water balance of hydrological cycles (Guo et al., 2020). Therefore, the determination of complex dynamics of climate and LULC change, through analysis of time series of various indicators and better understanding of trends, patterns, and variability of climate-related phenomena, is crucial to support sustainable water resource management. This complexity arises from multi-dimensional characteristics of climate change, lack of long-term observational datasets, and the intrinsic uncertainties in predictive models.

Land degradation and desertification are global environmental problems which are attributed to climate variability and human actions e.g., loss of biodiversity due to farming activities. As such, it is vital to consider biophysical as well as socio-economic drivers to combat desertification and land degradation (IPCC, 2023). The Okavango River basin is regarded as one of the most important freshwater landscapes located in the dryland of northeastern Namibia, Northwest Botswana, and South Angola. Nevertheless, the basin is under constant pressure due to climate variability, fast population growth and varying land use practices (Mendelsohn and El Obeid, 2004). The semi-arid characteristics of the lower Okavango River basin further enhance environmental sensitivity towards human induced land degradation and climate change. Pressure on natural resources, driven by increasing population and intensified farming in close proximity to the basin, strongly impact the river's hydrological dynamics such as streamflow conditions, sediment transportation and infiltration. Approximately Ninety-five percent of streamflow of the Okavango basin originates from Angola and passes through Namibia before dissipating into the Okavango Delta in Botswana (Andersson et al., 2003). Climate and LULC changes upstream will have a vital consequence downstream in the already water scarce environment.

Therefore, investigation of catchment behavior along with LULC and climate change predictions have the potential to provide insight into the feasibility of managing water and land demand and supply, while also supporting the agenda of Sustainable Development Goals (SDG) to whom these countries are signatories. A comprehensive approach to study human influence on natural resources for sustainable management of land and water resources involves assessment of watershed behavior under different land use and climate scenarios. The proposed research analyses streamflow responses of the lower Okavango River basin to climate and land use changes.

Climate and LULC changes play a vital role in predicting future hydrological responses. Researchers use projected climate data and LULC projections in conjunction with hydrological modelling to estimate future streamflow (Acharki, 2023; Ahiablame et al., 2017; Chawanda et al., 2024; Marhaento et al., 2018). Climate projection is typically produced using General Circulation

Models (GCMs) and Regional Climate Models (RCMs). GCMs are attributed with reliable climate simulation at a large scale with global coverage with RCMs additionally used to generate higher resolution data with smaller spatial coverage (Chen et al., 2013). Model Outputs from GCMs and RCMs are used to improve scientific understanding of climate systems providing necessary knowledge to support informed political decision-making. Although, GCMs are generally in coarse resolution, statistical and dynamic downscaling methods have lately been used to refine outputs and bridge the gap with RCMs. Several studies using deep learning and machine learning techniques have shown downscaled GCMs to be reliable for studies at regional as well aslocal scale (Polasky et al., 2023; Soares et al., 2024). The sixth Coupled Model Intercomparison Project (CMIP6) is the latest phase of the GCM dataset used by the Intergovernmental Panel on Climate Change (IPCC) for its sixth assessment report. Unlike its predecessors CMIP3 and CMIP5, a new set of SSP scenarios are included as well as modelling groups, advanced climate simulations and increased spatial resolution (Eyring et al., 2016). Research on assessing future climate change using CMIP6 datasets show consistency of climate predictions at regional scale (Chaturvedi et al., 2024; Gbode et al., 2025).

Land use predictions recommended by CMIP6 for the different SSP and RCP scenarios are produced using different Integrated Assessment Models (IAMs). IAMs aim to integrate multi-disciplinary knowledge between socioeconomic and biophysical processes to construct representative sectors from energy to economics to climate and ecology (Parson and Fisher-Vanden, 1997). Each model can predict several SSP-RCP scenarios. There are several IAMs such as GCAM, IMAGE, AIM, REMIND-MAgPIE that generate LULC products based on climate change impacts, energy and food demand, policy choices and socioeconomic trends using Shared Socio-economic Pathways (SSPs) and Representative Concentration Pathways (RCPs). The resolutions of most available global land use projection products are usually coarse ranging between 10-50 km (Meyers, 2012). However, scenario-based simulation using SSPs and RCPs of future LULC changes has become a powerful tool for change assessment, providing references for sustainable land management. One such product is the 1km resolution Global land projection dataset spanning 85 years (2015 -2100) for 20 land cover types (Chen et al., 2022). This datasets adopted SSP and RCP scenarios and is based on a Land-Use Harmonization (LUH2) project which reconstructed historical land use for future scenario land use patterns in a resolution of approximately 25 km (Hurtt et al., 2020). LUH2 land use projection datasets are used as input in CMIP6 Earth system models (ESMs) ensuring consistency across climate models. Therefore, making the 1 km projected global LULC datasets reliable and globally applicable to support research and applications in fields of climate change, land use planning and environmental monitoring (Chen et al., 2022) .

Hydrologic models can simulate and better understand and manage hydrologic processes through simplification of the real-world water resource system (Refsgaard et al., 2007). Accurate data to represent respective variables remains a significant challenge, even though these models integrate complex spatial and temporal variables to account for catchment heterogeneity (Mengistu et al., 2019). Specific parameters define models to represent the real-world conditions of hydrologic processes. Therefore, models that explain hydrological dynamics are critical for sustainable water resources management, especially in areas subject to extreme drought and flooding (Hrachowitz et al., 2013). Various models have been used to study streamflow responses, including the Soil and Water Assessment Tool (SWAT), Variable Infiltration Capacity Model (VIC), and Hydrologic

Engineering Center - Hydrologic Modeling System (HEC-HMS). Among these models, the SWAT model is widely used to simulate the water budget of a watershed. SWAT is a semi-distributed hydrologic model that is continuous over time and includes various parameters such as land use/land cover, soil properties, topography, and climate variables (Arnold et al., 2012). SWAT helps to predict system behaviour and analyse key processes, including streamflow dynamics, sediment and nutrient loads in catchments with varying LULC, climate, topography, and soil conditions (Vallam et al., 2014).

In our previous research (Negussie et al., 2022), the ability of the SWAT model to simulate streamflow dynamics in the semi-arid Okavango catchment was demonstrated, implying it as a reliable tool for hydrological modeling in this data-scarce region. Other studies done in southern Africa have shown that variations in land cover, together with climate change majorly affect streamflow variability, particularly in semi-arid basins where the hydrological process is very sensitive to vegetation cover and rainfall intensity (Funk et al., 2015; Kusangaya et al., 2014). Recent global assessments, including that of the Intergovernmental Panel on Climate Change (IPCC), show that future climate scenarios will render arid and semi-arid regions much drier hence making it more pressing to implement sustainable land and water management strategies (FAO and UNEP, 2020; IPCC, 2023). Based on this, another study (Negussie et al., 2024), determined the suitability of land for sustainable legume-based agriculture in the Okavango River basin under the assumptions that land use and climate changes would have an effect on streamflow. Since this assumption has never been validated empirically in our study area, the present study is set to fill in that gap by applying SWAT+ as an upgraded version of SWAT to simulate future streamflow responses under combined climate and LULC scenarios. In doing so, it will also verify our earlier assumptions made in assessing land suitability. More importantly, it brings to the forefront the significance of integrated hydrological modeling with land use planning and climate adaptation strategies in semi-arid transboundary river basins.

This study investigates the impact on streamflow response within the lower Okavango River basin considering future climate change predictions and LULC change factors. Results provide information on projected streamflow under combined climate and LULC change scenarios. The main aim of this research is to develop reference materials for water and land resource managers, policymakers and concerned professionals to make informed decision and improve resource management and planning contributing in developmement of future adaptation strategies. The specific objectives are to: i.) to evaluate SWAT+ model performance at monthly time steps of the lower Okavango River basin using historical data to expose catchment behaviour; ii.) to use SWAT+ with global daily downscaled climate projections derived from GCM of CMIP6 and the global land projection dataset to simulate future streamflow projections under climate and LULC scenarios for SSPs 4.5 and 8.5; and iii.) assess the changes of future streamflow in three periods (2025-2040), (2040-2070), and (2070-2100) using respective climate and LULC scenarios in comparison to historical periods.

3.2. Materials and Methods

3.2.1. Study Area

The study area as seen in Figure 3.1 below, focuses on the transboundary lower Okavango River Basin, which includes the Rundu townlands in northeastern Namibia and neighboring areas of southern Angola (Mendelsohn and El Obeid, 2004). The area around Rundu is situated along the Okavango River, forming a natural border between the two countries. The region shows a semi-arid climate receiving an average annual rainfall of 450-550 mm, mainly during the rainy season (October to April) with rainfall peaks during January and March (Atlas of Namibia Team, 2022). Major contributions to local livelihoods include smallholder farming, predominantly rain-fed subsistence agriculture being highly dependent on rainfall seasonality, complimented by livestock rearing (FAO, 2014).

Recently, a rapid increase in population size along the river has been observed. Rundu, the second most populated town in Namibia, is located at the heart of the study area. Since the last census, it has almost doubled its population to 120,000 inhabitants (Namibia Statistics Agency, 2011). Predominant crops grown in the area are pearl millet (in the local language, mahangu), maize, and sorghum, which are typically grown subsistently by local farmers on relatively small land between 2 and 5 hectares in size (Kamwi et al., 2015). The soils in the area differ substantially, with soils further from the river corridor mostly classed as low-nutrient arenosols, while river floodplains have nutrient-rich fluvisols and gleysols, supporting a higher degree of agricultural activity (Coetzee, 2020).

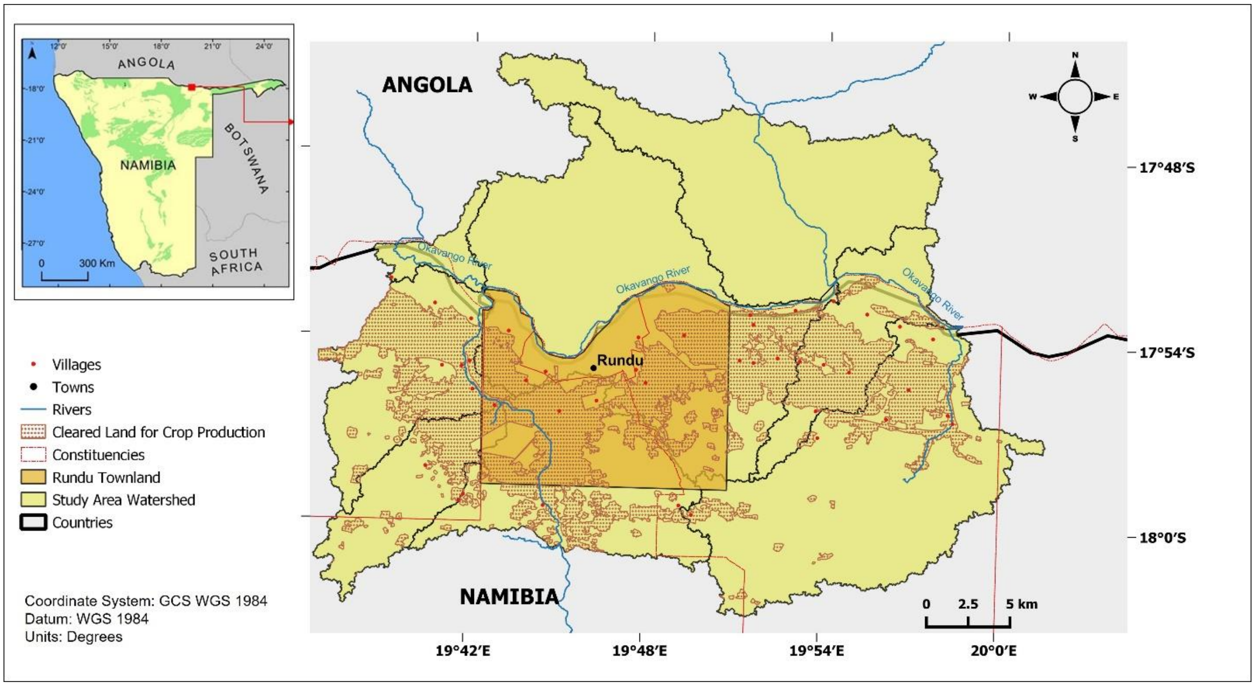


Figure 3.1: Locality map of the study area in the lower Okavango River Basin, spanning northeastern Namibia and southern Angola.

The study site has a very diverse and ecologically rich landscape including floodplain grasslands, woodlands, and wetlands (Mendelsohn and El Obeid, 2004). Nevertheless, there has been a significant shift in land use with more cultivation and expansion of urban sprawl, primarily in and around Rundu (Kamwi et al., 2015). Upstream precipitation from the Angolan highlands and LULC patterns are critical to regulate downstream flow regimes on the Angolan side, (Andersson et al., 2006). As a result, this localized watershed is a focal point for hydrological impact assessment within the broader Okavango system and highly susceptible to both climate variability and land use change (Wolski and Murray-Hudson, 2005).

3.2.2. Digital Elevation Model

Due to the uniform topography of northern Namibia and southern Angola, where our study area is located, we obtained a high-resolution TanDEM-X (DEM) from the German Aerospace Center (DLR), a product of the TerraSAR-X DLR mission. This product has a relative vertical accuracy of 2 meters and a spatial resolution of 12 meters (Wessel et al., 2018). The absence of high-resolution information such as TanDEM-X in the study site could potentially hinder or distort hydrological models, impacting the results of simulations. This high-resolution product proved vital in precisely delineating watershed boundaries, essential for creating HRUs and representing the smallest operational unit for streamflow simulation in the model. As demonstrated in Figure 3.2, the elevation map of the river basin derived by TanDEM-X is presented together with the generated subbasins of the catchment.

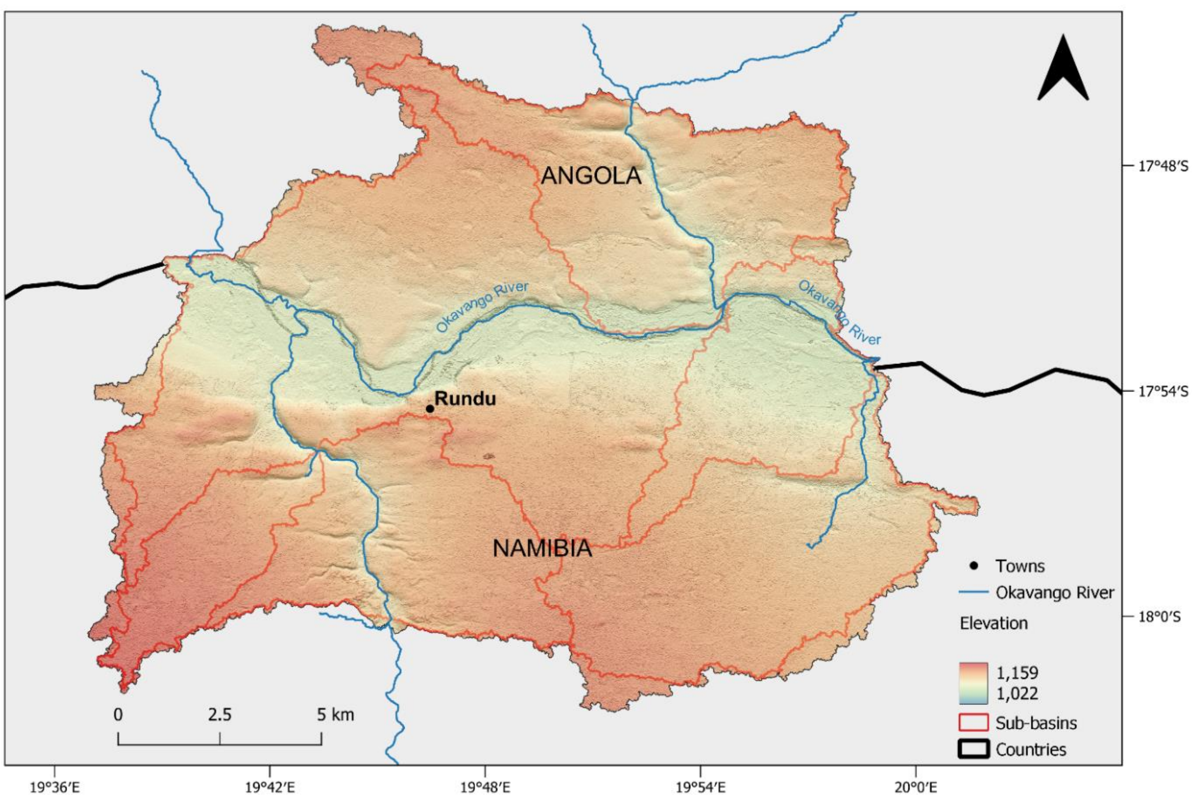


Figure 3.2: Elevation Map of the Okavango River Basin illustrating the elevation profile of the Okavango River Basin around the Rundu area.

3.2.3. Soil Mapping

The role of soil information in streamflow modeling is well documented. The incorporation of input variables such as soil information and resolution of soil data have significant impact on modeling streamflow in the SWAT+ model. A soil map of 1:250 000 scale was generated using soil sample profiles collected within the study area (Coetzee, 2020). Subsequently, using the acquired soil profile data, we extracted vital information for the model, including but not limited to texture classes, soil types, profile depth, and other soil attributes essential for model development. The study catchment identified seven soil classes: Cambisol, Fluvisol, Arenosol, Technosol, Fluvic Cambisol, Eutric Fluvisol, and Dystric Arenosol. The resulting soil map demonstrating the distribution of soil classes across the catchment is presented in Figure 3.3.

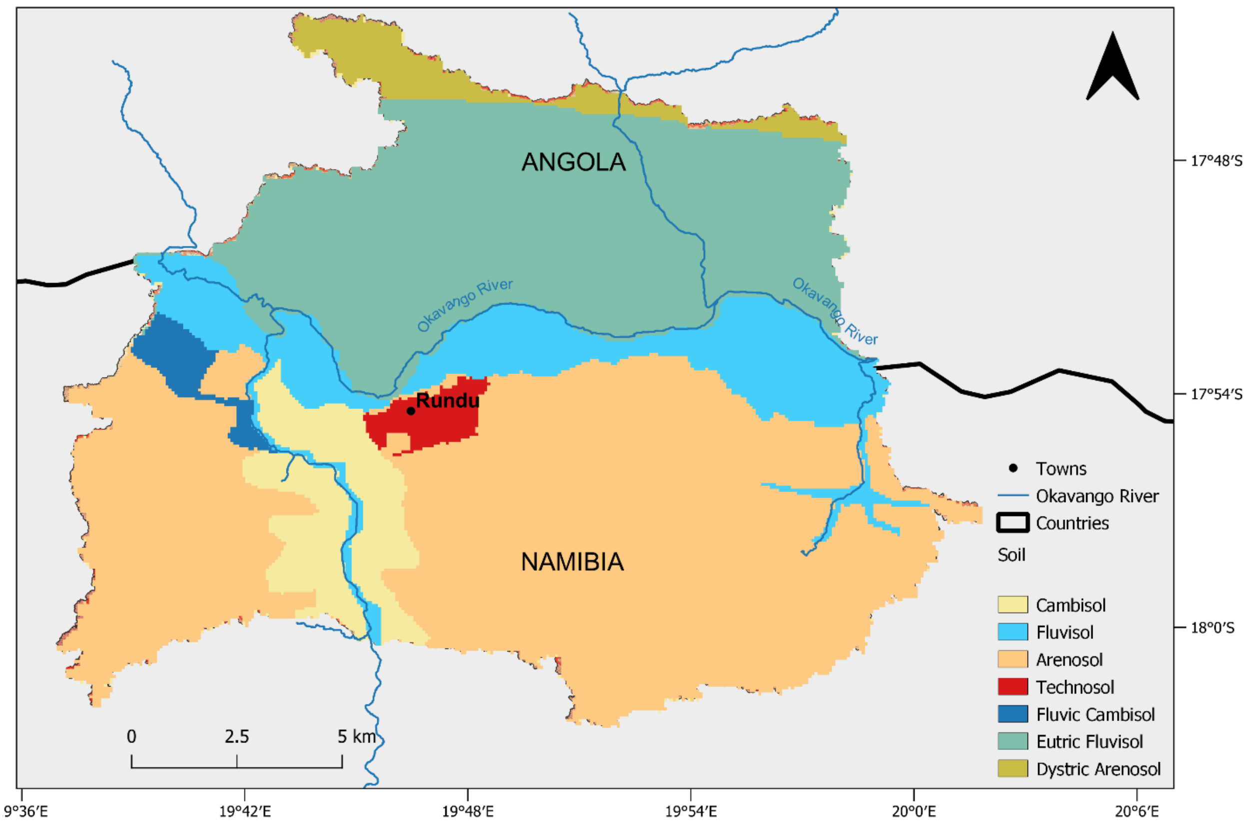


Figure 3.3: Soil Map of the Okavango River Basin presents the spatial distribution of dominant soil types within the Okavango River Basin near Rundu.

3.2.4. Model Setup and Calibration

A hydrological SWAT+ model was used to simulate the water balance components of the different sub-basins in the study area. The modeling process consisted of delineating the lower Okavango River basin, dividing it into sub-basins, and further subdividing into Hydrological Response Units HRUs to account for its spatial heterogeneity (see Figure 3.4). HRUs are the smallest spatial units within a catchment, having similar slope, soil, and LULC features. These units allow the simulation of water balance components, assuming that hydrologic characteristics vary between

HRUs. Climate, discharge, slope, LULC, and soil variables derive different SWAT+ scenarios (see Figure 3.4 for the overall workflow). Subsequently, these scenarios simulated the amount of water in each sub-basin, resulting in the total water departing and arriving at each time step in and out of the channel. The water balance was determined using the following equation.

$$\boldsymbol{SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{Seep} - Q_{gw}\right)} \tag{1}$$

where SW_t denotes the soil water content at time t, the initial soil water content is expressed by SW_0, R_{day} refers to the amount of precipitation on day i, Q_{surf} signifies surface runoff on day i, E_a is referring to the amount of evapotranspiration on day i, W_{seep} denotes the amount of percolation on day i and Q_{gw} indicates groundwater return flow on day i.

In a previous research, we evaluated SWAT model and found it to be suitable for water balance calculation in the Okavango catchment (Negussie et al., 2022). Therefore, in the current study similar model set-up was applied using related attributes, to compute water balance in the catchment and to avoid duplication of efforts. Due to the flat terrain characteristics of the lower Okavango catchment, TanDEM X high-resolution digital elevation product was used to delineate the river basin in SWAT+ model setup and to divide the catchment into sub-basins. Preliminary steps include filling DEM depressions, computing flow direction and accumulation, and setting stream definition thresholds to determine stream networks and sub-basins. Subsequently, unique pairings of LULC, soil, and slope information within each sub-basin created HRUs. The combined streamflow from each HRU make-up the sub-basin water flow enabling the calculation of channel's water balance for the catchment area. Six weather stations, optimally distributed throughout the study area, were identified for rainfall, temperature (Tmin and Tmax), relative humidity, wind speed, and solar radiation input data into the SWAT+ model. Finally, a two-year warm-up period (1981 and 1982) was used to run the simulation over a 35-year period (1981 to 2015). Warm-up is vital for model adjustment and reaching stable conditions (for example, flow values), as SWAT+ simulations typically underestimate basin initial conditions (Kim et al., 2018). Therefore, in this study, the hydrological parameters of the catchment were simulated for 33 years (i.e., excluding the warm-up period). This served as the baseline period through retrospective simulation to evaluate changes of prospective simulation under combined LULC and climate change.

Six sub-basins, ranging from 49 to 335 km^2 were delineated using TanDEM X which were further subdivided into HRUs. A slope map with four classes (0-5.5, 5.5-15.5, 15.5-34.5, >34.5) was generated using the same high-resolution DEM for the study area. LULC were identified from SWAT database resembling land types in the study site, such as AGRL, RNGB_SUDRF, WATR, URBN_WARM, SHRB, WETL, GRAS and BSVG representing dryland farming, tree cover, water bodies, built-up area, shrubland, wetland, grassland, and bare land and sparse vegetation, respectively. Seven soil classes were recorded for the study area namely Cambisol, Fluvisol, Arenosol, Technosol, Fluvic Cambisol, Eutric Fluvisol and Dystric Arenosol. Thereafter, a unique combination of LULC, Soil type and slope class generated 1857 HRUs. Surface runoff occurs when precipitation that accumulates on the ground surface exceeds the infiltration rate, resulting in water flow from the surface onto the ground. During a rain event in a particular catchment location, the Soil Conservation Service Curve Number, or SCS CN, determines the surface runoff. This runoff simulation considers soil moisture conditions, soil hydrologic group, and LULC types. Potential evapotranspiration (PET) in the catchment was estimated using Solar energy, wind speed, humidity, and temperature as input through the Penman-Monteith method (Allen et al., 1998). The water flow dynamics within the basin's stream network were simulated using the variable storage routing technique pioneered by Williams (1969).

Following our previous study in the catchment, eight parameters were selected that best represent the semi-arid characteristics of the catchment area. The SWAT+ parameters which were chosen based on their sensitivity to the study site are CN2, ALPHA_BF, GW_DELAY, OV_N, ESCO, SOL_AWC, CH_K2, and SURLAG which represent the potential for surface runoff, baseflow response to recharge, groundwater delay time, speed of overland flow, soil evaporation, water storage capacity of soil, water movement through the streambed, and delay between rainfall and the generation of surface runoff, respectively. Upon completion of SWAT+ simulation, calibration and uncertainty analysis were conducted in Sequential Uncertainty Fitting version 2 (SUFI 2) in SWAT-CUP package. A split sample technique for calibration and validation process was employed using Rundu gauge station monthly streamflow data with calibration period from 1983-1996 and validation from 1997-2001. During the calibration, the model parameters are refined by running four iterations of at least 500 simulated runs each, where each round of iteration recorded smaller values of parameter ranges. Results from simulation were compared using P-factor (recommended > 0.7) and R-factor (recommended < 1.5) indices to demonstrate a good fit. Furthermore, model performance was evaluated using objective functions such as Nash Sutcliffe coefficient (NSE), Coefficient of determination (R^2), Percent bias (PBIAS) and Ratio of RMSE (RSR) to demonstrate agreements between observation and simulation of streamflow. A performance rating criteria from (D. N. Moriasi et al., 2007) as shown on Table 3.1 was used to evaluate model performance.

Table 3.1: Performance Rating for a Monthly Time Step adopted from (D. N. Moriasi et al., 2007)

Model Performance Rating	RSR	NSE	R^2	PBIAS
Very Good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	$0.75 < R^2 \leq 1.00$	$PBIAS < \pm 10$
Good	$0.50 < RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$0.60 < R^2 \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < NSE \leq 0.65$	$0.50 < R^2 \leq 0.60$	$\pm 15 \leq PBIAS < \pm 25$
Unsatisfactory	$RSR > 0.70$	$NSE \leq 0.50$	$R^2 \leq 0.50$	$PBIAS \geq \pm 25$

3.2.5. LULC Scenario Setup

Global land projections from (Chen et al., 2022) at 1 km resolution (2015-2100) was used to run scenario-based analysis in our model. The initial future land use classifications of the global land projections were based on the 2015 European Space Agency's Climate Change Initiative (ESA CCI) land cover datasets. The process of creating future LULC data followed three steps, i) forcasting various land use using different SSP and RCP scenarios, ii) generating the highest resolution of global land use products to date at 1-km resolution with seven land use classes (i.e. forest, grassland, barren land, cropland, urban, water and permanent snow and ice) using future land use simulation model (FLUS), and iii) dividing the seven land classes into 20 plant functional types. The global land projection 1-km dataset based its simulation on CMIP6 recommended LULC product from LUH2 project. The SSP and RCP scenarios for LUH2 future land use dataset were reconstructed from various integrated IAM results. Our study focused on two LULC scenarios: SSP2, which represents a moderate socioeconomic pathway with balanced economic and environmental policies, and moderate greenhouse gas emissions (RCP 4.5); and SSP5, which represents a rapid economic growth pathway driven by fossil fuels, with high greenhouse gas emissions (RCP 8.5). The trajectory from 2020 to 2100 for global cropland and urban land use under SSP2-4.5 scenario showed a gentle and steep increase. Without policies for sustainable development and continuation of business-as-usual economic and environmental policies, agricultural activities will further increase, and urban centres will expand to meet demands of a rapidly growing population. Similarly, under SSP5-8.5 with rapid economic growth based on fossil fuels, grasslands are observed to decline, while urban areas are expected to double in size by 2100 compared to the initial prediction, presenting worst-case scenario. Furthermore, analysis performed in sub-Saharan Africa showed extensive forest degradation in scenarios other than SSP1 assuming lower levels of economic growth and greenhouse gas emissions indicating a more sustainable development due to biodiversity protection policies. Details of approach and analysis of land simulation processes and their different SSP scenarios are documented by (Chen et al., 2022).

A combination of twenty-four runs for climate change and LULC scenarios of SSP2-4.5 and SSP5-8.5 were performed in SWAT+ for three time periods between 2025-2040, 2041-2070, and 2071-2100, respectively When observing the projected LULC data in our study site for the above periods, we noticed an extreme decline in water bodies/wetlands. At the same time, a sharp increase in cropland was followed by a more gradual expansion of urban areas. The land types considered in our SWAT+ model were shrubland, tree cover, cropland, grassland, bareland, sparse vegetation, urban and water bodies. Future streamflow processes in the catchment were simulated in SWAT+ using climate change and LULC projections assuming soil and slope data to be constant.

3.2.6. Climate Scenario Setup

Climate projections required for this study were sourced from four CMIP6 GCMs namely GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, NorESM2-MM of the NEX-GDDP-CMIP6 global daily downscaled climate projections. These datasets went through a process of bias correction and spatial disaggregation to refine coarse-resolution outputs for regional and local scale climate change impacts. Making it possible to understand potential climate patterns at a regional or local scale (for example watersheds, urban areas and regional administrative boundaries). In this study we compiled a dataset from climate projections of the aforementioned GCMs across two SSPs (SSP2-4.5 and SSP5-8.5) for the period 2015 to 2100. These climate projections have been downscaled to a spatial resolution of approximately 25 km. Historical climate records from 1950-2014 were used to adjust future climate projections. These four GCMs were selected for three reasons: i) to use downscaled higher spatial resolution needed for applications in regional watersheds rather than using original coarser resolution, ii) availability of all required variables showing patterns at local and regional scale iii) documented use of these models near and similar areas of the catchment under investigation (Engelbrecht et al., 2011; Joubert and Hewitson, 1997; Karypidou et al., 2022; Ringler, 2010; Samuel et al., 2023).

Daily projected climate variables (precipitation, minimum and maximum temperature, wind speed, relative humidity, and radiation) were extracted from the four GCMs in six locations spatially distributed over the catchment. These variables were prepared in a format fit for SWAT+ and were used to simulate scenarios in a total of 24 simulations for the selected GCMs across SSP2-4.5 and SSP5-8.5. The approach combined the projected climate and LULC scenarios to observe effects on annual streamflow for three periods between 2025-2040, 2041-2070 and 2071-2100. Furthermore, comparative evaluations were performed between the baseline scenario and the three future scenarios.

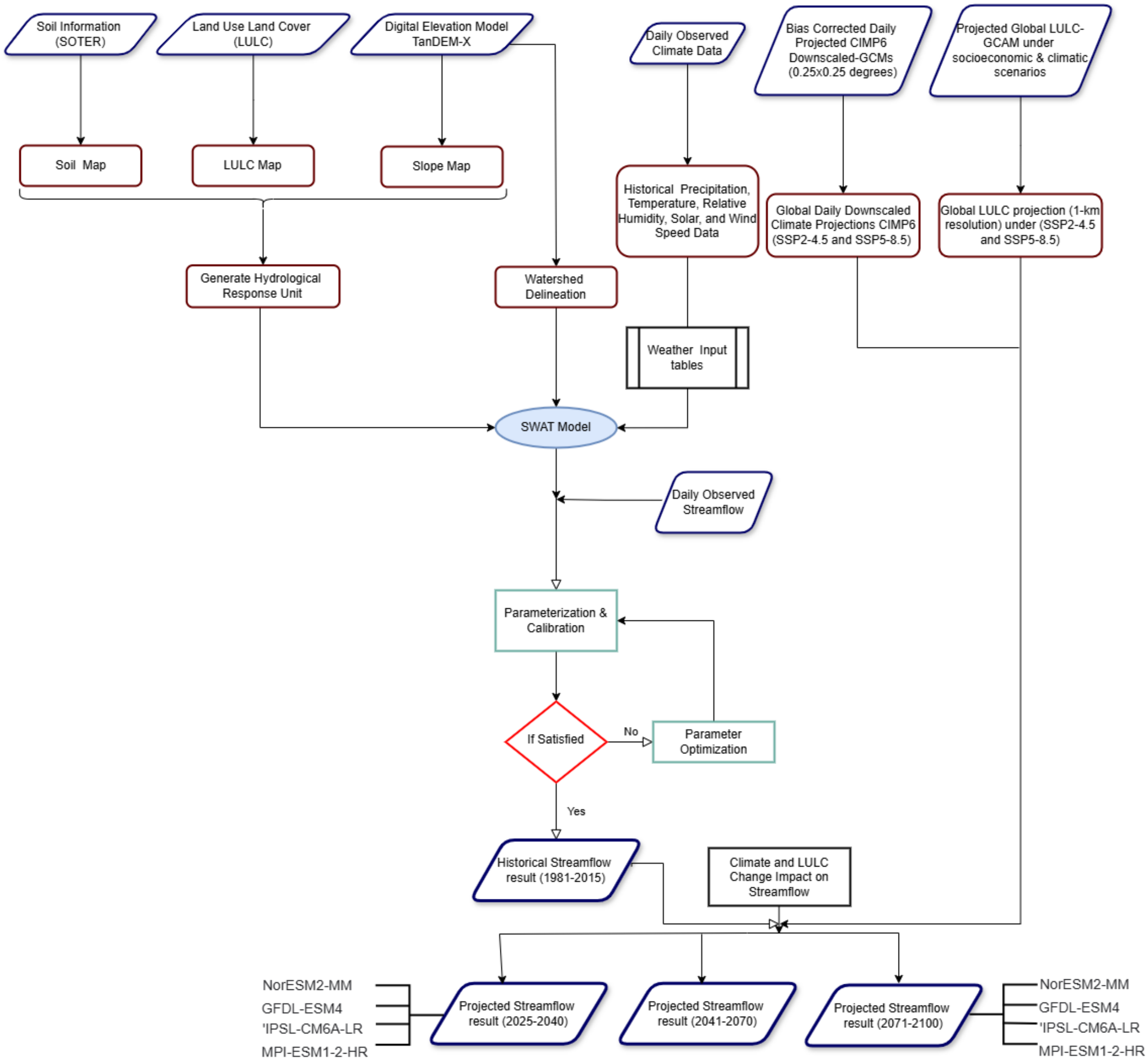


Figure 3.4: Methodological framework for assessing climate and land use/land cover (LULC) change impacts on streamflow in the lower Okavango River Basin using the SWAT+ model.

3.3. Results and Discussions

The analysis evaluates projected changes in precipitation, streamflow, and water yield using SWAT+ model output pre-conditioned by four CMIP6 GCMs. The analysis focuses on estimating changes in precipitation, streamflow, and water yield across three future time periods. Results are discussed in relation to land use and land cover projections in order to illustrate combined effects of climate change, effects of human-induced land transformation on water availability, spatial hydrologic patterns, and ecological sustainability in a transboundary watershed.

3.3.1. Projected Precipitation and Streamflow Changes

Precipitation and streamflow projections based on SWAT+ simulations forced with four CMIP6 GCMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, and NorESM2_MM) show a consistent drying trend over three future periods (2025-2040, 2041-2070, and 2071-2100) for the localized section of the Okavango River Basin near Rundu, Namibia. All four models predict a continuous decrease in rainfall relative to the historical baseline, especially during the peak rainfall period (January to March), with the decrease becoming more apparent towards end of the century. Similarly, runoff shows an even more significant and non-linear decrease compared to precipitation, with historically high runoff months (February through April) showing noteworthy decreases. These dynamics are illustrated in Figures 3.5a-f, where future monthly rainfall and streamflow changes are shown for the SSP2-4.5 and SSP5-8.5 scenarios. The level of streamflow decline exceeds the decline of precipitation. This highlights a higher hydrological sensitivity of the basin to climatic variability. Our findings align with observations made by (Ndhlovu and Woyessa, 2021) for the neighbouring Zambezi catchment. Their results indicated significant streamflow reductions despite low to moderate declines in precipitation, especially during dry months of the year.

Furthermore, this pattern is in line with the ‘dry gets drier’ paradigm, as examined and presented by Xiong et al. (2022) for terrestrial water storage projections. Their global evaluation based on terrestrial water storage anomalies led to the conclusion that semi-arid and transitional regions are strongly sensitive to climate-induced decreases in water availability even for modest precipitation variability. The Okavango Basin has already been stressed due to seasonal scarcity of water and high evapotranspiration; hence, it gets directly placed within this vulnerable category. Aich et al. (2014) and Goulden et al. (2009), in their respective studies of the Limpopo and Orange basins, reported similar findings. This further implies that semi-arid southern African river systems are highly sensitive to variability in rainfall patterns.

In the context of our study area, the persistent reduction in both precipitation and streamflow across scenarios and GCMs coupled with a clear inter-model consensus, provides strong evidence that the hydrological regime of the Okavango Basin will likely experience intensified stress in the future, particularly under high-emission scenarios. This reinforces global and regional assessments which suggest that semi-arid systems in sub-Saharan Africa will continue to exhibit increased sensitivity to climate change, further validating the “dry gets drier” paradigm projected for water-stressed environments.

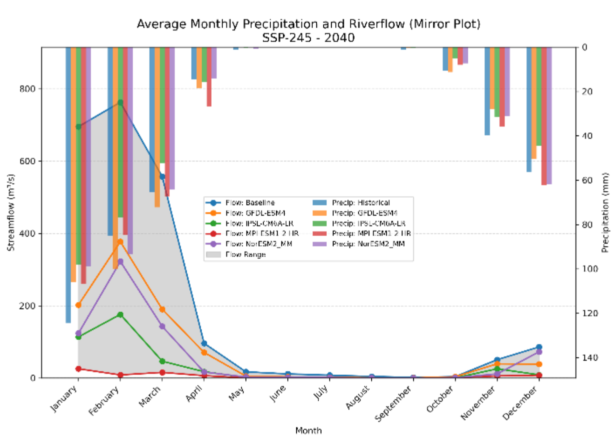
The above-mentioned patterns become more apparent when analyzed by period. By 2040, precipitation will decline slightly by about 5-10%, depending on the model, while runoff will decline significantly, particularly during the months of March and April. For example, January precipitation is projected to decline from a historical baseline of approximately 145 mm to around 135 mm under SSP2-4.5, while March decreases from 120 mm to approximately 110 mm. However, the corresponding streamflow drops more sharply from 130 m^3/s to approximately 110 m^3/s in January, and from 105 m^3/s to 85 m^3/s in March highlighting the basin’s nonlinear runoff response to even modest rainfall reductions. The variability between GCMs remains relatively high during this period, reflecting a higher uncertainty.

For the period between 2041-2070, precipitation decreases by a further 10-20%, while the decrease in runoff becomes much more noticeable, with extremely low runoff during the dry season (May-October). By mid-century, the predictions of all models begin to converge, indicating an increase of drying trend confidence. Precipitation in January drops to approximately 115 mm (SSP2-4.5) and 100 mm (SSP5-8.5), while streamflow falls to 90 m³/s and 75 m³/s, respectively. Similarly, March values decline to 95 mm and 85 mm in precipitation, with flow reducing to 60 m³/s and 50 m³/s. Dry season months such as August show near-zero rainfall and streamflow ranging from 1–5 m³/s, suggesting seasonal cessation of flow in most models.

The most significant decreases in precipitation, often exceeding 20% relative to baseline values, are observed between 2071 and 2100. During this time, dry season river flow will nearly cease, and wet season peak flows will be both lower and shorter in duration. By 2100, January precipitation drops to 100 mm under SSP2-4.5 and 85 mm under SSP5-8.5, with streamflow reducing to 65 m³/s and 50 m³/s, respectively. March rainfall declines further to 80 mm and 65 mm, while flow decreases to 45 m³/s and 30 m³/s. During August, several models simulate complete cessation of flow. These results confirm the transition toward shorter, weaker wet seasons and more extended, intensified dry periods.

Differences between different climate models' projections have narrowed, suggesting a growing consensus that a severe drying trend will persist by 2100. These results confirm projections made for neighbouring river basins, the Limpopo and Orange rivers (Aich et al., 2014; Goulden et al., 2009). They also reflect the global pattern as outlined by the “dry gets drier, wet gets wetter” paradigm (Xiong et al., 2022). The agreement among models by 2100, suggests that the Okavango River Basin is likely to experience a fundamental shift in its hydrological regime, with substantial implications for water availability as well as ecological sustainability and transboundary management.

a)



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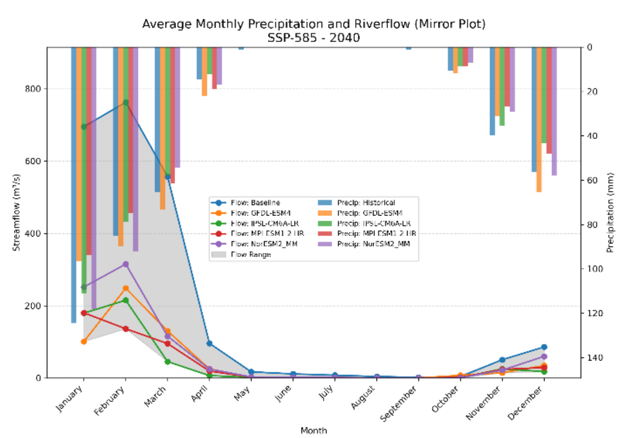


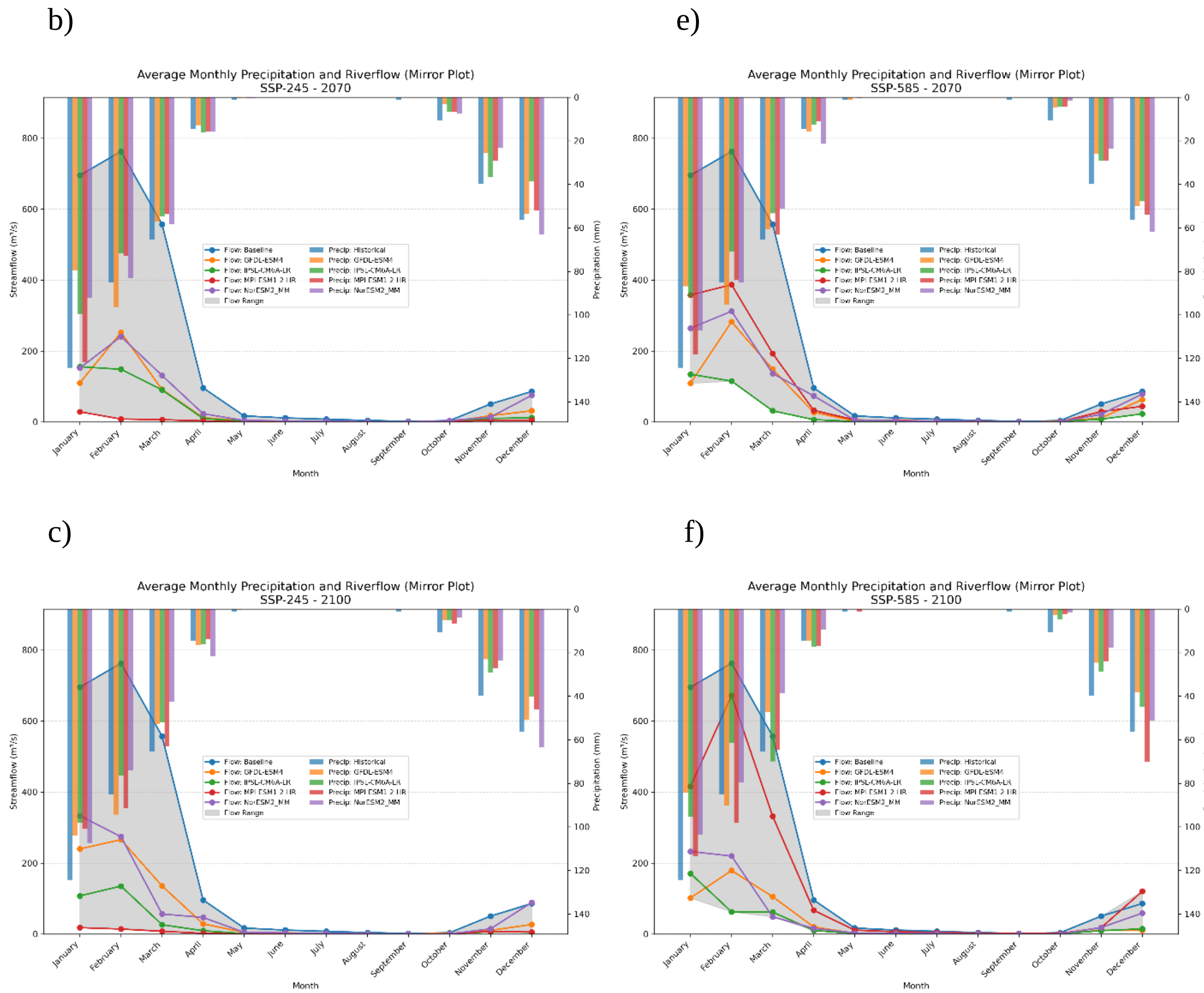


Figure 3.5: Projected average monthly precipitation and streamflow under different Shared Socioeconomic Pathways (SSPs) and time periods for the lower Okavango River Basin. Mirror plots illustrate the relationship between precipitation (bar) and streamflow (line) using four CMIP6 GCMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, and NorESM2-MM). (a) SSP2-4.5 for 2025–2040; (b) SSP2-4.5 for 2041–2070; (c) SSP2-4.5 for 2071–2100; (d) SSP5-8.5 for 2025–2040; (e) SSP5-8.5 for 2041–2070; (f) SSP5-8.5 for 2071–2100. Flow range is shaded in grey for historical baseline comparison. Precipitation decline and streamflow collapse are more pronounced under SSP5-8.5, especially in dry months.

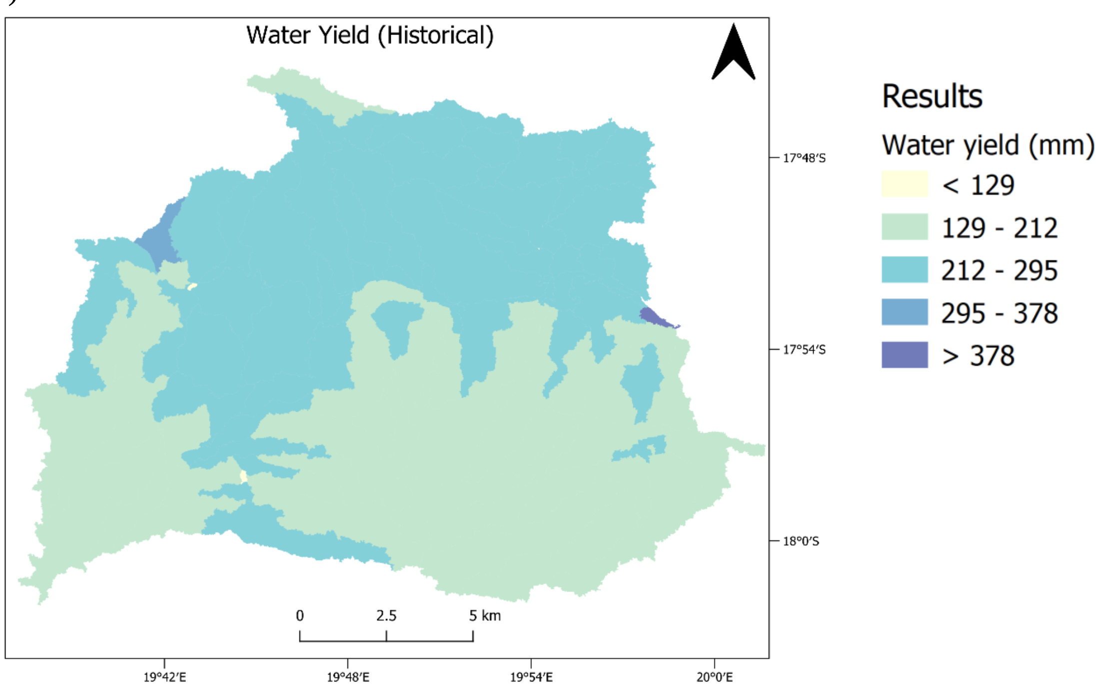
A closer examination reveals that streamflow responds disproportionately to changes in precipitation, showing that even modest rainfall amounts can lead to a significant decrease in river discharge. This highlights a high dependency of the Okavango River Basin hydrology on upstream rainfall from the Angolan highlands, where small changes in precipitation have large impacts on downstream water availability. Any reduction in upstream rainfall is likely to have an increased impact in the basin near Rundu, given that local rainfall contributes little to the total streamflow in this region. Similarly, susceptibility of semi-arid catchments to climatic variability were highlighted in a study on Rietspruit river in South Africa where climate projections in SWAT using multiple GCMs were investigated and found considerable decline in streamflow under different future climate scenarios (Banda et al., 2024). As a result, the projected decline of river flows poses a serious risk to water security and may affect domestic water supplies, irrigated agriculture, and the ecological sustainability of the Okavango. Traditional crop growing seasons could be disrupted, drought stress worsened, and reliance on already scarce groundwater resources increased by the loss of distinct seasonal flow peaks.

While there is still uncertainty in the early projection periods (2025-2040), the GCM outputs tend to converge by 2100, allowing for higher confidence in the direction of the projected changes. While there are still uncertainties concerning the extent of change, all models agree on the general direction of drying. The intensity of these hydrologic impacts is directly associated with the emission scenarios. Specifically, the drying trend exhibits greater severity under higher emission scenarios, such as SSP585. In contrast, the most significant hydrological impacts may be mitigated to some extent through strategic reduction of global emissions, thereby offering a potential counterbalance. In general, the predictions indicate an essential need for integrated water management and climate adaptation efforts to ensure the conservation of water resources and livelihoods dependent on the Okavango River in the surrounding region.

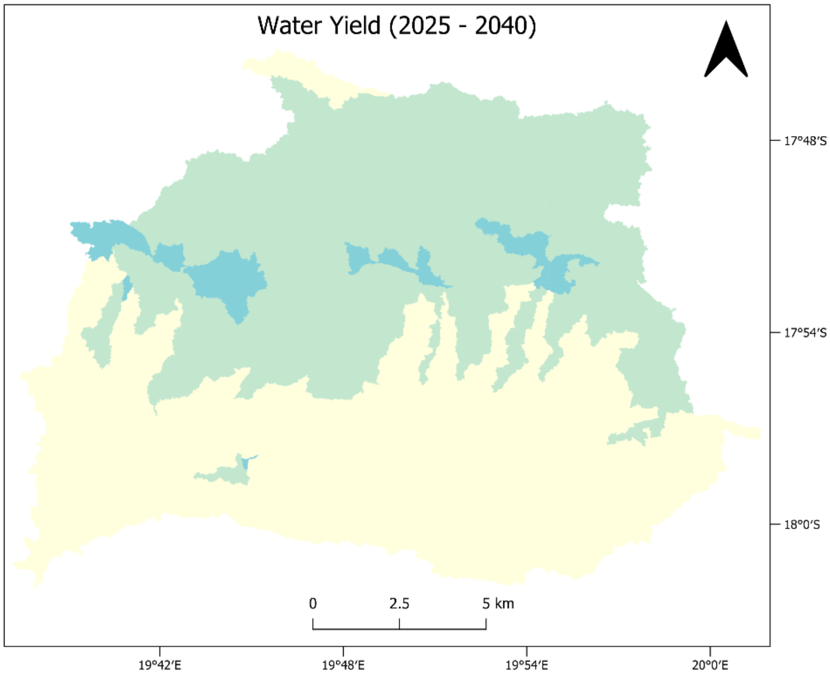
3.3.2. Projected Water Yield and Land Use Land Cover Change

Using the SWAT+ model, our analysis of projected water yield and LULC changes indicates a shift towards and expansion of drying conditions in the Okavango Basin near Rundu between the baseline period and 2100. During the historical baseline, the study region’s northern parts, coupled with some portions in the center, demonstrated water yield potential above 200 mm/yr. Figure 3.6a–d illustrates the spatial distribution of annual water yield across different time periods featuring prominent areas between 212-378 mm/yr and local peaks surpassing 378 mm/yr. These high-yield areas were associated with dense wetlands and tree cover-indicating a system that has been supported by natural vegetation, rainfall-driven infiltration, and base flow storage in the past.

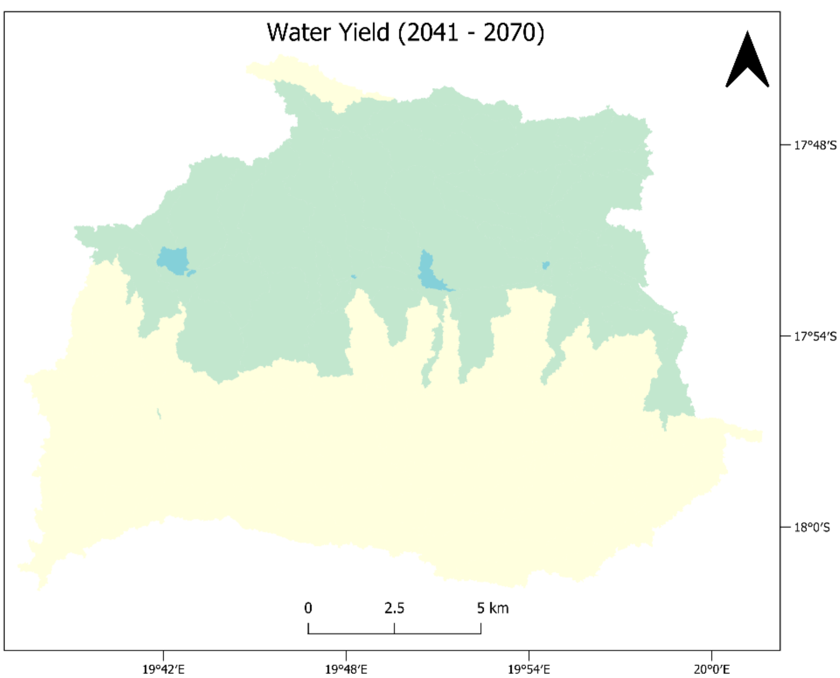
a)



b)


Water Yield (2025 - 2040)
17°48′S
17°54′S
18°0′S
0
2.5
5 km
19°42′E
19°48′E
19°54′E
20°0′E

c)


Water Yield (2041 - 2070)
17°48′S
17°54′S
18°0′S
0
2.5
5 km
19°42′E
19°48′E
19°54′E
20°0′E

d)

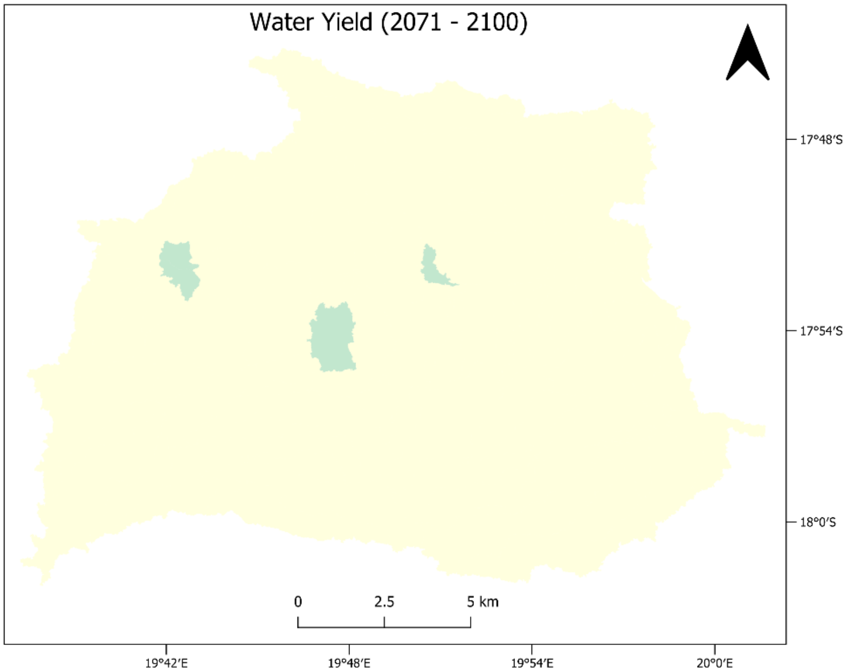


Figure 3.6: Spatial distribution of simulated annual water yield (mm/year) in the study area of the lower Okavango River Basin under different time periods and scenarios. (a) Historical baseline period (1981–2015), (b) near-future period 2025–2040, (c) mid-century period 2041–2070, and (d) end-century period 2071–2100.

The years between 2025 and 2040 show a significant decrease in the number of high-yield zones, with the highest yield class (> 378 mm/yr) completely disappearing. Areas with a water yield of <129 mm/year expand southward, while areas with higher water yields become increasingly concentrated along river corridors. This shift is consistent with LULC projections that show an increase in cropland and urban development near Rundu, coupled with significant reduction of wetland extent over the study area. Cropland cover increases dramatically between 2021 and 2040, going from about 30% to over 45% of the total basin area. Urban land also grows very fast, nearly doubling in size around Rundu during this period. A significant increase in water bodies is seen in the 2040 projection mostly in the flood-prone areas next to the Okavango River in what might be attributed to modelled inundation resulting from high runoff concentration or possible overrepresentation of ephemeral flood storage areas captured under surface water classes. However, this increase is not carried forward into subsequent projections and therefore probably represents a short-term hydrological artifact rather than a structural enhancement of water availability.

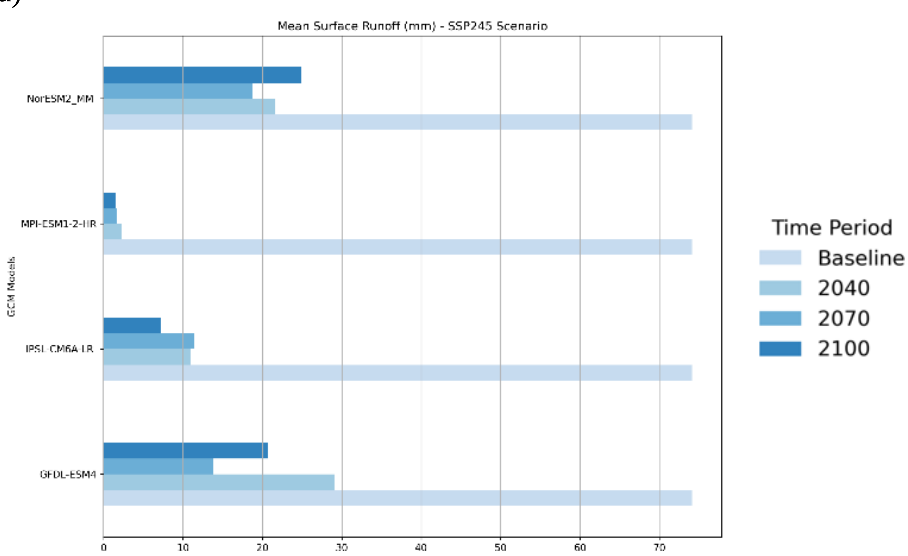
These results are consistent with our previous findings of SWAT model simulations of the Okavango-Omatako catchment and indicate significant water yield and baseflow reductions due to land use conversion from vegetation into cropland (Negussie et al., 2022). A previous study by Vushe, et al. (2014) found that land use and land cover changes, such as the conversion of forests and grasslands to urban and agricultural areas, have significantly impacted the streamflow of the Okavango River, underscoring the substantial influence of human activities on river flow dynamics. These changes suggest that human-induced alterations to the land, particularly the conversion of wetlands to impermeable or low-infiltration surfaces, are exacerbating the already projected moderate declines in rainfall, as modeled by the GCMs.

A phase of increased aridity is projected to occur between 2041 and 2070, where only limited parts of the landscape remain within water yield classes of 212 to 295 mm/yr. The majority of the basin, particularly the southern and northern regions, will be characterized by the lowest water yield class. Simultaneously, LULC predictions show extensive urbanization, substantial loss of wetland cover, and the predominance of arable and shrubland across the landscape. By 2070, cropland accounts for almost 60% of the total study area, as urban areas grow more in the west and central parts of the basin. Wetlands shrink and are mostly taken over by cropland and shrubland. These results highlight the combined effects of climate and land use changes on streamflow reductions. This trend is also supported by Figure 3.7a–b, which shows declining surface runoff across all GCMs and future periods under both SSP2-4.5 and SSP5-8.5.

In particular, under SSP2-4.5 (Figure 3.7a), models such as GFDL-ESM4 and NorESM2-MM project a consistent decline in mean surface runoff from baseline values of 72 mm to approximately 29 mm and 24 mm by 2040, and further to around 21 mm by 2100. Similarly, the IPSL-CM6A-LR and MPI-ESM1-2-HR models show very low runoff projections throughout, declining to below 10 mm by the end of the century. This suggests that these models are more sensitive to precipitation declines and possibly more responsive to land degradation assumptions embedded in the SWAT+ outputs.

Under SSP5-8.5 (Figure 3.7b), the decreasing trend remains evident, though some inter-model variations are observed. Notably, MPI-ESM1-2-HR projects comparatively higher runoff values, peaking near 52 mm by 2100, likely reflecting internal variability in rainfall distribution. However, GFDL-ESM4 and IPSL-CM6A-LR under this high-emission scenario also simulate sustained runoff decreases, aligning with predictions of reduced infiltration and enhanced surface runoff due to land cover changes.

a)



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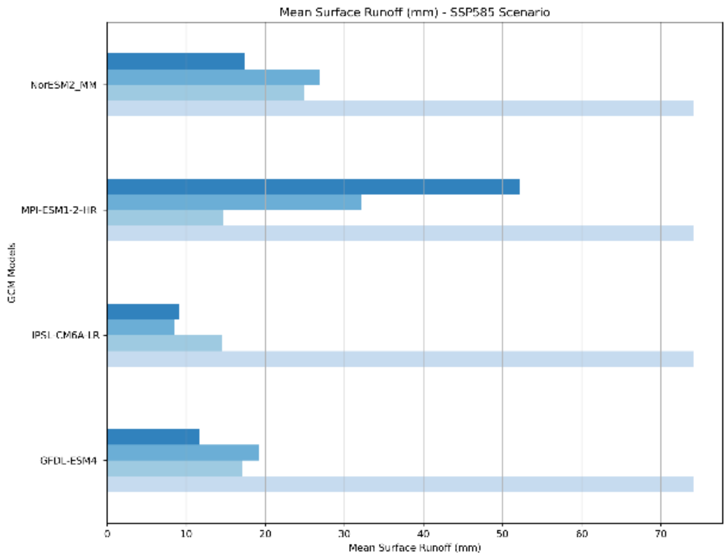
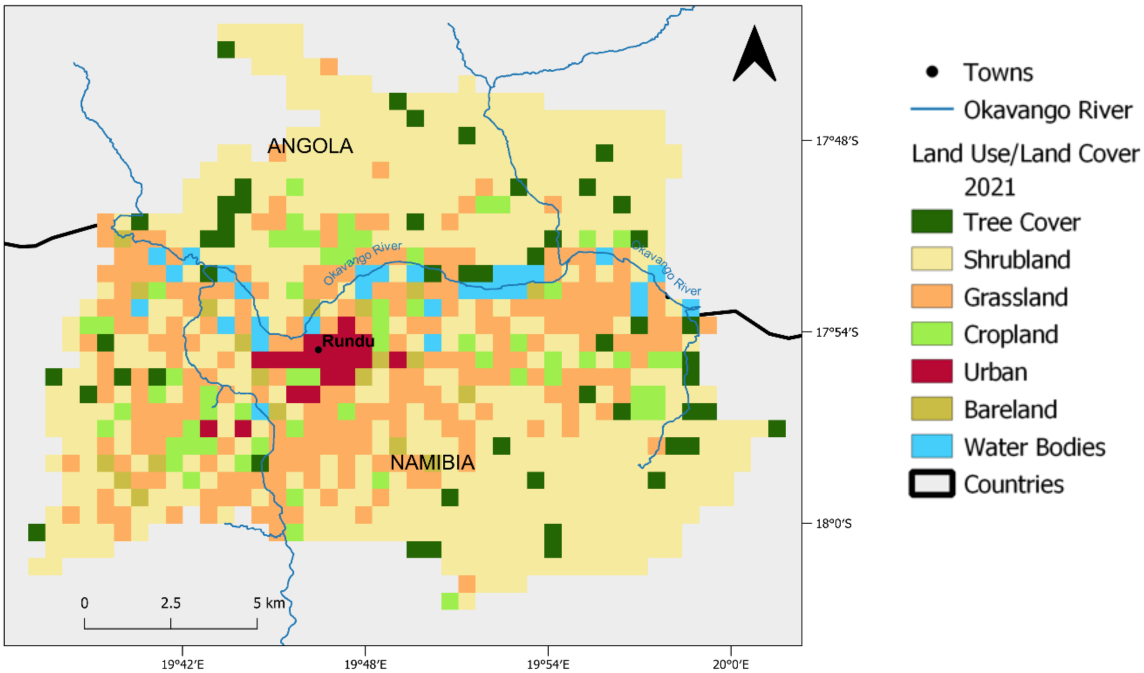


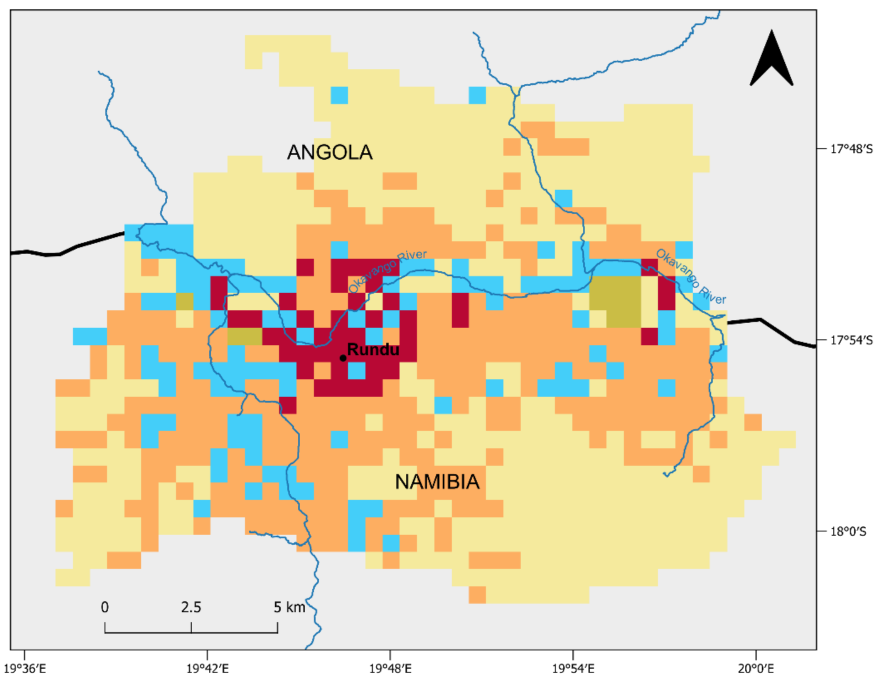
Figure 3.7: Mean annual surface runoff (mm) simulated using the SWAT+ model under two climate scenarios (a) SSP2-4.5 and (b) SSP5-8.5 for four GCMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, and NorESM2-MM) across baseline (1981–2015) and three future periods (2040, 2070, and 2100).

By 2100, water yields across the basin reach critically low values, with almost all areas falling below 129 mm/yr. Moderate yields are maintained only in a few isolated areas near the river corridor. LULC projections for this period indicate that cropland will become the dominant land cover in the basin with a total area coverage of approximately 65%, with urban areas, primarily around Rundu, also expanding, while notable decline in wetlands from the catchment. Most natural vegetation buffers and wetland areas disappear in the basin. These gradual shifts demonstrate a definite move toward significant LULC changes, harming ecosystem benefits and worsening surface water losses. This is clear from Figure 3.8a–d, with projections of land use change from 2021 to 2100.

a)


ANGOLA
NAMIBIA
Rundu
Okavango River
Okavango River
17°48′S
17°54′S
18°0′S
19°42′E
19°48′E
19°54′E
20°0′E
0
2.5
5 km
Towns
Okavango River
Land Use/Land Cover
2021
Tree Cover
Shrubland
Grassland
Cropland
Urban
Bareland
Water Bodies
Countries

b)


ANGOLA
NAMIBIA
Rundu
Okavango River
Okavango River
17°48′S
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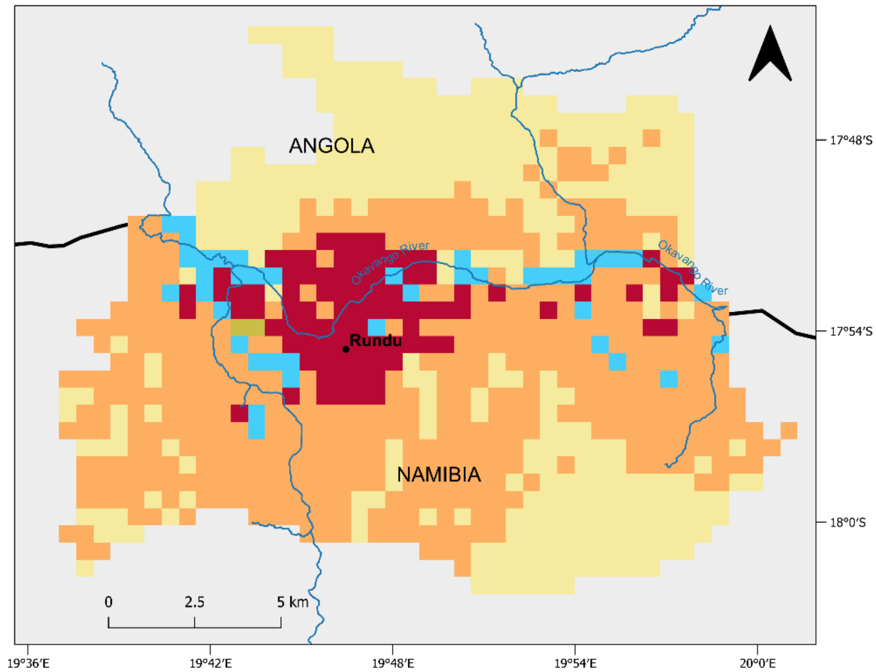
19°48′E
19°54′E
20°0′E
0
2.5
5 km

c)



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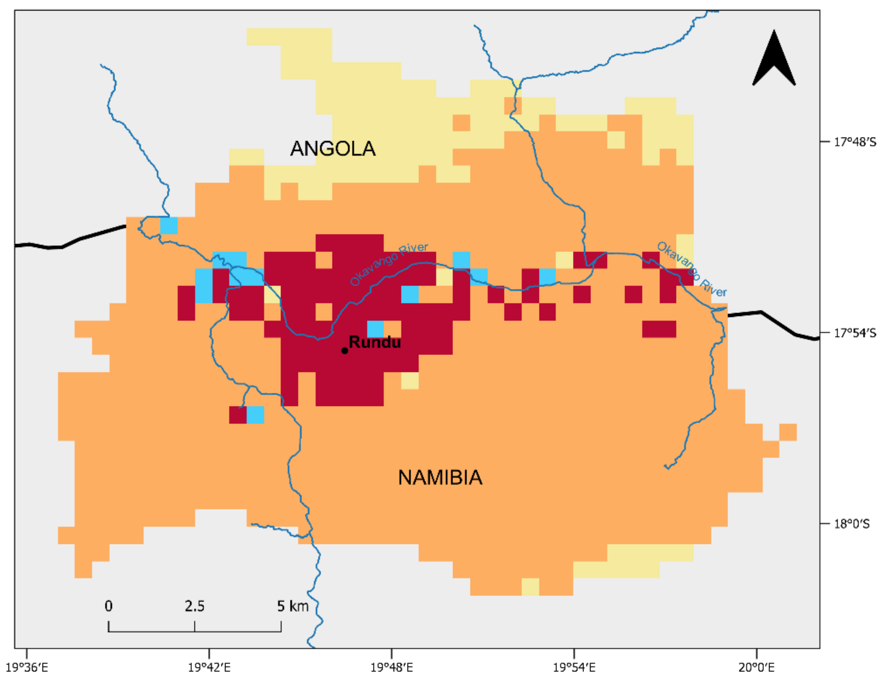

Figure 3.8: Land use and land cover (LULC) changes in the transboundary lower Okavango River Basin for the years: (a) 2021 (baseline), (b) 2040, (c) 2070, and (d) 2100. LULC data were derived from the 1-km global land projection dataset by Chen et al. (2022), consistent with SSP scenarios.

3.3.3. Combined Effects of Climate and Land Use Change on Basin Hydrology

The simultaneous occurrence of severe precipitation and streamflow reductions alongside extensive land degradation suggests that the region is approaching or may have already crossed ecological thresholds beyond recovery, prompting irreversible damage, even under best-case future climate scenarios. These trends reveal three critical dynamics: (1) the significant impact of climate-induced drying on water yield patterns; (2) the growing significance of land-use change, particularly the loss of wetlands and the expansion of urban areas, in exacerbating hydrologic loss; and (3) the emergence of stark spatial inequalities in water availability, with only limited areas near rivers retaining significant water yields by end of the century.

These trends are consistent with the broader regional context, as highlighted by Kusangaya et al. (2014), who observed the effects of climate change on water resources in Southern Africa. Their research underscores the compounding effect of LULC changes and climate variability on reduced water yield and increased vulnerability to water scarcity. A report by the Food and Agriculture Organization (FAO, 2014) on the Okavango River basin notes that population growth and land use changes, such as the expansion of cropland and urban areas, have led to changes in streamflow patterns and water quality. This has serious consequences for local water security, agriculture and ecological health which will be increasingly endangered. Vast parts of the basin could become hydrologically unsustainable by 2100, if climate change coupled with land use transformations run unabated along current emissions pathways. Findings motivate an urgent need for targeted policy interventions to conserve wetland ecosystems, to manage land development, and to provide buffers against further hydrological collapse.

3.4. Conclusion

This study presents a projected assessment of hydro-climatic changes in the lower Okavango Basin near Rundu. Using SWAT+ simulations driven by CMIP6 GCMs and LULC projections, we examined precipitation, streamflow, and water yield responses under SSP2-4.5 and SSP5-8.5 scenarios, relative to a historical baseline dataset spanning 1981–2015. The following key findings are summarized below:

- Nonlinear streamflow response to precipitation decline: While projected rainfall decreases are modest (approx. 5–20%), streamflow declines are far more severe (up to 60% by 2100), with several models simulating the end of dry season flow. This confirms the "dry gets drier" paradigm and highlights the vulnerability of semi-arid, downstream-dependent basins like the Okavango.

- Accelerated hydrological degradation due to land use change, particularly the conversion of wetlands to cropland and urban land is projected to reach over 65% of the basin area by 2100. This transition reduces infiltration capacity, increases runoff, and eliminates ecosystem buffering functions enhancing the climate impacts on streamflow.

- Spatial hydrological inequalities are expected to intensify, with water yield becoming increasingly concentrated along river corridors, while most southern and northern parts of the basin fall to extremely low yield conditions below 129 mm/year by end-century. The decline in spatially distributed water yield across the basin raises equity concerns for water access and ecosystem support.

- Model convergence after mid-century especially under SSP5-8.5 enhances confidence in long-term drying trends, particularly under high-emission pathways. The agreement across models strengthens the case for urgent adaptation and mitigation responses focused on land use regulation and water resource planning.

These findings not only confirm regional trends observed in the Zambezi, Limpopo, and Orange catchments (Aich et al., 2014; Goulden et al., 2009), but also emphasize the combined role of climate and human-induced LULC changes in undermining hydrological resilience.

Namibia has laid important policy foundations through the Integrated Water Resources Management Plan (IWRM, 2010) and the Water Resources Management Act (Act No. 11 of 2013). However, basin-scale integration with land use planning and climate change adaptation remains weak, especially for transboundary coordination with Angola and Botswana. To respond to the combined challenge of climate and LULC changes, sustainable strategies are proposed; i) implementation of nature-based solutions such as wetland protection and riparian buffer restoration in high wateryield areas, particularly upstream and near Rundu, to retain water and enhance recharge. ii) adopting conservation agriculture by implementing drought resistant farming practices like legume-based cropping systems, which are not widely practiced locally. These approaches allow to reduce evapotranspiration demand, soil retention, groundwater recharge and support food security in drier conditions. iii) Strengthen the mandate and implementation capacity of OKACOM to embed climate and land-use scenario planning in transboundary agreements and water allocation protocols. iv) Enhance monitoring and scenario-based planning for transboundary basins, with integrated datasets on land use, groundwater, and evapotranspiration to reduce modeling uncertainty and guide spatial adaptation strategies.

Without these coordinated actions, the lower Okavango is likely to cross irreversible ecological thresholds by the end of the century. Therefore, the study serves as a decision-support tool to inform water resource managers and policy makers, for integrated land-water-climate strategies that are both locally informed and regionally coordinated to prevent a systemic collapse in water security.

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Chapter 4: Assessing Land Suitability for Leguminous Crops in the Okavango River Basin: A Multicriteria and Machine Learning Approach

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Abstract

This study aimed to create a model to identify land suitable for growing sunn hemp (*Crotalaria juncea*) and pigeon pea (*Cajanus cajan*) in the Okavango River basin of the Kavango East region of Namibia. The researchers used advanced tree-based ensemble learning models to improve the accuracy of the analysis. These learning models are derived from original models such as Random Forest, Extra Trees, Gradient Boosting, and XGBoost, combined with a multivariate regression analysis. The Random Forest and XGboost models exhibited outstanding performance, as evidenced by their respective accuracy values of 0.97 and 0.96. In addition, this study proposed an innovative approach through the integration of subjective and objective analytical methods, which are independent of one another. The subjective component of the analysis employed a Multi-Criteria Decision Making-Analytic Hierarchy Process (MCDM-AHP). On the other hand, the objective component used a data-driven multivariate approach supported by tree-based learning algorithms. The researchers considered twenty-two variables, encompassing climatic conditions, hydro-geomorphologic features, soil characteristics, vegetation patterns, and socio-economic factors. These variables played a crucial role to identify the most suitable areas for growing the selected leguminous crops. The MCDM-AHP method utilised expert evaluations to rank the importance of variables, identifying water sources, slope, and soil properties as key factors. A suitability mapping analysis revealed that 17.63% of the area was highly suitable and 62.77% moderately suitable, while 10% was less suitable and 9.59% unsuitable for growing these two legumes. According to the data driven methodology, soil fertility and nitrogen content emerged as key determinants for land suitability. This is particularly relevant for nitrogen-fixing leguminous crops such as sunn hemp and pigeon pea, which play a central role in improving soil quality and ensuring food security.

Keywords: Multi-Criteria Decision Making (MCDM), Ensemble Learning Models, Leguminous Crops (sunn hemp, pigeon pea), Land Suitability, Okavango River Basin, Namibia.

4.1. Introduction

Food security poses a significant challenge in Sub-Saharan Africa. As the population rapidly expands, numerous households are unable to meet their essential nutritional requirements (FAO, 2023). Salgado Baptista et al. (2022) estimate that approximately 12% of the population in this region is currently experiencing food insecurity. This is attributed to a combination of natural and human-induced factors, such as floods, droughts, rapid population growth, conflict, and the overall impact of climate change. The report by the FAO and UN Water (2021) underscores the growing risk of water scarcity, particularly in areas where agriculture relies on rainfall. This situation has already led to a 50% reduction in crop production, significantly impacting food availability (IPCC, 2014). In pursuit of their developmental objectives, nations have incorporated the sustainable management of land and water resources into their strategic frameworks, recognising these as pivotal elements in achieving food security and environmental stability.

Inter-annual climate variations, soil erosion and loss of nutrients have been identified as significant factors related to yield decline in this region (IFAD, 2021; Sharma et al., 2011). One of the challenges faced in many parts of southern Africa is the decrease in soil fertility in semi-arid regions (Ncube, 2007). Proper soil and water management could mitigate the effects of climate change on crop productivity. Predictions indicate that by mid-century, several countries including Angola, Malawi, Mozambique, Lesotho, and Zimbabwe will witness a substantial decrease in arable land, rendering it unsuitable for growing staple crops such as beans, cassava, maize, millet, pigeon pea, sorghum, and wheat, as well as cash crops (IFAD, 2021).

The state of food insecurity in Namibia mirrors the conditions found across sub-Saharan Africa. According to the latest Integrated Food Security Phase Classification (2023) twelve out of the fourteen regions are experiencing severe food insecurity, with 22% of the total population in dire need of food assistance. The main cause of the crisis is the occurrence of unpredictable climate shocks, including prolonged periods of drought, fluctuations in annual rainfall, and economic hardship. Kavango East and Kavango West, both located in the Okavango River Basin, were expected to face severe food insecurity from 2023-2024 (Republic of Namibia Office of the Prime Minister, 2023).

The transboundary freshwater ecosystem of the Okavango River basin located in the Southern Angola highlands receive more rain than its downstream counterparts in the semi-arid regions of northeastern Namibia and Northwest Botswana (Mendelsohn and El Obeid, 2004). The basin has experienced land degradation due to inappropriate land use, and inadequate water conservation strategies, from the prevalence of ad hoc farming practices along the basin, highlighting the need for efficient planning, development, and management of land and water resources in areas of high rainfall variability (NEPAD Water Centres of Excellence, 2013). Irrigation and flood recession agriculture in the Okavango River basin have enhanced crop yields for small-scale farmers, thereby increasing household food security, especially in the semi-arid regions of Namibia and Botswana (Mosepele et al., 2019).

For better understanding of how to manage the interplay between supply and demand for water and land resources, it is helpful to conduct research that examines the behaviour of watersheds and land use practices in the region. One approach is the assessment of land suitability. This evaluates the potential of the land to support various uses by considering factors such as soil quality, topography, climate, and water availability (Sys et al., 1991). By determining the optimal land use for agriculture, agronomists, agricultural extension officers, land-use planners and policymakers can make informed decisions regarding resource allocation, promoting a balance between economic development and environmental sustainability.

Land suitability assessment is a crucial component of land use planning. It provides valuable information to support decision-making to optimise the utilisation of land resources in a specific area. This assessment considers a broad spectrum of characteristics and requirements (FAO, 1993, 1976). Furthermore, it can assist in identifying the locations of greater importance and quantifying the extent to which a particular piece of land is suitable for specific purposes such as agriculture, urban development or conservation (Yalew et al., 2016).

In most comparable studies of land suitability, commonly used parameters fall under categories of climate, hydro-geomorphology and soil features (Bhullar et al., 2023; Sarkar et al., 2023). Depending on the investigation, different combinations of parameters may be employed to determine the suitability of a piece of land for crop farming. Parameters receive a weighted score through a multi-criteria evaluation approach. A multi-criteria decision making (MCDM) approach such as the Analytic Hierarchy Process (AHP) from Saaty (1987) is commonly used to determine land suitability for agriculture. However, several studies have emphasised the lack of objectivity in the MCDM-AHP method, which relies on expert opinions to assess the agricultural land suitability (Arab and Ahamed, 2022; Pramanik, 2016; Sarkar et al., 2023). A subsequent multivariate model enables researchers to analyse the individual contributions of various factors and their interactions to the observed suitability class, uninfluenced by subjective views. The most frequently used methods for evaluating the suitability of crop land are the Analytic Hierarchy Process (AHP) and fuzzy sets. These are subjective in nature and define members of pixels within suitability classes and categorise pixels that belong to unsuitable classes (Zadeh, 1965). Using the AHP approach (Moisa et al., 2022; Tashayo et al., 2020) conducted crop suitability assessments in semi-arid environments, classifying the suitability for maize production into three categories. However, they identified crop-specific suitability analysis as a limitation. Similarly, studies by Adem et al. (2023) and Waleed et al. (2020), successfully used AHP to identify irrigation potential for crop growth, but noted the subjective nature of relying on expert opinions. Additionally, a research by Arab and Ahamed (2022) and Özkan et al. (2020), used fuzzy expert system to identify suitable areas for agricultural production. While they achieved to establish a representative suitability ranking, uncertainties related to expert opinions were also highlighted.

Machine learning, combined with remote sensing and GIS, is an emerging technique to address the shortcomings in evaluation of MCDM models traditionally used in land suitability assessment. This avoids the subjective nature of commonly used approaches, such as AHP and fuzzy sets. Recent research has used ensemble learning to maintain objectivity in the evaluation of agricultural land suitability (Bhullar et al., 2023; Ismaili et al., 2023; Mohammed et al., 2023). Various ensemble learning models have been used to assess suitability of agricultural land based on random forest (RF) (Dolsiririttigul et al., 2022), extreme gradient boosting (XGBoost) (Hao et al., 2024), support vector machine (SVM) (Sarmadian et al., 2014), and artificial neural networks (ANN) (Ahmadi and Layegh, 2015). Comparisons of machine learning models for land suitability assessment found that RF and XGBoost predicted better than SVM, ANN and k-Nearest Neighbor algorithms (Ganesan et al., 2021; Ismaili et al., 2023). Most importantly, tree-based ensemble models can handle categorical and continuous variables for classification and regression. Data-driven suitability models are becoming increasingly prevalent, due to their capacity to handle large amounts of data and their ability to capture complex non-linear relations. Consequently, machine learning algorithms enable researchers to model each variable's influence and their interactions towards an observed suitability classification based on data-driven attributes.

Namibia lacks crop suitability studies, especially in communal small-scale farming areas. Thus far, only a limited number of studies have focused on general agro-ecological zoning and suitability of livestock farming (De Pauw and Coetzee, 1998; Strohbach, 2018). One study on land evaluation highlighted the potential for growing multiple crop varieties through intercropping, using a year-round irrigated water supply (FAO, 1984). A separate study examined land evaluation of an individual commercial resettlement farm in the north central Oshikoto region of Namibia (Mwazi, 2006). To our knowledge, no previous studies on the Okavango River basin in Namibia have been conducted to assess leguminous crop suitability, despite a significant increase in crop growing in the area (Fortunato and Enciso, 2023). This indicates a knowledge gap of land uses and their feasibility to support crop farming activities in Namibia's north and northeastern communal areas. To determine suitable land for agriculture in the Rundu area of Namibia, located along the Okavango River basin, it is necessary to identify and utilise key variables representing biophysical and socio-economic elements in a multi-criteria assessment. This approach employs parameters that have been extracted from previous investigations in other parts of the world with comparable biophysical characteristics (Roy and Saha, 2018; Tashayo et al., 2020).

The objective of this study was to investigate the degree of land suitability for leguminous crops, namely sunn hemp (*Crotalaria juncea*) and pigeon pea (*Cajanus cajan*) along the Okavango River basin. The focus was on the sub-basins surrounding Rundu in Kavango East region of Namibia. The viability of land use for agriculture in the basin is crucial due to rapid population growth and high demand for food. This is particularly important because the basin already faces extreme climate conditions caused by climate change in an already water-scarce semi-arid environment. Additionally, there are more informal farming activities along the basin. Sunn hemp and pigeon pea are legume crops mainly cultivated in tropical and sub-tropical regions for human consumption and/or as livestock feed. These leguminous cover crops may help to suppress weeds by the allelochemicals found in their biomass (Javaid et al., 2015). Many smallholder farmers in semi-arid regions view pigeon peas as a green manure alternative, as they are drought-resistant, high-protein cover crops that can improve soil nutrients (e.g., nitrogen fixing) (Cook et al., 2020; Sharma et al., 2011). In a similar vein, sunn hemp is renowned for its exceptional resilience to environmental stress and is employed as a green manure to enhance soil nutrients and increase livestock fodder supply. This legume crop can increase soil organic matter, raise nitrogen levels, and sequester carbon (Chaudhary et al., 2015; FAO, 2022). Since both these legumes improve soil moisture, enhance organic matter, and decrease soil erosion, they are typically interplanted with cash crops such as maize, sorghum, and pearl millet to increase yields. Smallholder farmers intercrop legumes as green manure cover crops with cereals in drought-prone semi-arid regions with low soil fertility. This improves soil nutrient contents and boosts output (Mashingaidze et al., 2012; Simon and Itanna, 2019). Following an in- depth literature review on suitable approaches in semi-arid regions of sub-Saharan Africa and discussions with agronomists, the two leguminous crops were selected to identify areas suitable to grow them in. The study was motivated by the numerous benefits that can be obtained from intercropping legumes, as demonstrated by several researchers (Odunze et al., 2004; Rani et al., 2019; Sharma et al., 2011; Tsubo et al., 2005). These benefits include soil rehabilitation, drought tolerance, as well as nutritional and economical values. The crop characteristics and information on environmental requirements for sunn hemp and pigeon pea were collected to determine optimal land for enhanced yields. Both legumes mainly grow in similar climatic regimes, demand similar soil properties and require matching topographical features (Cook et al., 2020; FAO, 2022; Orwa et al., 2009; Zimmermann, 2023).

In this study, our objectives are: i.) to subjectively assess and estimate land suitability for sunn hemp and pigeon pea using an MCDM-AHP approach; and ii.) to evaluate an objective data-driven non-linear multivariate approach, in conjunction with supervised learning models to understand the relationship amongst the selected variables and allocate crop suitability scores in the basin. In addition, this study seeks to evaluate the capability of the Okavango River basin to grow leguminous crops through investigation of the biophysical and socio-economic characteristics of the area. This research contributes towards a better understanding of the interdependence of the Okavango River basin and its adjacent land use near Rundu.

4.2. Materials and Methods

4.2.1. Study site

The study area, as shown in figure 4.1, is located in the semi-arid environments of seven sub-basins surrounding the Rundu municipality in the Kavango East region of northeastern Namibia. These sub-basins are part of the greater Okavango basin. The Okavango River flows from wetter highlands of Southern Angola, passing through Namibia, and dissipates downstream in northwestern Botswana. This transboundary river system is occupied by approximately 1 million inhabitants, predominantly engaged in small-scale farming (EPSMO-BIOKAVANGO Eflows Team, 2009).

The Rundu municipality and its surrounding sub-basins were chosen as a study site, as the area mainly subsists through crop production and shows the highest population density within the basin. According to the 2011 census, Rundu had a population of 63,431. With an annual growth rate of 5.4%, the current estimated population is close to 120,000. This makes Rundu the second most populated town in Namibia (Namibia Statistics Agency, 2011). Rundu is a potential market for agricultural products, and is located along the Trans-Caprivi Corridor, a trade route linking land locked neighboring countries. On the Namibian side, the population along the basin mainly relies on farming pearl millet (known as mahangu in the local language), and to a lesser extent on sorghum, maize and vegetables such as cabbages and tomatoes. The major constraints for farming inland away from the river are the poorly suited soil types, which are mostly Arenosols characterised by low water and nutrient storing capacities. Along the river, Fluvisols and Gleysols are the prevailing soil types. These soils consist mainly of silty clay loam and sandy clay loam, which contribute to their high nutrient content and water storage capacity (Atlas of Namibia Team, 2022).

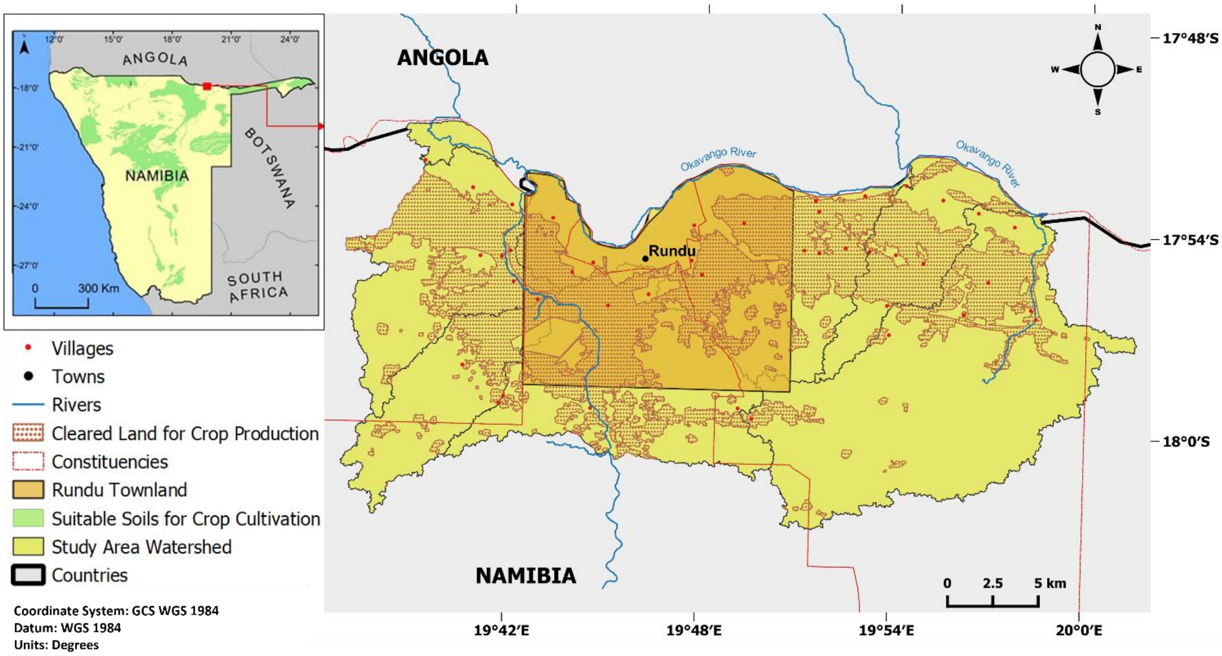

Figure 4.1: Location of the study area: Okavango River sub-basins surrounding Rundu, Namibia.

Approximately 70% of the population in the Kavango East region, where Rundu is located, are settled along the Okavango River basin. This is due to the availability of water, arable soil, and pastures suitable for agricultural activities (Brown et al., 2010). 53% of households are engaged in crop farming which is higher than the national average of 32.8% (Mwinga et al., 2018). The rainy season in northeast Namibia typically occurs between October and April, coinciding with cultivation activities. However, increased rainfall variability and intermittent drought occurrences can be observed in this semi-arid environment, causing reduced crop yields (Awala et al., 2019; Lu et al., 2016; Mendelsohn et al., 2002). As a result, small-scale farmers found in Rundu, the rapidly growing capital of Kavango East region are highly dependent on rainfed agriculture.

The study site has a mean annual rainfall ranging between 450 to 550 mm during the rainy season. Light rainfall occurs at the beginning of the rainy season in October and November and towards the end of April (The World Bank Group, 2021). Furthermore, an increase in rainfall is typically recorded between December and March. Most farming activities take place during this time to maximise yield. The typical size of a crop farm along the study area varies between 2 and 5 hectares, and usually belongs to an individual household. Similar to other valleys found along rivers, the Okavango valley is dominated by floodplain grasslands and woodland vegetation (Mendelsohn and El Obeid, 2004). However, much of this land has been cleared for accelerated crop production resulting in soil degradation caused by erosion, which adversely affects the levels of organic matter and nutrients.

4.2.2. Data and methods

Variables used in this study were derived from previous literature, agricultural land evaluation guidelines and expert recommendations. Similar to typical land suitability assessments, a collective twenty-two climatic, hydro-geomorphologic, soil, vegetation and socio-economic variables (see Table 4.1) were identified to determine the suitability of leguminous crops in the study area. These variables were all resampled to 100 meters spatial resolution considering the processing capacity requirements for the collective variables. The variables were grouped into five different categories, covering 22 significant biophysical and socio-economic characteristics for crop cultivation. These characteristics were further classified into the following five subclasses: Highly suitable, suitable, moderately suitable, less suitable, and unsuitable**.** Primary and secondary data for the study site (see Table 4.1) were obtained from various sources and processed to identify suitable areas for intercropping sunn hemp and pigeon pea through multi criteria decision making approach and multivariate regression.

Table 4.1: Summary of variables for land suitability of leguminous crops and their description, sources, spatial and temporal resolution.

Parameters	**Description**	**Data Source**	**Res.**	**Time**
Elevation	Elevation	TanDEM-X (HRTI-3) - TerraSAR-X DLR mission	12 m	Fixed
Slope	Slope	TanDEM-X (HRTI-3) - TerraSAR-X DLR mission	12 m	Fixed
LULC	Land use land cover	ESA WorldCover 2021	10 m	Fixed
Distance from river	Distance from river	TanDEM-X (HRTI-3) - TerraSAR-X DLR mission	12 m	Fixed
Drainage density	Drainage density	TanDEM-X (HRTI-3) - TerraSAR-X DLR mission	12 m	Fixed
Ground water depth	Ground water depth	Hydrological Services of Namibia		Fixed
Proximity to market	World Settlement Footprint	Deutsches Zentrum für Luft- und Raumfahrt (DLR)	10 m	Fixed

Proximity to road	Distance from road	Directorate of Survey and Mapping (DSM), Namibia		Fixed
Soil bulk density	Soil bulk density	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil cation exchange capacity	Soil cation exchange capacity	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil organic carbon	Soil organic carbon	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil fertility capability classification	Soil fertility capability classification	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil depth	Soil depth to bed rock	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil nitrogen	Soil nitrogen	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil phosphorus	Soil phosphorus	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil pH	Soil pH	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil texture	Soil texture	Innovative Solutions for Decision Agriculture Ltd. (iSDA)	30 m	Fixed
Soil type	Soil type	Updated Soil Map and Soil Profile Database of Namibia (Coetzee 2020)	250 m	Fixed
Soil water content	Soil water content	EnvirometriX Ltd	30 m	Fixed

NDVI	Mean Normalized Difference Vegetation Index (October – April)	NASA's Land Processes Distributed Active Archive Center (LP DAAC)	250 m	2013 - 2023
Precipitation	Mean of daily mean precipitation rate (October – April)	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)	5566 m	2013 - 2023
Evaporation	Mean of daily mean evaporation rate (October – April)	ERA5-Land - Copernicus Climate Data Store	11132 m	2013 - 2023

4.2.3. Climatic variables

The climate variables considered in this study were the daily amounts of precipitation and evaporation recorded over a ten-year period from 2013 to 2023. The months between October and April are usually considered as rainy season in Namibia, with the highest precipitation recorded in December, January and February (The World Bank Group, 2021). Crop growing season is also typically regarded to occur during these months with a relative abundance of rain. During this period, December, January, and February have the highest temperatures and evaporation rates. CHIRPS Daily precipitation dataset with 0.05° resolution from the Climate Hazards group Infrared Precipitation with Stations (Funk et al., 2015) is used to extract the daily mean, minimum and maximum of the study area. Daily aggregated ERA-5 Land ECMWF (European Centre for Medium-Range Weather Forecasts) climate reanalysis (Copernicus Climate Change Service, 2019), is used to extract mean, minimum and maximum evaporation at 0.1° resolution for the duration of the growing season.

4.2.4. Hydro-geomorphologic variables

The hydro-geomorphological variables considered in this study were elevation, slope, drainage density and ground water depth. The first three variables were generated using a TanDEM-X Digital Elevation Model with 12 m spatial resolution and relative vertical accuracy of 2 m, obtained from German Aerospace Center (DLR) (Wessel et al., 2018). Ground water depth was generated through inverse Distance Weighting (IDW) interpolation using observed data from Geohydrology Division at Ministry of Agriculture, Water and Land Reform in Namibia. Elevation for the study site ranges between 1063 and 1152 m above sea level, whereas a dominant gentle slope is observed in most of the study region, between 2° to 5°. The drainage density varied between 0.4 to 4.5, with most of the area concentrated between 2 and 3.5 km/km^2.

4.2.5. Soil variables

This crop land suitability assessment took into account soil physical and chemical properties to determine the potential for increased crop yield, with a focus on soil nutrients such as nitrogen, organic carbon and phosphorus; soil pH measuring the level of alkalinity or acidity; cation exchange capacity measuring soil ability to store nutrients; soil bulk density, texture, and type determining its porosity and structure; water content defining the amount of soil moisture and soil fertility capability classifying its capacity to grow crops. All soil data were retrieved from Innovative Solutions for Decision Agriculture Ltd. (iSDA), except for soil water content from EnvirometriX Ltd (Hengl and Gupta, 2019) and soil type from updated soil map and soil profile database of Namibia (Coetzee, 2020). Their characteristics were divided into five different classes representing different categories of suitability as per reviewed literature and expert’s opinion. Soil properties suffer negative consequences due to high intensity farming causing soil degradation and eventually reduction of crop productivity. Sunn hemp and pigeon pea, also referred to as leguminous green manure cover crops (GMCC), have a positive impact on soil chemical properties improving soil nutrients, holding capacity, and cation exchange capacity (Simon and Itanna, 2019). They also play an important role in soil nitrogen fixing, maintaining pH level, enhancing phosphorus uptake, and weed management through allelopathic potential. Furthermore, improved soil physical properties can be observed resulting in improved water holding capacity, decreased soil erosion, increased porosity and allowing aeration and percolation (Rani et al., 2019). According to Fan et al. (2016) and Hag Husein et al. (2021), a majority of crop’s root biomass is located in the upper 30 cm of soil profile. However, in their study on data-driven multilayer crop suitability prediction, Bhullar et al. (2023) found that the median root depth ranged from 8.4 to 19.8 cm. They also emphasised that the model's accuracy was improved when considering a soil depth of 10 cm. In light of these observations, the extracted soil dataset for our study area were at the depth ranging between 0 – 20 cm mapped at 30 m spatial resolution, using the iSDA data assimilation of remotely sensed products (i.e., Sentinel-2, Landsat, DEM products, etc.), and over 100 thousand soil samples (Hengl et al., 2021).

4.2.6. Socioeconomic variables

The socioeconomic criteria considered in this study were the proximity to the nearest population settlements and the Euclidean distance to roads. These criteria determine potential marketplaces to connect buyers and sellers, as well as facilitate transport infrastructure for farming inputs and market accessibility for smallholders. The proximity to population settlements was extracted from the World Settlement Footprint (WSF) dataset by Deutsches Zentrum für Luft- und Raumfahrt (DLR), derived from Landsat-8 and Sentinel-1 products, and validated by ground-truth samples (Marconcini et al., 2020). Population settlement data in the study area were used as indicator for potential marketplace for crop yields to satisfy the demand and supply. The major roads dataset sourced from Namibia’s Directorate of Survey and Mapping (DSM) were used to compute accessibility to agricultural extension services, access to technology, and access to market for smallholder farmers. The dataset was generated by applying the Euclidean distance metric to assign a distance value to each pixel within the study area based on its proximity to the major roads.

4.2.7. Vegetation variables

This study used Land Use Land Cover (LULC) product from ESA WorldCover (Zanaga et al., 2022), which directly correlates with the expected outcome of crop suitability. LULC is used to filter out the constraints such as built-up area from the final suitability map during AHP. A multivariate setting crop land from LULC is used to see the probability of suitability classification and rate the importance of a variable for this suitability classifier. The Normalized Difference Vegetation Index (NDVI) was extracted from MOD13Q1.061 Terra Vegetation Indices collection (Didan, 2021), for the duration of ten years (2013-2023), and used as a proxy for suitability in the multivariate regression.

4.2.8. Analytic Hierarchy Process

The AHP method, developed by Saaty (1987), was used to determine the weights of different variables influencing growth of the two legumes was conducted through pair-wise comparison. Expert opinions collected from 5 experts to evaluate the relative importance of each variable was carried out, resulting with the weights of each variable ranging from 0 to 1. This was done to identify appropriate land for growing leguminous crops in the sub-basins surrounding Rundu along the Okavango River. Several criteria categorised under climatic, soil, hydro-geomorphic, socioeconomic and vegetation factors, as shown in figure 4.2, were ranked to compare the relative importance of each individual criterion. Based on Saaty (1987), the relative scale ranges between 1 indicating "both criteria contribute equally to the objective" and 9 representing "evidence favors a criterion over another in the highest possible order". Thereafter, the pair-wise comparison matrix is computed based on the outcome of the relative importance scale using the {ahp} package in R (Glur, 2024), as shown in Equation 1.

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \tag{1}$$

Once the comparison matrix is computed, the weight of each criterion is determined using a priority vector (i.e., normalized eigen vector) method. The derived normalized eigen vector represents the average values of each row of variables, showing the relative weights of each individual criterion being compared. At this point, a consistency check is crucial, as inconsistencies may occur due to randomly generated matrixes. The consistency index which measures the expert judgements of the variable comparison is measured using the consistency ratio (CR), as seen in Equation 2.

$$CR = \frac{CI}{RI} \tag{2}$$

CI refers to the consistency index and RI stands for the random consistency index. The acceptable value for the CR must be equal to or lower than 10%. If the value is less than 10%, the inconsistency will be tolerable, and the parameter will further be used in the suitability analysis.

However, if CR is greater than 10%, the variable will be omitted, as it cannot be trusted for the analysis process.

4.2.9. Weighted Overlay Process

Finally, a crop suitability map will be generated based on the acceptable criteria weights. This is achieved using a weighted overlay analysis in ArcGIS 10.5 through the application of normalised criteria and their associated weights (Drobne and Lisec, 2009). A weighted overlay application creates a common scale for varied and heterogenous input values. This allows an integrated criteria analysis to address complex spatial problems in the classification of suitability. The application of the weighted overlay method, combined with the AHP, enables the integration of different thematic layers to assess how various factors affect crop suitability. The relative importance of individual criteria towards land suitability is resolved through a Pairwise comparison matrix. The weight of each variable is multiplied by the suitability score of that variable, and the resulting values are summed to compute a crop suitability map, as illustrated by the equation (Cengiz and Akbulak, 2009; Owusu et al., 2017).

$$\mathrm{LS} = \sum_{i=1}^{n} w_i x_i \tag{3}$$

Where LS is suitability, w_i denotes weight of variable i, and x_i denotes score of variable i.

Given the subjective nature of the MCDM-AHP method, which employs expert opinion to assess the suitability of land for agricultural productivity, a subsequent multivariate statistical approach is proposed in order to assess the parameters objectively.

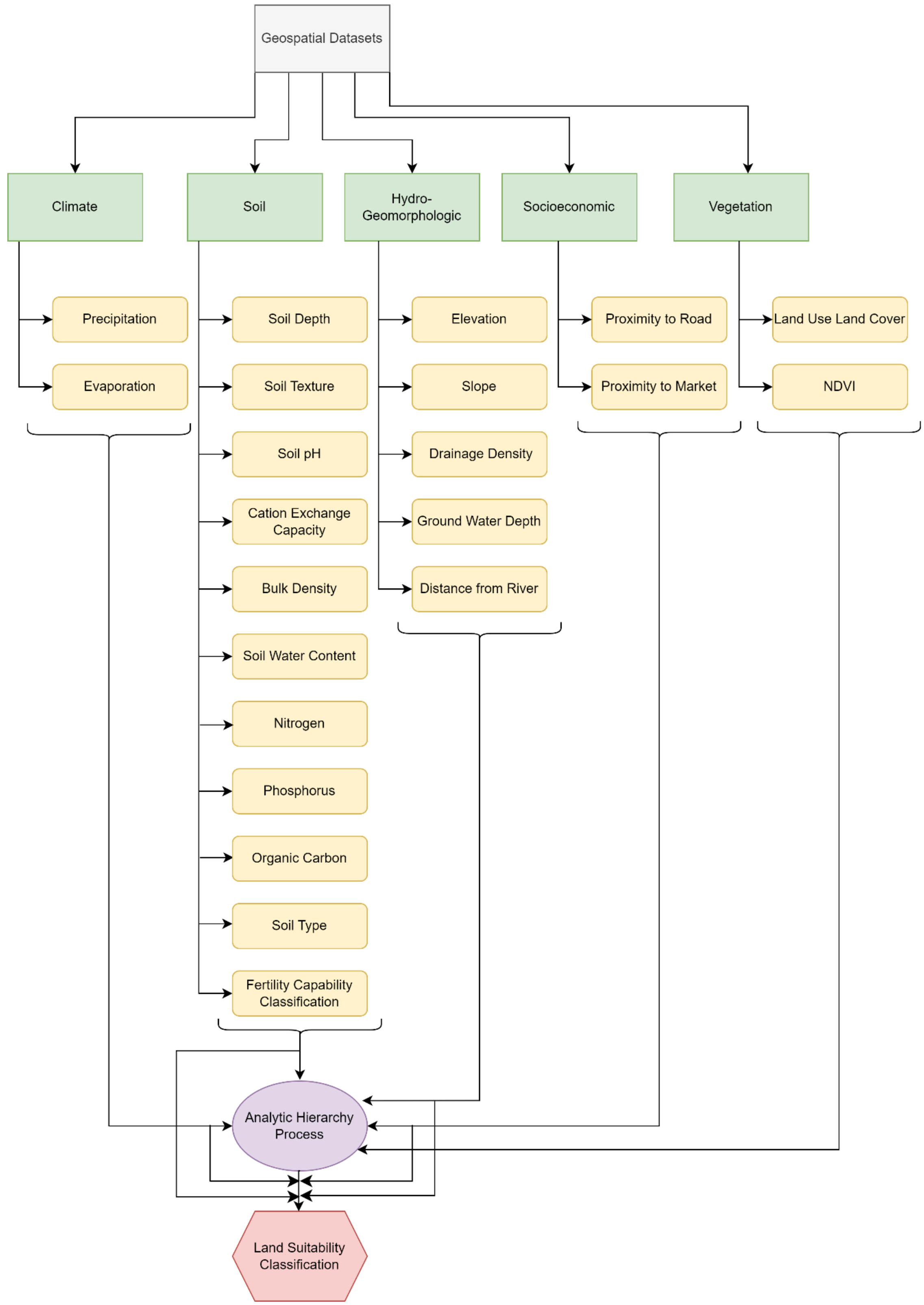

Figure 4.2: Workflow diagram showing geospatial datasets used as input variables for AHP criteria weighting for land suitability classification.

4.2.10. Data-driven crop-suitability approach

Our study utilised a dichotomous approach to assess crop suitability. While the AHP method was used to assess land suitability with expert-weighted variables, the machine learning models were trained exclusively on the original, unweighted environmental variables. No expert-derived weights or outputs from the AHP analysis were incorporated into the machine learning models. As such our machine learning approach is purely data-driven, without propagating any expert bias (Figure 4.2 & 4.3). The method allowed us to compare empirical data with subjective assessments, leading to a better understanding of the factors that affect crop suitability. We used the health and vigor of the vegetation using the NDVI as a proxy due to the lack of data from the two key crops. This index is closely related to crop suitability (Junges et al., 2017; Yan et al., 2023). Furthermore, we used land use classification data to analyse the various potential factors that influence crop cultivation.

The primary focus of the approach is to achieve two main objectives. First, we aimed to examine the complex relationships between different environmental factors and their effect on crop suitability. We focused on identifying and understanding how different elements of the natural and socio-economic environment interacted to influence crop suitability. Second, the goal was to build a robust set of predictive models capable of accurately identifying the most influential factors for crop suitability. The models aimed to provide precise predictions and offer insights into the relative weight of various environmental and socio-economic factors in determining crop cultivation suitability.

The machine learning model training and analysis were conducted using the Python programming language, utilising scikit-learn for machine learning models and XGBoost for gradient boosting algorithms. The computations were executed on a High-Performance Computing Platform (HPCP) equipped with 128 GB of RAM and 64 CPU cores.

4.2.10.1. Ensemble machine learning models:

Using decision trees, we created and evaluated ensemble learning models. These models incorporate numerous decision trees to improve prediction accuracy and flexibility, making them suitable for dealing with complex datasets. We employed tree-based ensemble learning models, including Random Forest, Extra Trees, Gradient Boosting, and XGBoost (see Figure 4.3). During training, these models build several decision trees and return the mode of the classes for classification or the mean prediction for regression of the individual trees.

The Random Forest is an ensemble learning method that builds multiple decision trees on bootstrapped training samples and a random sample of predictors (James et al., 2013). It provides outputs based on the average or majority voting of the individual trees (Breiman, 2001). Extra Trees are another ensemble learning approach that, similar to Random Forest, generates numerous decision trees and outputs the average prediction of the individual trees. However, Extra Trees uses the full dataset and random thresholds for splitting (Geurts et al., 2006). On the other hand, Gradient Boosting combines weak predictive models to generate a powerful predictor by sequentially building an ensemble of trees, with each tree correcting the mistakes of the previous ones (Chen and Guestrin, 2016; Natekin and Knoll, 2013). XGBoost is an optimised distributed gradient boosting library that provides a scalable and accurate implementation of gradient boosting.

4.2.10.2 Multivariate regression analysis:

In addition to using tree-based models, we conducted multivariate regression analyses to determine evidence of association between various variables and suitability. This approach yielded coefficients that indicate the strength of the relationship between each predictor and the outcome variable (Figure 4.3). The basic goal of multivariate regression is to estimate the coefficients associated with the independent variables in order to minimise the difference between the observed and predicted values of the dependent variable, as indicated by the regression equations (James et al., 2013). Linear regression methods are used to express multivariate regression when dealing with continuous variables such as NDVI. On the other hand, when dealing with dummy variables (crop land), a logistic model is used to represent the regression.

$$y_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{4}$$

$$\log\left(\frac{p(X)}{1 - p(X)}\right) = \beta_0 + \sum_{i=1}^{n} X_i + \varepsilon \tag{5}$$

In equation (4), y_I represents the dependent variable, which refers to the suitability level of a particular pixel (NDVI). β_0 represents the intercept term, β_I are the coefficients associated with the independent variables X_1, X_2, ..., X_i respectively, and ϵ denotes the error term capturing unexplained variability (James et al., 2013). Similar, $log(p(X)/(1-p(X)))$ in equation (5) represent the log odds or logit.

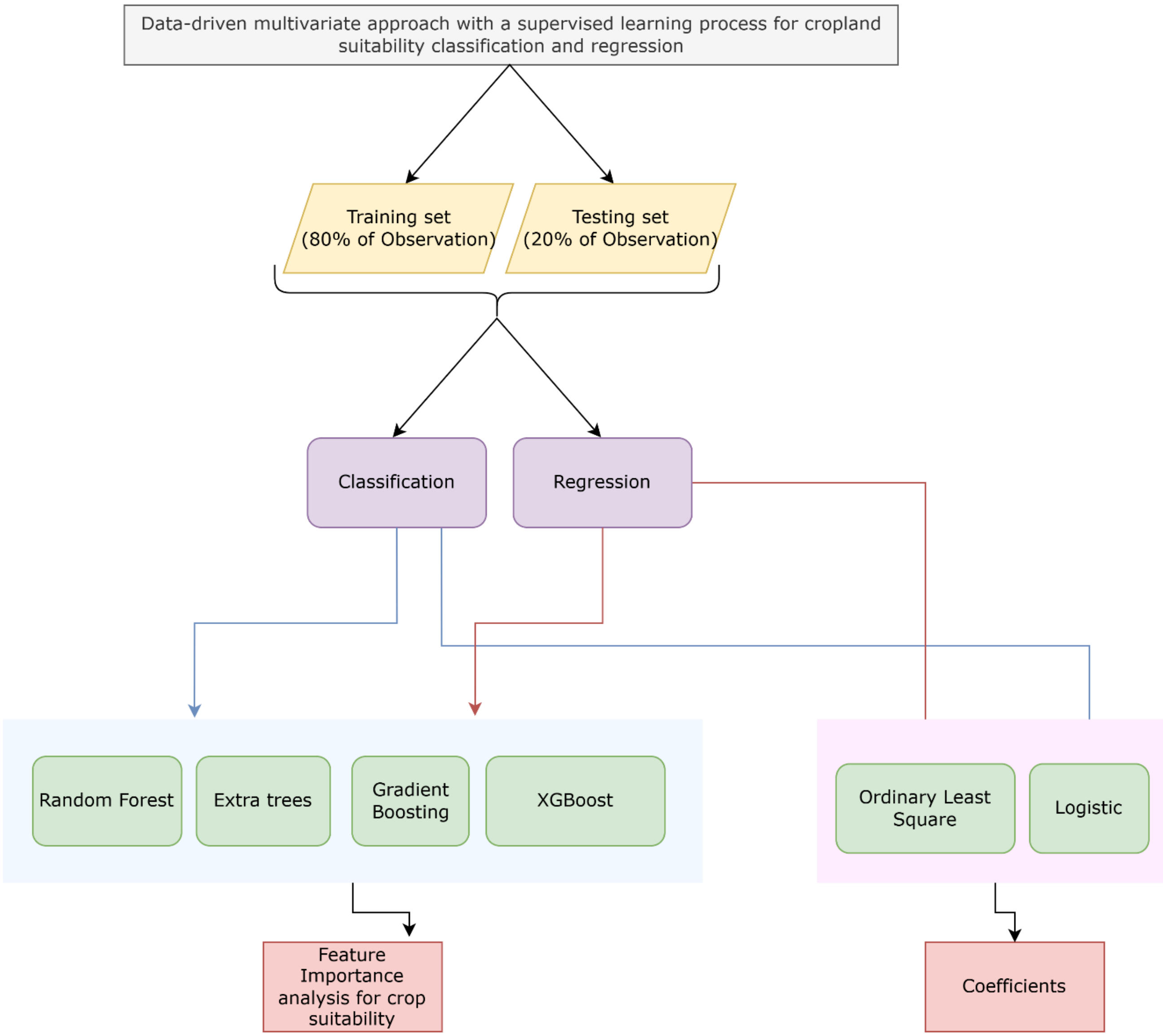

Figure 4.3: Ensemble learning models for crop cultivation suitability.

4.2.10.3. Data preprocessing and estimation

To ensure numerical stability during model estimation, we standardised continuous variables using mean normalisation and variance scaling. We also transformed categorical variables into a binary matrix using one-hot encoding, in order to make them compatible with the different learning algorithms.

We partitioned the dataset into five sets and used a 5-fold cross-validation method. Each set was used once for validation, while the remaining four datasets were used as training sets. This would mitigate overfitting risks and improve the generalisability of the results (James et al., 2013). We also used performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2). We analysed the models that achieved the highest R2 values to evaluate their ability to capture variance within the dataset. Additionally, we optimised the ensemble models through hyperparameter tuning (see table 4.2). We fine-tuned parameters such as subsample, learning rate, and tree characteristics to improve model performance.

Table 4.2: Hyperparameters of ML models.

Parameter	Values
model__learning_rate	0.01, 0.1, 0.2, 0.3, 0.4
model__subsample	0.5, 0.6, 0.7, 0.8, 0.9
model__colsample_bytree	0.5, 0.6, 0.7, 0.8, 0.9
model__reg_alpha	0.1, 0.001, 0.00001
model__reg_lambda	0.1, 0.001, 0.00001

The optimised model was assessed using training and testing datasets. Primary evaluation metrics included accuracy, precision, recall, and F1-score, providing a comprehensive outlook on the model's ability to reliably classify cropland. To identify potential overfitting or underfitting, the bias-variance trade-off analysis was crucial in evaluating this model. Overfitting occurs when a model performs better on the training set than the validation set, indicating that the model is too complex for the data. On the other hand, underfitting is suggested by equally high error rates on both sets, indicating that the model is too simple. A Feature Importance analysis was conducted for both regression and classification models to compute and visualise the relative importance of each characteristic. This analysis identified the most important factors which can be used to inform environmental policy decisions.

4.2.10.4. Model evaluation framework

To evaluate model performance, a variety of metrics were considered. Classification models were evaluated for accuracy, precision, recall, and F1-score. While regression models were assessed using R-squared and Root Mean Squared Error (RMSE). Tree-based models identified crucial variables affecting crop suitability. Furthermore, the multivariate regression technique provided an insight into the direction and magnitude of the effect of each factor.

Model performance in the Ordinary Least Squares (OLS) regression was evaluated with R2 to indicate the proportion of dependent variable variance explained by predictors, and RMSE to reflect the average magnitude of prediction errors. The logistic regression results display changes in the log odds of an area's suitability for cropland in response to predictor variable variations.

4.3. Results and Discussion

4.3.1. Cropland suitability evaluation

A comprehensive literature review was conducted, and the input of five experts was sought based on their informed judgement. This was done to assign weights and rank selected variables according to their relative importance through AHP to determine suitable areas for sunn hemp and pigeon pea cultivation at pixel level. Based on the framework of land evaluation from FAO (1976), five suitability classes reflecting the degree of suitability for agricultural land use were defined (i.e., Highly Suitable, Suitable, Moderately Suitable, Less Suitable and Unsuitable). Land that is highly suitable for crop growth has no significant limitations. If minor limitations do occur, they will not increase inputs beyond an acceptable level to achieve expected productivity. Suitable class is associated with land that has few or no limitations that would negatively affect its productivity, and it requires minimal inputs to achieve optimal crop yield. Moderately suitable agricultural land is considered to have substantial input requirements to realise balanced productivity. Despite the fact that it may be attractive to farmers, it is still considered inferior to the Suitable class. The class of land that is less suitable represents land used for agricultural purposes. It has significant constraints that pose challenges for sustainable use and requires substantial inputs to acquire benefits. Consequently, it is regarded as marginally viable. The unsuitable class represents a piece of agricultural land that is incapable of being used sustainably for its intended purpose. No amount of input could justify its sustainable use. In the decision-making process, pair-wise comparison was performed using a relative scale between 1 and 9, as stated in section 4.2.8. This comparison aimed to determine the preference of one criterion over another and compute its comparison matrix. The weights of each criterion were then derived using a priority vector with an acceptable consistency ratio of 8.85%.

4.3.2. Climatic factors

In search of appropriate location for leguminous crop production, two variables were specifically considered: precipitation and evaporation. These factors were used to determine the suitability of the climate conditions in the study region. The average daily rainfall over crop growing period ranged between 0 and 2.27 mm, as shown in figure 4.4. Local experts in conservation agriculture advised an average daily rainfall of at least 1.5 mm for intercropping legumes with pearl millet (Zimmermann, 2023). Moreover, the ECOCROP database indicates a minimum average daily precipitation requirement for sunn hemp and pigeon pea at 1 mm and 1.8 mm, respectively (FAO, 2022). Accordingly, the optimum precipitation rate was set to be between 2.27-2.24 (i.e., 15.6% of the total study area size), while the least suitable class of 2.18 – 0 was assigned as unsuitable, representing 9.39% of the whole study area. The potential mean evaporation rate in the study region is approximately four times higher than the mean rainfall. This is consistent with a high evaporation rate observed by The Permanent Okavango River Basin Water Commission (2011) and The World Bank Group (2021), and a mean daily maximum temperature recorded between 30-35 °C in the Namibian basin. However, both leguminous crops possess a high tolerance to withstand drought, which enables them to remain resilient to temperatures as high as 40-45 °C (FAO, 2022; Zimmermann, 2023).

4.3.3. Hydro-geomorphologic factors

In order to assess the hydrological and geomorphological conditions of the study site, five variables were analysed: slope, elevation, ground water depth, drainage density and distance from the river. The objective was to establish the suitable hydro-geomorphological characteristics for the crops under consideration. Areas with lower elevations were categorised as highly suitable, while their suitability decreases as the altitude increases. This was confirmed through compiled datasets by various sources from experts and availed for farmers, agricultural extension personnel and researchers (Cook et al., 2020; FAO, 2022; Orwa et al., 2009). *Crotalaria juncea* (aka sunn hemp) optimally grows between 0-300 m above sea level (Orwa et al., 2009; USDA, 1999). However, there have been recorded cases of sunn hemp and pigeon pea crops between 0-1500 m and 0-3000 m, respectively (Cook et al., 2020; FAO, 2022). Nevertheless, sluggish growth is observed due to lower temperatures at high altitude. Rundu and its surrounding basin are located between 1063-1152 metres above sea level. This semi-arid sub-tropical climatic regime experiences warmer climate even if it has a high elevation. This makes most of the study area suitable for growing leguminous crops. The topography of the area is characterised as mainly gentle slope ranging between 2-12 degrees, representing over 98% of the study area. Harmoney (1999) demonstrated over three growing seasons that legume crops performed best on slopes between 2 and 10 degree. Guretzky et al. (2004) highlighted that the most successful slopes for legumes were observed between 8 and 12 degrees. Drainage density in the study area ranges from 0.1-4.6 km/km^2 and strikes a good balance between very high and low densities. Low to moderate drainage densities (85% of the study area) were classified as suitable for optimal sunn hemp and pigeon pea cultivation. As noted by Dragičević et al. (2019), a higher drainage density is usually linked to low suitability due to erosive tendencies of the land. On the other hand, a low drainage could result in waterlogging adversely affecting the root zone of the leguminous crop (Kaur et al., 2020). Ground water depth is a predominant influencing factor for crop cultivation. The water table exhibits a range of 9.34 to 76.62 metres, with more than 70% of the study area experiencing groundwater levels between 30 and 60 metres below the surface, which aligns with Worqlul et al.'s (2017) finding that there is a moderate potential for irrigation using groundwater. One of the primary determinant factors for successful cultivation of the leguminous crops under investigation is their proximity to the river. Almost 60% of the study area is within 1.5 km of the river, thus creating an optimum situation for extracting water for crop fields. In addition, a study by Zhang et al. (2018) conducted in an arid environment demonstrated consistent higher soil water content within 2 km distance from a river, followed by a significant decline beyond the 2 km limit. Considering this scenario, more than 80% of the study region is located within the 2 km range of higher soil water content, thereby establishing conducive conditions for arable land.

4.3.4. Soil factors

This study examined soil physical and chemical properties to assess suitability for leguminous crop cultivation. The soil properties utilised for identifying regions with potential for enhanced crop yields include nitrogen content, soil organic carbon, phosphorus, pH, cation exchange capacity, bulk density, soil depth, soil water content, fertility capability, soil texture and soil type.

Soil pH recorded in the study area is between 5.2 and 6.8, which is moderate to slightly acidic and neutral. The optimal pH range recommended by Cook et al. (2020) and Orwa et al. (2009) for cover crops sunn hemp and pigeon pea varies from 4.5 to 8.4. Nevertheless, these crops thrive in pH 6-7 FAO (2022), considering this 43.35% of the entire area well suited for enhanced crop yields. In the sub-basins surrounding Rundu, the total nitrogen content ranges between 0 – 1.6 g/kg, with 99% of the study area comprising nitrogen levels from poor to fairly moderate. This occurs due to lack of nutrients received from external sources, combined with extreme climatic conditions such as high temperature and low precipitation. Therefore, to sustain and improve soil fertility and nutrient levels such as nitrogen, smallholders must consider practicing cover crop leguminous crops such as sunn hemp and pigeon pea, as recommended by Awala et al. (2019), and Hag Husein et al. (2021). Phosphorus levels in the study site are significantly low, ranging from 0 – 17 ppm, with the majority of areas showing poor phosphorus levels ranging from 0 – 8 ppm. Soil Organic Carbon (SOC) holds an immense potential in determining the suitability of agricultural land, due to its ability to improve soil biological, chemical, and physical properties, water-holding capacity, and structural stability. It also plays an integral part in the formation of soil's organic acids that influence soil minerals dissolutions and availability to plants and nutrient leaching. The SOC in the research area varies in concentration between 0 – 19 g/kg, with dominant values ranging between 0 – 6 g/kg. Areas with moderate to rich carbon contents only amount to 8.5 % of the entire study area. Intensification of sunn hemp and pigeon pea has shown potential to increase the level of soil phosphorus and carbon (Singh et al., 2023). Moreover, leguminous crops have shown to demand 20% less phosphorus than non- leguminous crops such as pearl millet, which is the dominant crop in the study area (Li et al., 2011). Cation exchange capacity in the study area falls in the range of 1.63 – 26 cmol(+)/kg. This variable indicates the overall potential of soil fertility. Only 8.85% of the entire study area demonstrated moderate to high fertility, whereas the remaining 91.15% exhibited low fertility. This aligns with the findings by Githae et al. (2011) that soil CEC < 16 cmol(+)/kg is low in fertility for leguminous crops. The spatial variation of bulk density in the study region ranged from 1.41 – 1.56 g/cm3 with 49.4% displaying a moderate bulk density falling between 1.41 – 1.51 g/cm3, and the remaining exhibited soil with compacted texture spanning from moderate to high. A higher bulk density restricts root growth, which in turn reduces crop yield. Nevertheless, leguminous crops have shown enhanced resistance to higher bulk density improving compacted soil textures. This was confirmed by Odunze et al. (2004)in their study on grain legumes and their potential to improve soil bulk density. Sandy loam and silt with coarse and medium texture are the dominant classes with 82 % coverage. The primary soil types were Arenosols (78.73 %), followed by Fluvisol (10 %) and Fluvic gleysol (9 %). Legume crops such as sunn hemp and pigeon pea perform best in sandy soil, with 5 – 10 % clay and sandy loam in semi-arid environments (Jacobi, 2008). Soil depth to bedrock varied from 13 – 200 cm, with over 97 % of the area observed to be 2 meters or below the top surface. Classes indicating soil fertility capability reflect varying levels of constraints for potential farming area within the study region. Out of the entire area, only 9.3 % exhibited no constraints. Predominantly, areas with only one constraint constituted 43.3 %, followed by 36.4% representing regions with two constraints.

4.3.5. Socioeconomic factors

In socioeconomic analyses for suitable agricultural land, key features such as population, infrastructure, and markets are the primary factors to determine optimal locations for legume crop cultivation. Two variables, proximity to market and accessibility to roads, were central to understand the social and economic influences to classify the suitability of croplands. Potential crop lands were classified to determine their proximity to major roads. The categories ranged from < 1000 metres, which were the most accessible, to distances > 8000 metres, which were the least accessible. Roads distances spanning from < 1000 to 4000 metres were classified to be highly to moderately suitable, which represented approximately 77 % of the study area. This demarcates regions where economically feasible production of leguminous crops is viable, as well as facilitates easy access to transport raw agricultural inputs. Similar studies by Pramanik (2016), and Sarkar et al. (2023), also reported comparable findings. The distance to the market was measured using population settlement data signifying spatial distribution over the study site. This is significant to determine the proximity of markets to sell potential sunn hemp and pigeon pea yields within the study region. For this purpose, the spatial distribution of settlements was classified into five classes according to their distance from clustered settlements. Areas within 3.5 km from potential market had the highest coverage with 40.7 %. This is attributed to the urban settlement of Rundu found within our study site.

4.3.6. Vegetation factors

The vegetation parameters considered in this study were NDVI (used to measure vegetation density and health) and LULC (used to monitor the landscape and its various uses). The spatial distribution of vegetation health, as measured by the NDVI, was categorised into five classes with values ranging from 0 to 0.68. The robust with NDVI values between 0.39 and 0.68, accounted for 51.6% of the entire study region. Vegetation with moderate health was observed in 25.9% of the study area. The Land Use and Land Cover (LULC) data was primarily utilised as a criterion to identify potential limitations in the study area, such as built-up areas and water bodies, and exclude these classes from the final suitability map.

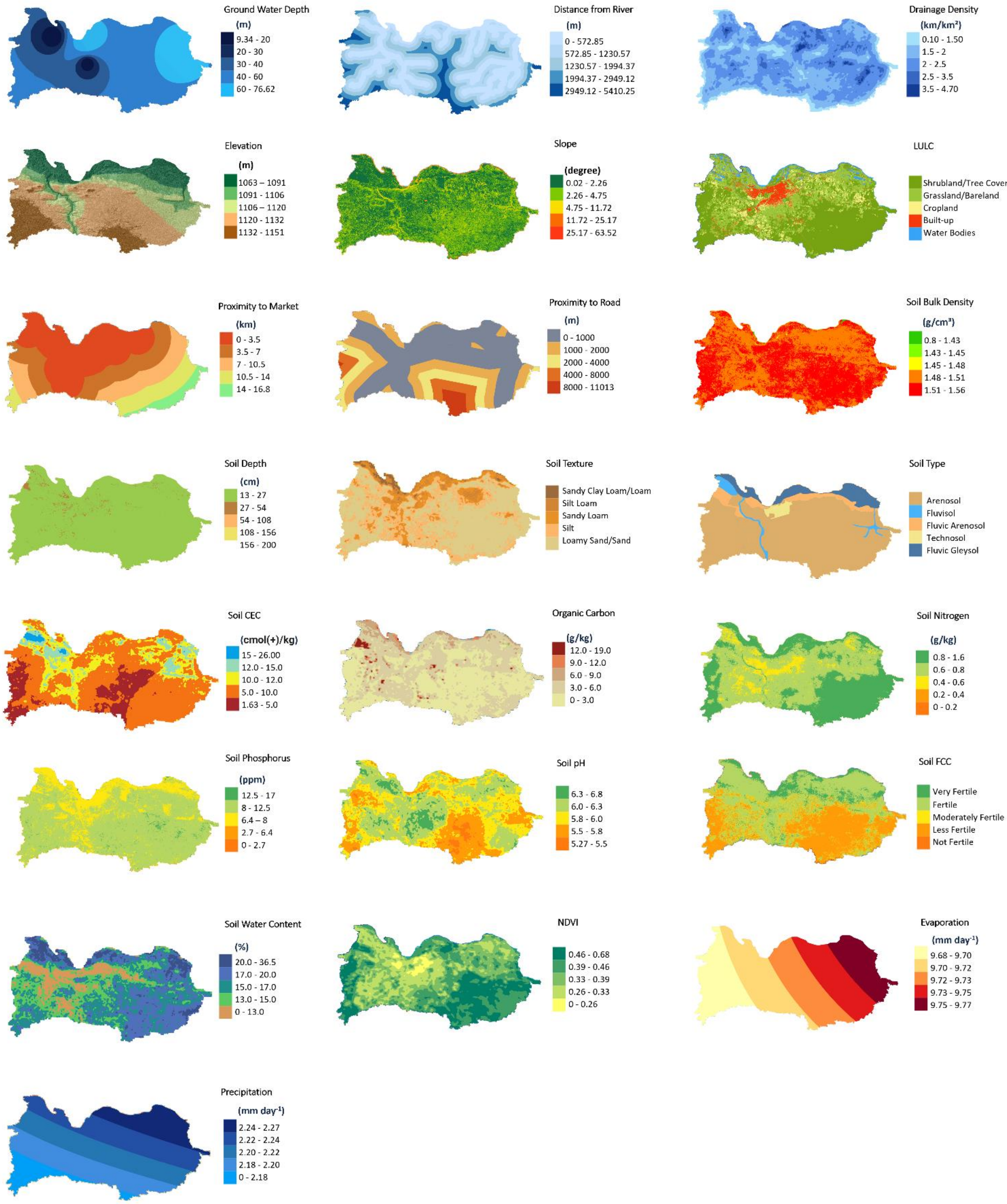

Figure 4.4: Classification data layers of the study area with variables from climatic, hydro-geomorphologic, soil, socioeconomic and vegetation categories.

4.3.7. Land suitability evaluation using Analytical Hierarchical Process

Through AHP approach, weights were assigned (figure 4.6) for twenty-two variables in five distinct categories (see figure 4.4). Distance to River (8.48%), Precipitation (8.14%) and Soil water content (8.02%) scored the highest weights signifying that water is an important element for suitability ranking during the cultivation of leguminous crops, even if considered to be drought resistant. For crops to achieve maximum yield in the semi-arid study region, they need to be closer to the river for ease of irrigation. Moreover, as discussed by Zhang et al. (2018), soil water content is observed to be highest in soils usually found in the riverbanks. In areas further away from the river, smallholders are highly dependent on rainfall availability. This aligns with similar research findings (Adem et al., 2023; Ammar et al., 2016; Zhang et al., 2018), that showed crops in arid and semi-arid environments are highly dependent on rainfall, irrigation and availability of water in soil to maintain or increase yields. Furthermore, Evaporation (1.89%), Proximity to Roads (2.08%) and LULC (2.70%) had the lowest weights. Evaporation is reduced by shades created from legume cover crops reducing direct sun light reaching the soil. This further reduces soil temperature minimising soil moisture loss and consequently, making sunn hemp and pigeon pea drought resistant cover crops that could potentially be intercropped with maize and millet in semi-arid environments. Tsubo et al. (2005) developed a cereal-legume model to demonstrate the significance of intercropping for sustainable crop production in developing countries. During the expert's discussion, the importance of proximity to roads was not considered to be as significant as other variables such as soil physical and chemical properties. These properties were deemed to be more crucial for crop health and higher yields. For example, soil type and texture both recorded a weight of 5.1% and were considered to be more important to grow legume cover crops in the study area. LULC also had one of the lowest weights, as this class is mainly used to deal with constraints such as built-up area and waterbodies. Built-up area was considered as a constraint, as intensive agricultural productivity cannot be implemented in this land-use type apart from small activities such as backyard gardens. Moreover, recession farming, which is a form of agricultural cultivation on a floodplain where farmers practice agriculture by successively planting in the flooded areas after the waters recede, is also not acceptable, as the two crop types considered do not cope well in a waterlogged environment. Soil nutrients such as nitrogen (4.57%), organic carbon (4.39%) and phosphorus (4.1%) scored weights ranging between 4% and 4.6%. This indicates that the expert team considered leguminous crops as specialised crops that require fewer nutrients from the soil. These crops are commonly used to improve the nutrient content of the soil in the study area. This has been discussed in the specialised literature (Cook et al., 2020; Sharmaet al., 2011; Simon and Itanna, 2019; USDA, 1999), emphasising the ability of leguminous crops such as sunn hemp and pigeon pea to rehabilitate soil physical and chemical properties.

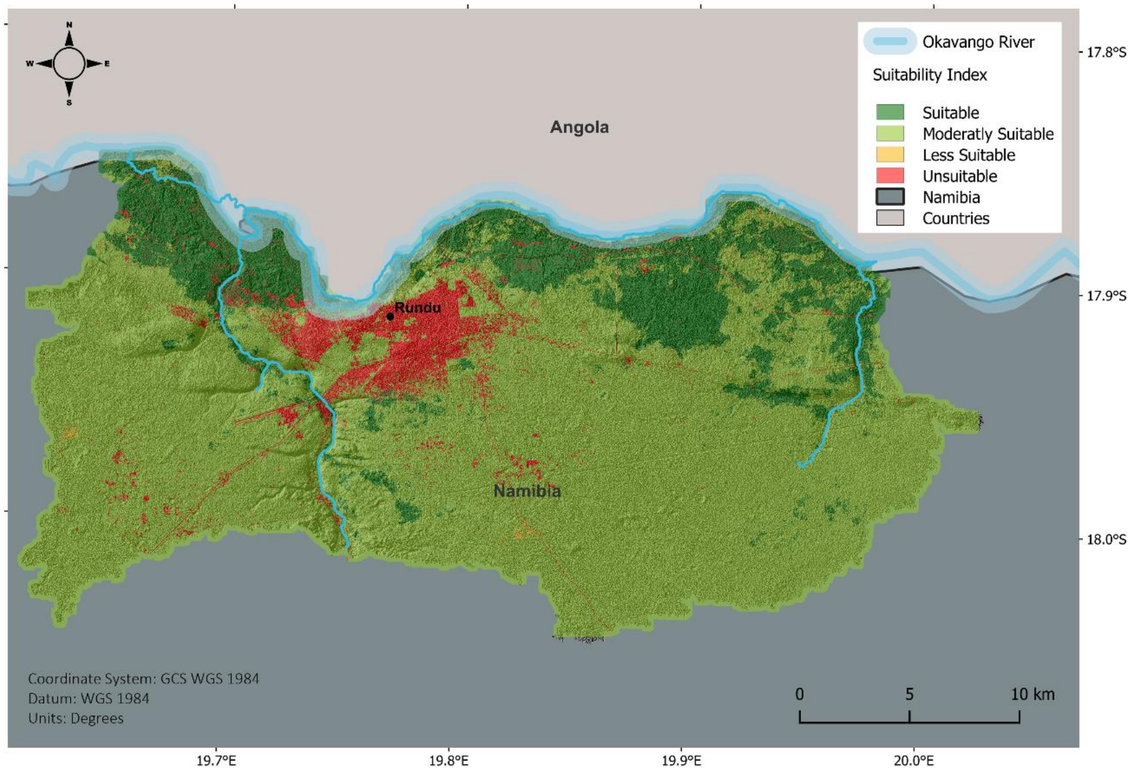

Figure 4.5: Leguminous Crop suitability map using AHP method.

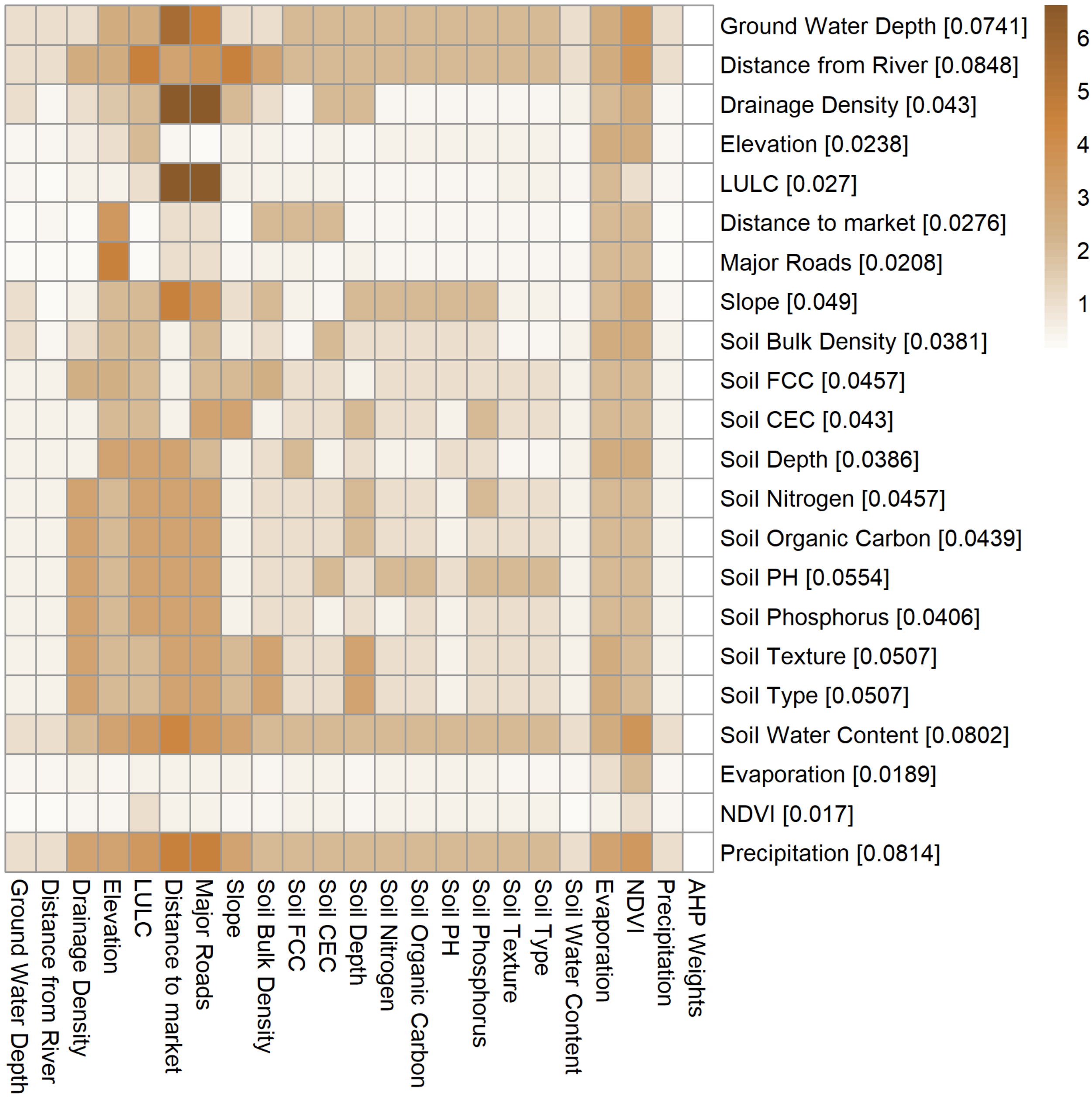

Figure 4.6: AHP criteria ranking and weight.

Sunn hemp and pigeon pea are known for their soil rehabilitation traits, lowering soil temperature, preventing erosion and water retention capacity. This is highly influential as they can be treated as an intercropped legume with the widely cultivated mahangu (Pearl millet) and maize in the study region. This has been discussed by various studies (Rani et al., 2019; Sharma et al., 2011; Tsubo et al., 2005), where leguminous crops exhibited regenerative potential in poor soil quality regions, mostly in semi-arid environments. According to the AHP ranking, the study area suitability map resembled the characteristics of only four of the five classes mentioned above. The overall suitability map in Figure 4.5 exhibited 17.63% of the total study area to be suitable for leguminous crops, signifying the land to have minor constraints and requiring less inputs for enhanced productivity. A visual analysis of this outcome reveals that most of the suitable land is in close proximity to the river and its tributaries. This is attributed to the requirement of water for crop growth in this semi-arid environment and the fluvic-gleysol soil types with silty and sandy loam texture, which have an enhanced capacity to hold nutrients and water. Even though gleysols in Namibia are usually associated with waterlogged places such as rivers and dams (Atlas of Namibia Team, 2022), which is a detrimental factor for the cultivation of sunn hemp and pigeon pea, the river basin usually recedes by the end of the dry season. As a result, most of the floodplain becomes devoid of water but retains high soil moisture. This creates an opportunity for cultivating these legumes during the light rainy season in October and November, before waterlogging becomes a problem.

On the suitability map, most of the coverage is classified as Moderately Suitable, with 62.77% of the entire study area falling within this class. This means that the constraints identified in this class limit its performance. To achieve optimal growth of legumes and maximise the expected yield from this land use, a higher level of input will be necessary compared to areas with a suitable classification. However, this remains appealing to farmers. The suitable class was the second largest with 17.63% of the entire study area showing the highest potential for crop yield. Most of this class's coverage is within 2 km distance from the river and its tributaries, influencing soil moisture contents to be high and anticipating potentially higher nutrient contents. This becomes clear when examining Soil Nitrogen and Phosphorus classes, as defined in figure 4.4. Soil CEC and soil organic carbon seem to be moderately low in the moderately suitable class. However, two of the three highest weighted variables (i.e., distance to river and precipitation) seem to agree with the outcome of this class. Classes with less suitability are mainly located in the southern parts of the study area representing 10% of the entire region. This class is characterised as having severe constraints for agricultural land use and reduced crop yield is expected. Land within this class is likely to demand a higher level of input for marginal gain. Several of the variables used to generate the suitability map agree with this classification: i) the least suitable areas have the lowest rainfall; and ii) areas located in higher elevation were the furthest away from waterbody representing the least fertile land and with the least capacity to hold soil nutrients. Unsuitable classifications were observed in 9.59% of the study site and these areas have the highest limitations to practice leguminous crop cultivation with unsustainable use and require infeasible inputs to increase productivity. As seen in Figure 4.5, these areas are mainly concentrated in the built-up area and within the water body. This is due to the unavailability of land use for farming. In addition, it is interesting to note that soil fertility classification is similar to the final suitability map.

4.3.8. Models' performance

In evaluating crop suitability classification models, comprehensive metrics were used to assess performance (Figure 4.7), including Accuracy, Precision, Recall, F1 Score, and ROC AUC. The Random Forest Classifier and XGB Classifier demonstrated exceptional performance in all metrics. The Random Forest Classifier exhibited exceptional accuracy (0.97), precision (0.96), and recall (0.97), as well as an F1 Score and ROC AUC of 0.97 and 0.99, respectively. These results indicate its remarkable capacity to accurately categorise both positive and negative cases with minimal error. The XGB Classifier exhibited a superior degree of precision (0.98) and accuracy (0.96) alongside a moderately lower recall (0.93), indicating a heightened emphasis on curbing false positives, while retaining elevated true positive count. The high value of ROC AUC (0.99) for both models provides evidence of their discriminatory power.

In contrast, the logistic regression had a moderate precision (.76), a good balance between precision (.73) and recall (.83), which can be very important when trying to identify the most positive cases. Both classifiers had a balanced performance with high precision and recall, indicating their effectiveness in general classification tasks. The Gradient Boosting Classifier has a precision score of 0.97, and a recall score of 0.89. The Decision Tree Classifier has an accuracy score, a precision score, and a recall score all around 0.93. The Gradient Boosting Classifier and the Decision Tree Classifier both have strong classification abilities. The Gradient Boosting Classifier has a precision score of 0.97 and a recall score of 0.89, while the Decision Tree Classifier has accuracy, precision, and recall scores all around 0.93. The models also have different ROC AUC values, ranging from 0.83 to 0.99. This confirms their strong ability to distinguish between different aspects of the classification task.

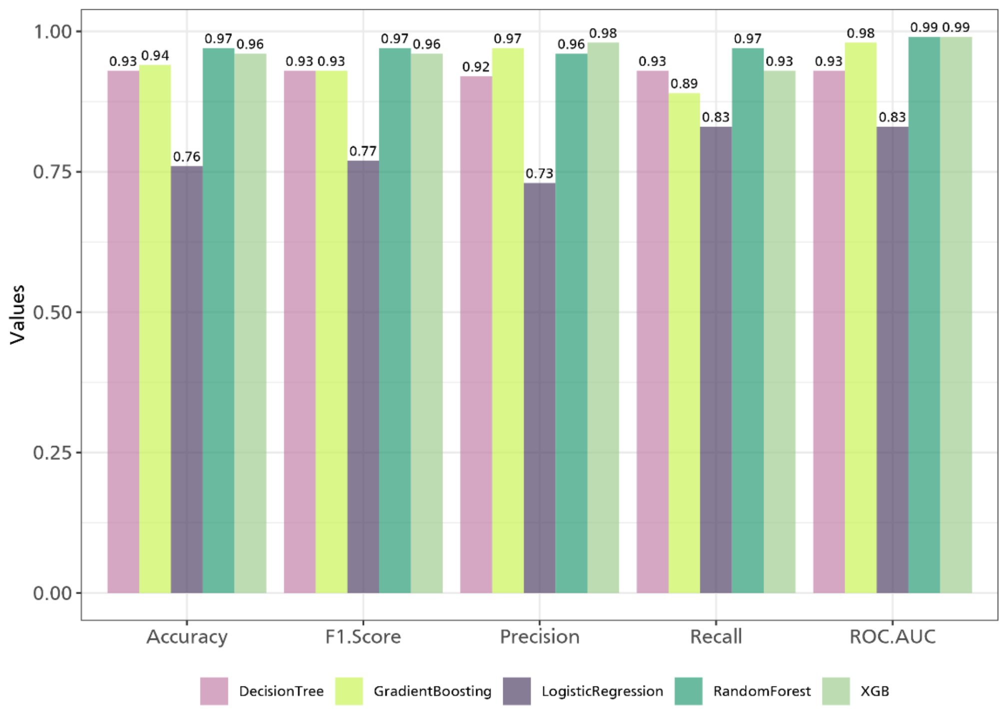

Figure 4.7: Classification Metrics.

Analysing the various crop suitability models yields relevant results that may be differentiated by performance indicators such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2). These metrics indicate the accuracy of each model and its ability to highlight variations in the dataset. The ensemble models perform satisfactorily, especially the Random Forest Regressor and Extra Trees Regressor. The findings demonstrate their ability to capture complex, perhaps non-linear relationships in the data, as indicated by the lowest RMSEs (Figure 9) and high R2 values (Figure 4.8). Ridge regression and linear regression have only moderate results, possibly due to their limitations in the representation of complex and nonlinear interactions. The slight variations in performance among the ensemble models can be attributed to differences in their methods of model construction, error minimisation, and sparse data management.

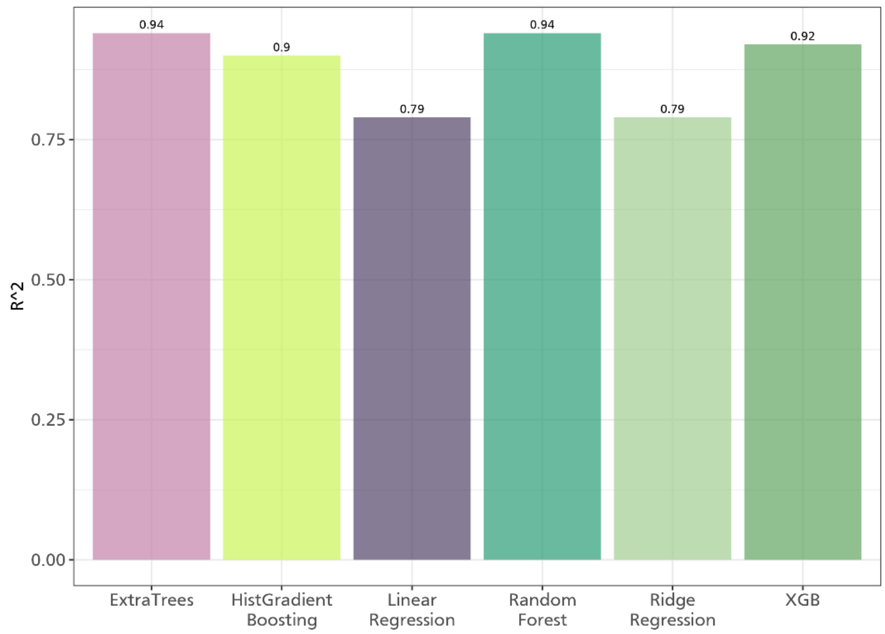

Figure 4.8: Regression Metrics (R^2).

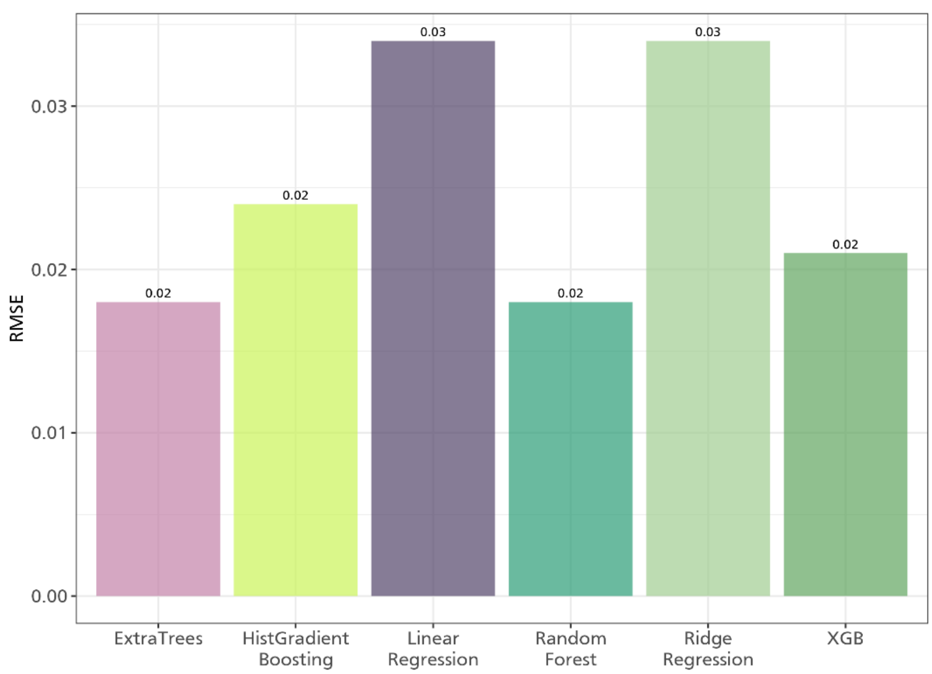

Figure 4.9: Regression Metrics (RMSE).

The tree ensemble models are clearly the better choice, which is an indication of their robustness and effectiveness in environmental modeling. This comparison shows the importance of selecting appropriate modeling methods depending on the characteristics of the dataset and the complexity of the relationships within it.

4.3.9. Covariate importance

The feature importance analysis of the crop suitability model (Figure 4.10) provides significant insight into the predictors that are critical for determining crop suitability using NDVI to assess vegetation health. Feature importance scores in XGBoost reflect how each variable contributes to the model's ability to distinguish between suitability classes. These scores are indicators of the influence each variable has on predicting suitability classes, providing insights into the variable's relative effect on land suitability as determined by the model. The analysis shows a clear hierarchy of feature importance, with "Fertility Capacity Class 2" as the top factor, with an importance score of 0.7884. According to the model, the fertility of the soil is the most important factor in determining crop suitability.

Other features also contribute to the assessment of crop suitability, but to a lesser extent. The second most influential feature is the level of soil nitrogen in Band 1, which has an importance score of 0.0764. The significance of soil physics in agricultural output is emphasised by presenting 'Soil Texture', and its corresponding classification of 'Soil Texture class 9' (soil_texture_9.0). The examination also highlights the importance of diverse soil types in the study, yielding importance scores of 0.0203 and 0.0177, respectively.

The suitability of crops is significantly affected by the specific soil classification of Cambisol (importance score: 0.0156), Fluvic Arenosol (0.0114), and Technosol (0.0087). Additionally, accessibility and logistics may impact crop cultivation viability, as Distance to Market is identified as a significant factor (importance score: 0.0124).

Soil fertility, especially nitrogen content, is crucial for crop suitability. This is emphasised by the presence of Soil Nitrogen Band 2, which has an importance score of 0.0076. Additionally, the soil's cation exchange capacity, with a score of 0.0055, supports crop growth, although it is less influential than other features. This analysis highlights that soil characteristics, such as fertility and texture, play a crucial role in determining crop suitability. Factors such as proximity to markets and specific soil types also contribute to this determination. The prevalence of specific aspects, particularly soil fertility classifications, highlights the complexity of evaluating land suitability for agriculture.

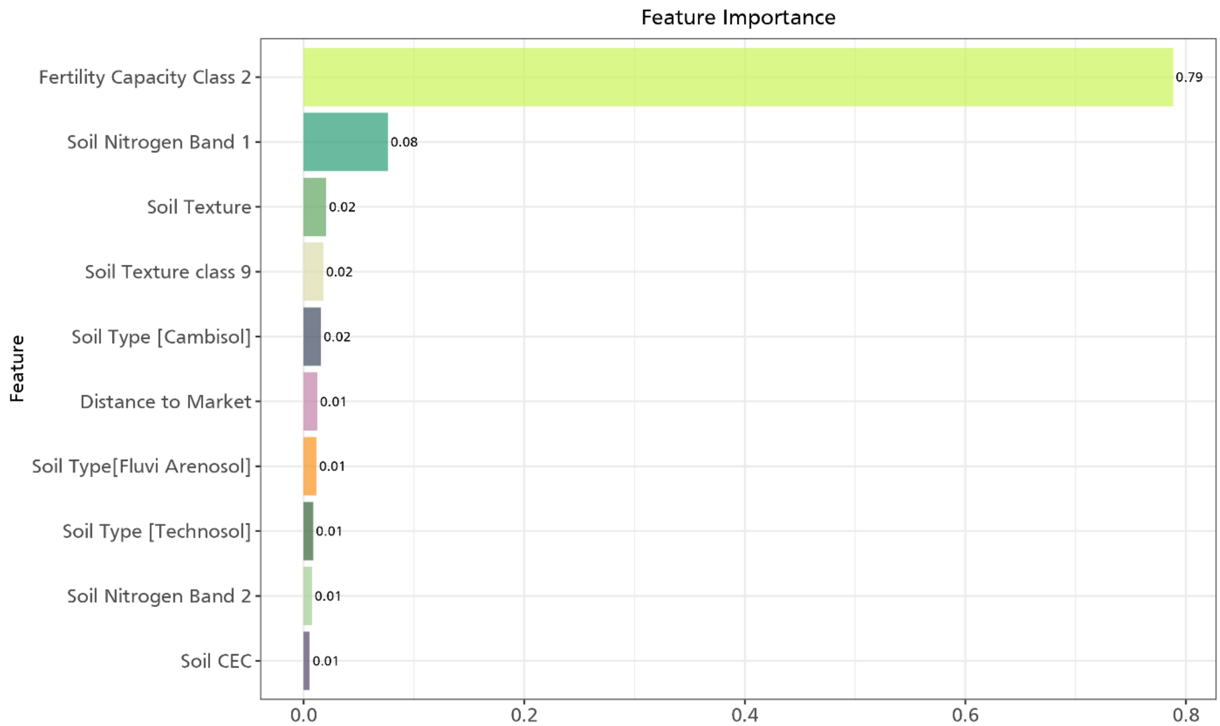

Figure 4.10: Feature Importance (XGB Regressor).

Figure 4.11 shows the various soil and environmental factors with a significant impact on the crop production potential according to the cropland classification. The highest-ranked feature is 'Fertility Capacity Class 1', with an importance score of 0.257. Soil fertility plays a crucial role in agricultural decision-making and the nutrient profile and soil health are critical factors in the feasibility of crop cultivation.

Specific soil classifications, such as Technosol and Cambisol, are more suitable for agriculture than others. Technosol has an importance score of 0.128, while Cambisol scores 0.033. These soil types have different characteristics that are important for crop growth, such as water retention, nutrient availability, and structural stability.

Soil physical properties have a significant influence on plant growth. Bulk density and texture are particularly important, with importance scores of 0.085 and 0.075, respectively. These factors affect root penetration, water and air movement, and overall soil health. Soil chemistry is crucial in determining land suitability for agriculture due to the availability and presence of essential nutrients, such as phosphorus and nitrogen. These nutrients play a critical role in plant growth and crop yields, as indicated by their respective importance scores ranging from 0.063 to 0.066.

The model shows that elevation affects agricultural suitability (importance score of 0.035). This means that altitude-influenced geographic and climatic conditions impact the ability to carry out agricultural activities. Considering elevation points to a wider environmental context, where temperature, precipitation patterns, and potential frost risks related to altitude can impact crop viability.

The regression and classification models show how various soil properties and environmental factors are interdependent in determining the suitability of land for agriculture. The research provides insight into the main factors that determine agricultural land suitability. This underscores the complexity of agricultural ecosystems and emphasises the need for a multifaceted approach to managing and assessing land for crop production. These findings can support effective and sustainable use of land resources, aiding in agricultural planning and policymaking.

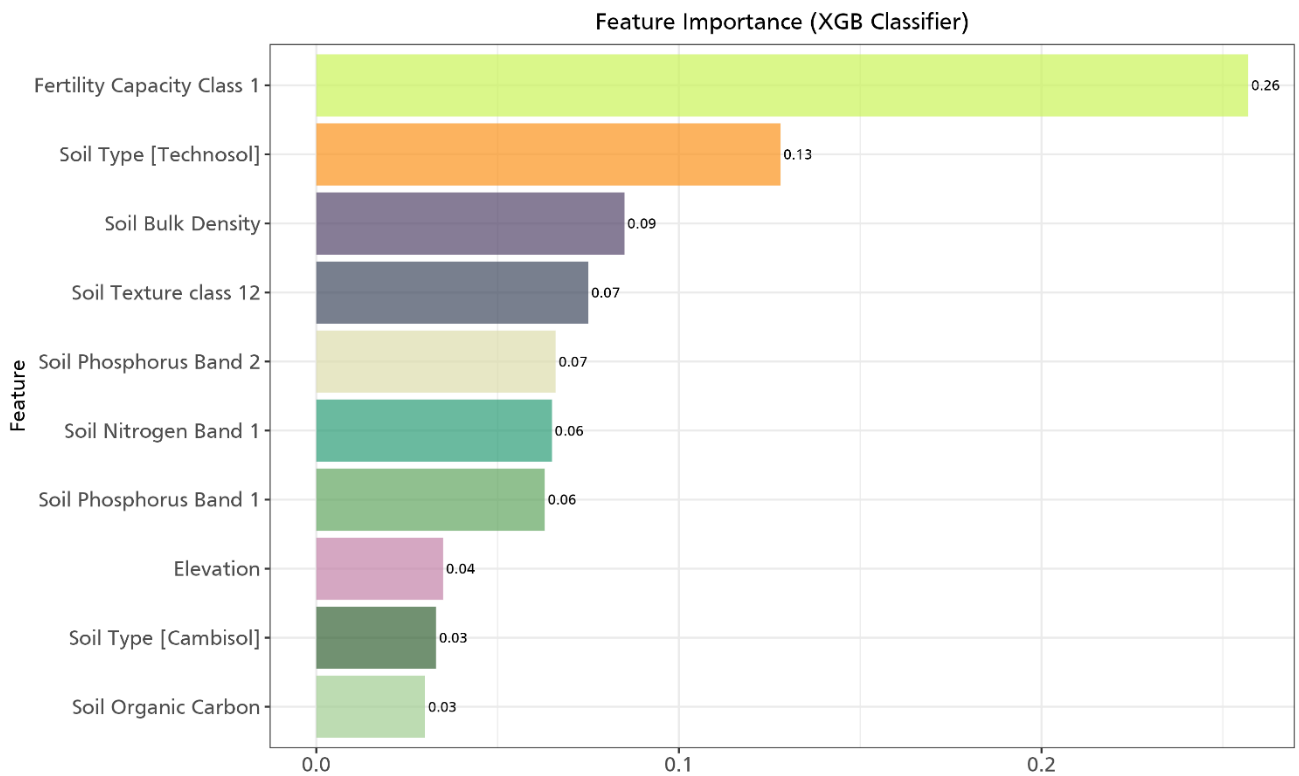

Figure 4.11: Feature Importance (XGB Classifier).

4.3.10. Insights from logistic regression and OLS analysis

The logistic regression revealed correlations between environmental, geographical, and soil parameters and their impact on agricultural land use (categorizing land as cropland).

Increased levels of precipitation (-0.5597) and evaporation (-0.4989) have a negative impact on the suitability of land for agriculture, indicating the influence of climatic conditions. The negative coefficient for precipitation indicates that crop production is currently practiced in areas with limited rainfall. Similarly, geographical aspects like Distance to Market (-0.5418) and Distance to Major Roads (-0.066) show negative relationships, indicating that increased remoteness reduces the likelihood of a parcel being cropland. The findings for Elevation (-0.1569) and Slope (-0.0931) underscore the preference for flatter and lower lands in agriculture, as steep and elevated terrains are less likely to be cultivated.

Soil Characteristics and Fertility Capacity: The regression analysis in Figure 4.12 displays significant variations in how soil properties affect cropland probability. Soil Bulk Density and Soil pH, with their negative impacts, suggest that denser and more acidic soils are less favorable for agriculture. Conversely, positive coefficients for Soil CEC and Soil Depth indicate their beneficial roles. The notable negative coefficient for Soil Nitrogen (-0.6699) points to a complex relationship with land use, potentially influenced by factors such as nutrient management practices. Interestingly, specific soil textures, particularly Sandy Loam and Loamy Sand, with high positive coefficients (4.2312 and 3.9782), emerge as highly conducive for agricultural use. The Fertility Capacity Classes (FCC) further illuminate the nuances of soil fertility on land use, with FCC 2 showing a distinct negative effect. This highlights the variability in agricultural suitability across different fertility levels.

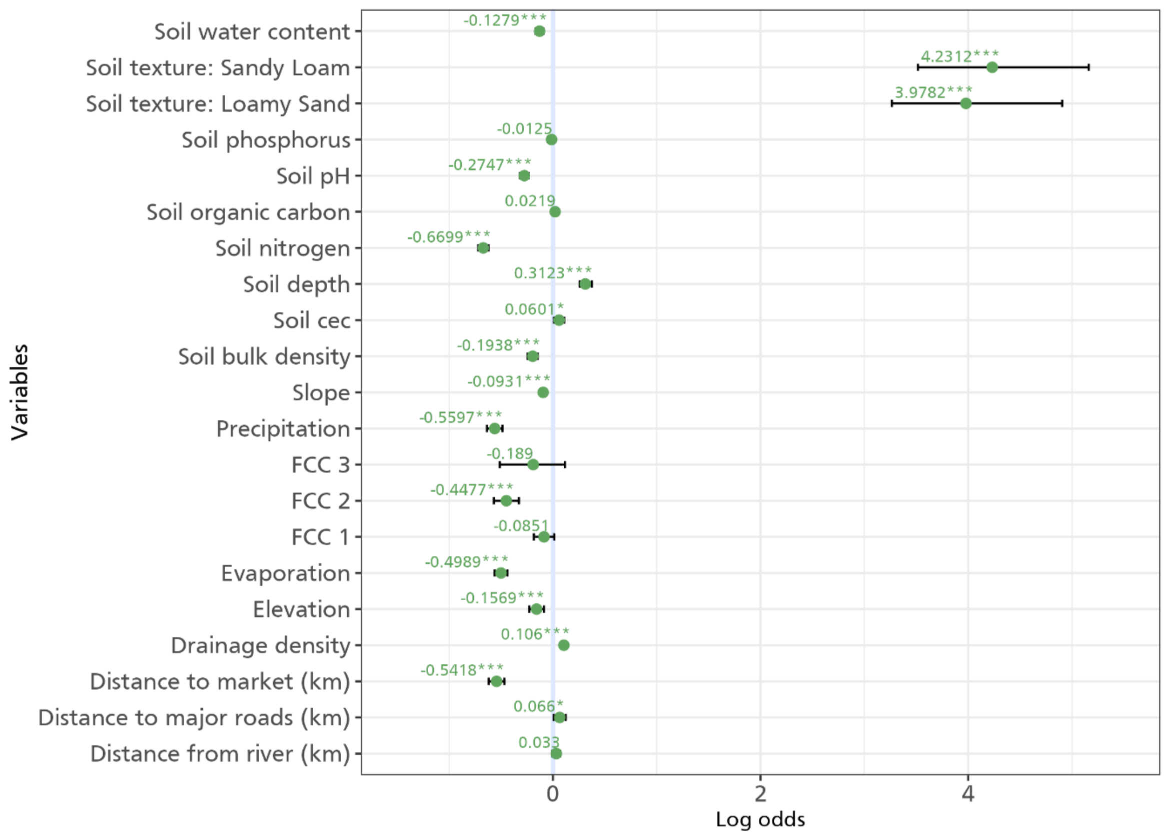

Figure 4.12: Cropland Regression Analysis.

The OLS regression analysis (Figure 4.13), with NDVI as the outcome variable, explores how different environmental, geographical, and soil factors impact vegetation health according to NDVI values.

In terms of environmental and geographical factors, evaporation and precipitation exhibit negative correlations with NDVI, with coefficients of -0.0021 and -0.0045, correspondingly. These findings suggest that increased levels of evaporation and precipitation are connected to decreased NDVI values, which may signal reduced vegetative growth in regions with more severe hydrological conditions. The positive coefficient for Distance to Market (0.0096) is particularly interesting from a geographical perspective, implying that areas situated farther away from markets may exhibit a higher NDVI, possibly due to less disturbance arising from anthropogenic activities. The slight positive effect of Distance from River (0.0005) and the significant positive impact of Drainage Density (0.0059) emphasizes the significance of water availability and drainage in vegetation support.

Furthermore, Topographical and Soil Factors show negative associations with NDVI. Elevation and Slope coefficients are -0.007 and -0.0013, respectively, indicating that steeper slopes and higher elevations may hinder vegetative growth. Soil characteristics play a crucial role in vegetation health. Soil Bulk Density and Soil pH have negative effects, implying that denser soils and more acidic conditions could hinder vegetation growth. In contrast, Soil CEC displays a significant negative relationship (-0.0128), reflecting complex interactions between soil chemistry and plant growth. On the other hand, Soil Nitrogen and Soil Organic Carbon, exhibit positive coefficients (0.0201 and 0.0033), highlighting their role in promoting vegetation health.

Fertility Capacity Classes (FCC) and Soil Texture: The beneficial coefficients for FCC 1 and FCC 2 (0.0021 and 0.0075) suggest that these fertility levels promote higher NDVI values. Nevertheless, FCC 3 exhibits a negative impact (-0.0031), indicating irregularity in the influence of fertility on vegetation. The substantial negative coefficients for soil textures, such as Sandy Loam and Loamy Sand (-0.0307 and -0.015), indicate that these textures may be less conducive to vegetative growth compared to other soil types.

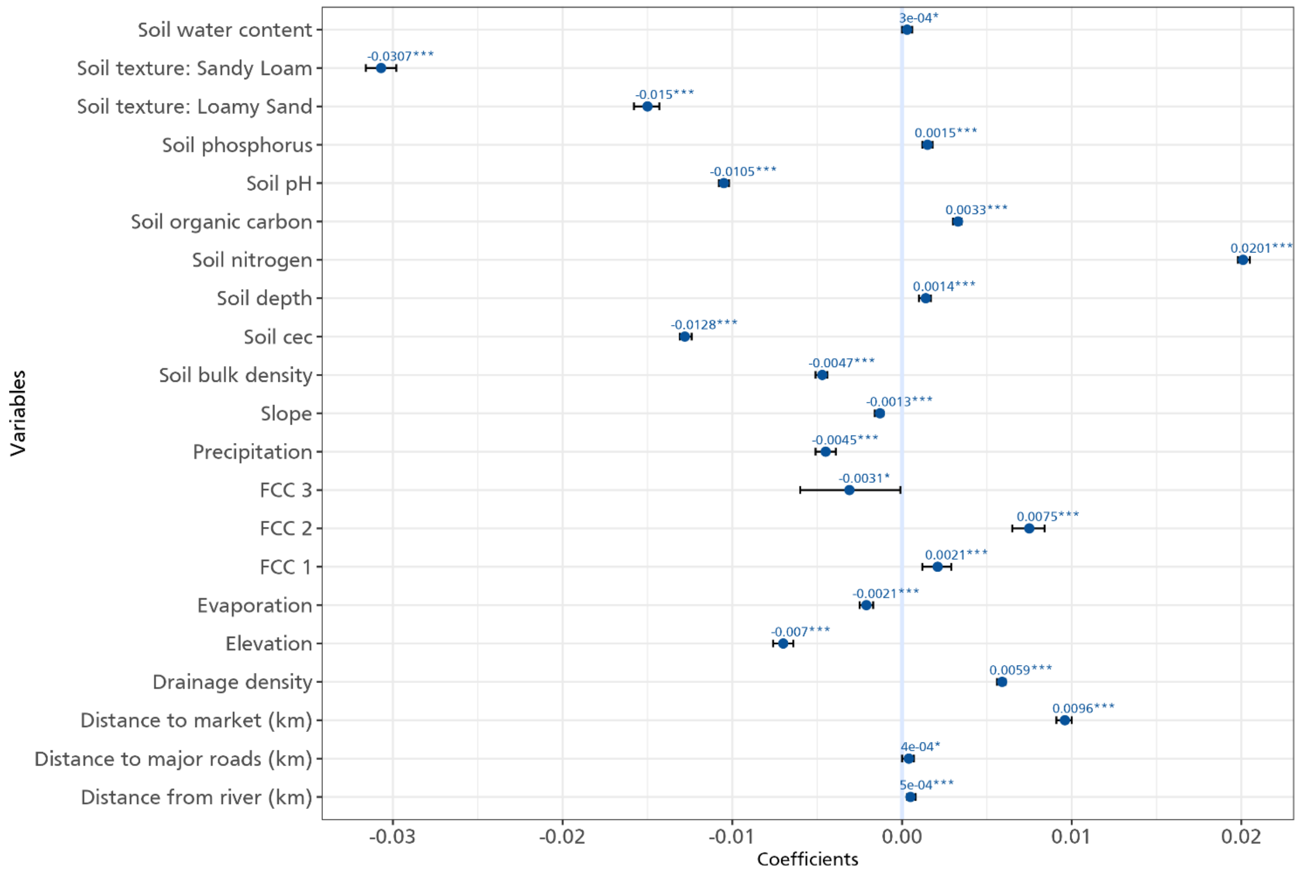

Figure 4.13: NDVI Regression Analysis.

4.3.11. Perspectives of subjective Analytic Hierarchy Process and objective, data-driven statistical approaches

The primary goal of the study was to present a detailed comparison between the data-driven machine learning models and the expert-based AHP approach. The aim was to highlight the strengths and differences of each method rather than using machine learning to add objectivity to the subjective nature of the AHP. By utilising an (AHP) approach and objective data-driven statistical methods, we successfully evaluated various variables and their level of importance in determining the agricultural potential in the study area. AHP criteria weights were influenced by characteristics of the semi-arid environment and biophysical requirements of legumes proposed to be grown in the study area. Source of water recorded the highest weights, ranging between 8-8.5%, followed by slope, soil physical and chemical properties with weights varying from 3.8-5.5%. Lowest weights were observed in socio-economic and vegetation criteria categories with varying weights less than 2.7% determined by the process of expert valuation. The data-driven statistical approach exhibited unconventional results, with soil fertility capacity classification being the paramount variable with an importance score of 0.7884. The subsequent significant factor (soil nitrogen band 1) recorded much lower importance, with a score of 0.0764. Additional soil physical and chemical properties, such as soil texture and types, as well as cation exchange capacity, were also discovered to have a lesser impact on predicting suitable agricultural land.

A noteworthy observation of the data-driven approach is that the model has the capability to rank categorical variables and discern the importance of individual categories while the subjective based method solely assigns weights to the variables as a whole. Nevertheless, the subjective approach has the advantage to carry out a weighted ranking based on specific biophysical and socio-economic requirements of the crop types. In view of this, the data-driven method showed that soil physical and chemical factors were dominant, ranking at the top of the importance hierarchy. In contrast, the subjective assessment ranked water and soil factors as the highest. Section 4.3.9 describes the statistical method used to predict land for crop cultivation. The top ten features with the highest importance were soil physical and chemical factors, along with distance to market and elevation. These features were determined to have the greatest influence on the prediction process, while others made meaningful contributions, albeit to a lesser extent. Crop cultivation areas determined by AHP approach (section 4.3.7), considered source of water, as well as the physical and chemical properties of the soil, as the most influential factors. Even though subjective land suitability assessment using MCDM is most common, data-driven statistical models are gaining recognition in the discipline. This is due to the emergence of algorithms and processing capacity to handle complex data and their relations. Thus, both approaches could offer a better insight into land suitability assessment and enhance crop yields for smallholders.

4.4. Conclusion

Crop farming is the primary activity extracting water in the Rundu area of Namibia within the Okavango River basin. Therefore, the responsible use of this scarce resource promotes the practice of conservation agriculture to ensure the sustainable continuation of agricultural activities in the basin. The purpose of this research was to develop reference materials for agricultural extension officers, agronomists, land-use planners, and decision makers to facilitate the adoption of conservation agriculture strategies, ultimately leading to food security for smallholders. This study utilised climate, soil, hydro-geomorphology, socioeconomic and vegetation indicators to assess the suitability of potential agricultural land in the Rundu area, encompassing 722 Sq. km of rural and urban land. Two approaches of multi-criteria decision-making and data-driven multivariate models were employed to investigate suitability of agricultural land to grow legume crops, primarily relying on remotely sensed data. The study´s findings are presented as follows:

- Machine learning data-driven approach avoids subjectivity and reliance on expert knowledge in the design of suitability analysis. However, it should be noted that machine learning models require well-balanced datasets and may exhibit a higher degree of uncertainty in predicting suitability in areas where crops are not typically grown or underrepresented in the data. Furthermore, while machine learning methods provide a more robust and objective means of variable importance classification, AHP approach also demonstrated its ability to classify land suitability for leguminous crops through comprehensive and systemic process of expert consultation. Although, the AHP approach remained sensitive to expert knowledge, it was more susceptible to subjective biases.
- AHP assessment indicates that the moderately suitable class is geographically predominant, accounting for 62.77% of the area, followed by the suitable class (17.63%) and the less suitable and unsuitable classes (10% and 9.59%) of the area, respectively. Over 70% of the suitable class coverage is observed within a 2 km radius from the river or

its tributaries due to higher soil moisture and potentially higher nutrient levels found in soil types near rivers.

- Machine learning approach showed soil physical and chemical properties as the most important features to predict suitability. Among these properties, soil fertility capability class had the highest importance score as predictor for suitability of leguminous crops. The favourable condition for crop land use is established by the positive relationship between sandy loam and loamy sand textures. On the other hand, environmental and geographical factors, including evaporation, precipitation, elevation, slope, distance to market and proximity to major roads, are negatively associated with the probability of land being classified as suitable.

Future studies should focus on improvements of suitability analyses through remote sensing by incorporating extensive in-situ datasets such as soil moisture content, soil nutrients, as well as socio-economic variables such as labour income, financial capacity of smallholders, and accessibility to farming technology, among others. In developing sub-Saharan countries such as Namibia, Botswana and Angola, facing data scarcity, adopting an alternative solution such as reanalysis data will improve accuracy in crop suitability assessments. Additionally, machine learning results could further be used as inputs in AHP to enhance the analysis and remove subjective biases. The feature importance findings based on data-driven method could be used to determine the weights of criteria for the subjective approach and evaluate changes in the crop suitability map. These methods offer improved understanding into land suitability modelling through substitution of the subjective criteria weights in the AHP by a more objective, data-driven approach. Such an approach will enhance the framework for sustainable land and water resource management which could provide reliable tool for agricultural planning and environmental conservation.

This study examined the challenges and factors fundamental to the process of identifying suitable land for agricultural purposes in a comprehensive manner, primarily relying on reanalysis data as the most viable option in regions with limited data availability. The application of our proposed methodology to identify agricultural land can serve as a valuable decision-making tool for planning and assessment of land suitability. This approach could assist in optimal resource allocation, the development of irrigation strategies, the implementation of conservation agricultural practices and guiding future agricultural expansions while promoting sustainable land management.

4.5. References

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