INVESTIGATING THE SENSITIVITY OF TROPICAL CATCHMENTS TO CHANGES IN PRECIPITATION AND EVAPOTRANSPIRATION UNDER DIFFERENT CLIMATIC CONDITIONS

BY

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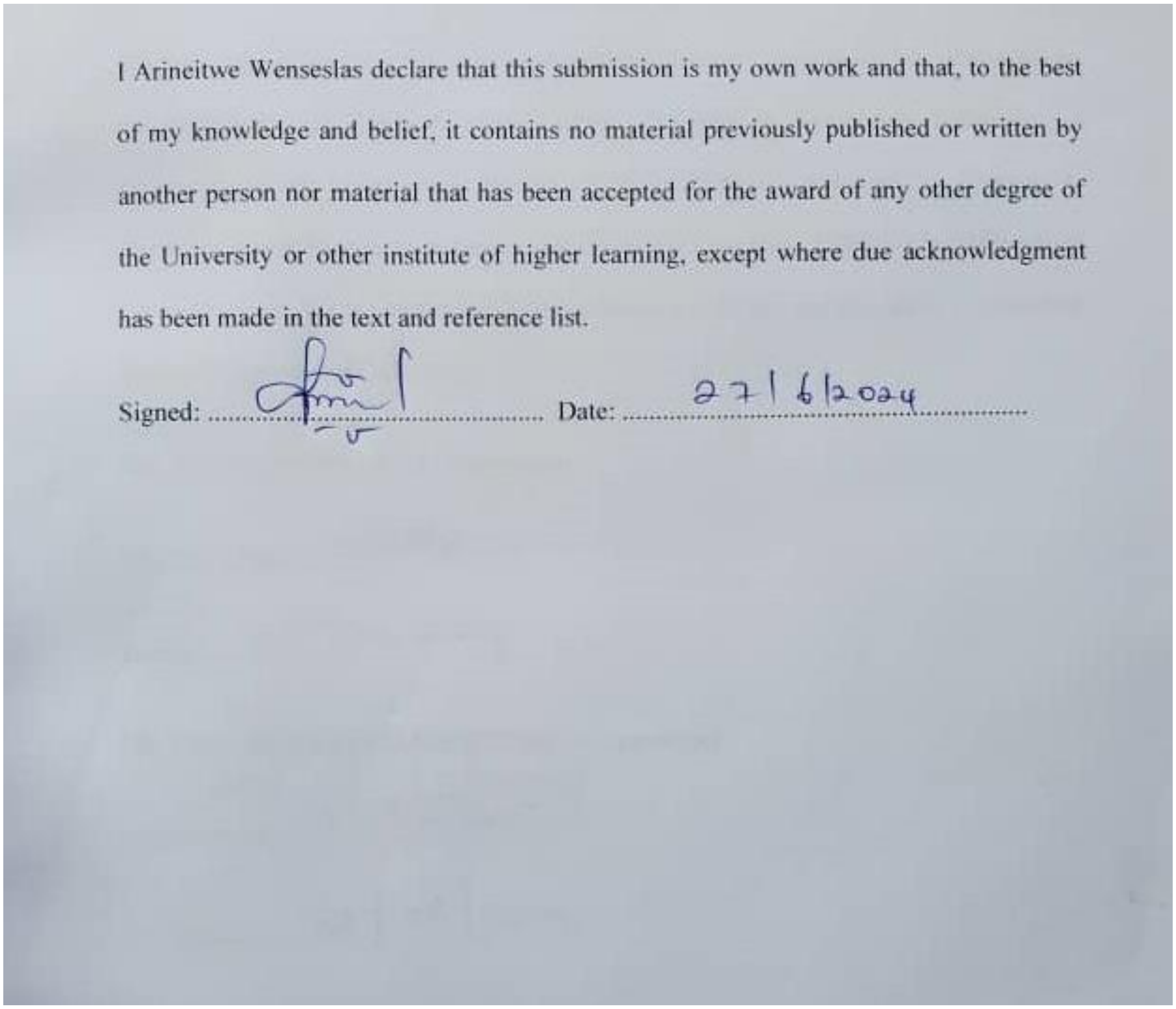
DECLARATION



I Arineitwe Wenseslas declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material that has been accepted for the award of any other degree of the University or other institute of higher learning, except where due acknowledgment has been made in the text and reference list.

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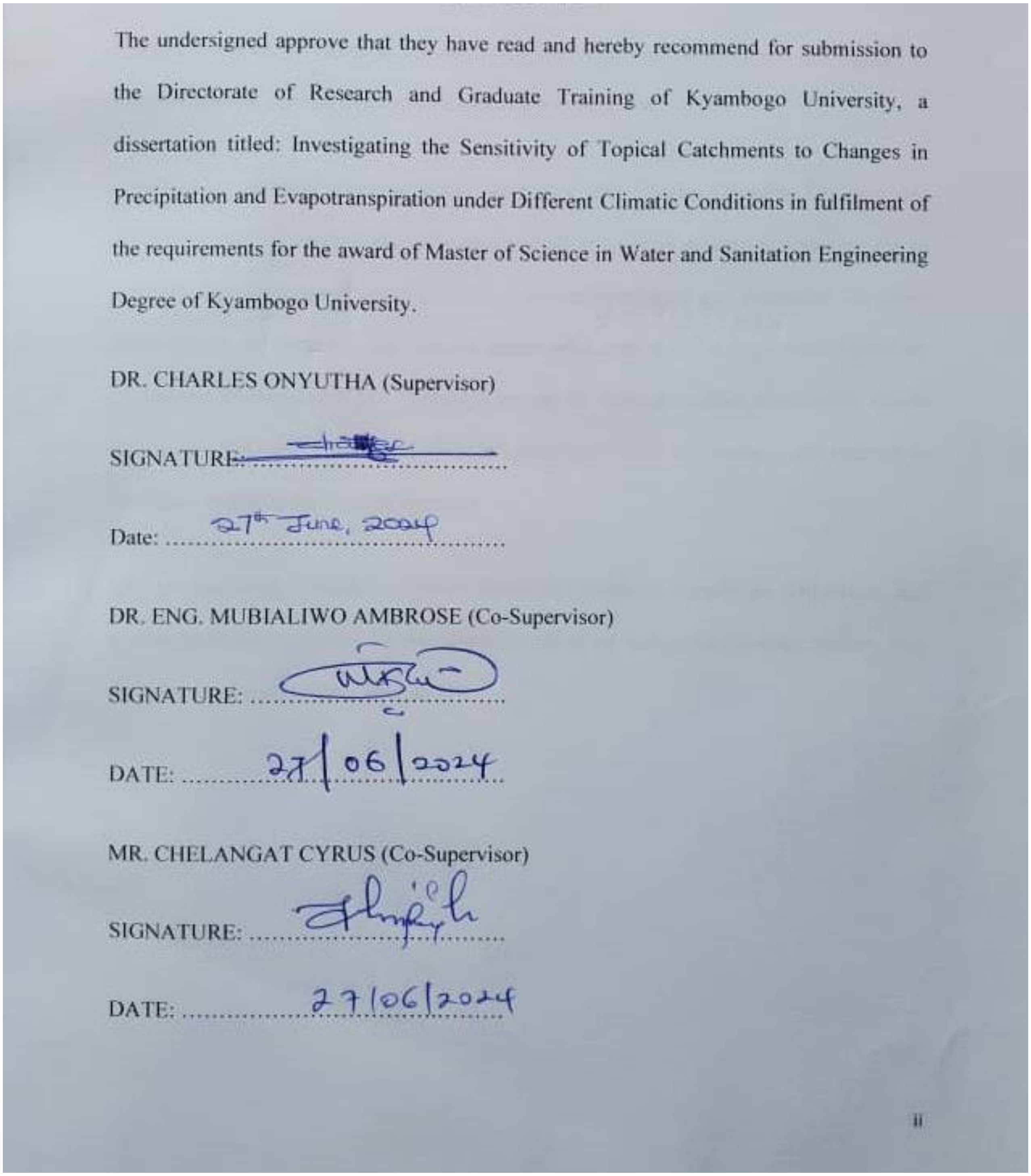

The undersigned approve that they have read and hereby recommend for submission to the Directorate of Research and Graduate Training of Kyambogo University, a dissertation titled: Investigating the Sensitivity of Topical Catchments to Changes in Precipitation and Evapotranspiration under Different Climatic Conditions in fulfilment of the requirements for the award of Master of Science in Water and Sanitation Engineering Degree of Kyambogo University.

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Last but not least, I thank my family members, friends at Kyambogo University, and colleagues at the workplace for the support given to me during my graduate studies. May the good Lord reward them abundantly.

DEDICATION

I dedicate this dissertation to my late father, Omugisha Leo (may he rest in eternal peace), my mother, wife, children, brother, sisters, aunts, and all my relatives.

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LIST OF ABBREVIATIONS

ARB	Awash River Basin of Ethiopia
AWBM	Australian Water Balance Model
BSPU	Basin-Scalable Parameters and Uncertainty
CV	Coefficient of Variation
DFID	Department for International Development
ECMWF	European Centre for Medium-Range Weather Forecasts
EOF	Empirical Orthogonal Function Analysis
EPA	Environment Protection Agency
ET	Evapotranspiration
FAO	Food and Agriculture Organization
GISS	Goddard Institute for Space Studies
GPCP	Global Rainfall Climatology Project
GSSHA	Gridded Surface Subsurface Hydrologic Analysis
HBV	Hydrologiska Byråns Vattenbalansavdelning
HEC	Hydrologic Engineering Centre
HMS	Hydrologic Modeling System Model
HMSV	Hydrological Model Focusing on Sub-Flow Variation
HRU	Hydrological Response Unit
IFS	Integrated Forecast System
IFS	Integrated Forecast System
IPCC	Intergovernmental Panel on Climate Change

ITCZ	Inter-Tropical Convergence Zone
KWMZ	Kyoga Water Management Zone
LS	Large Scale
LULC	Land Use and Land Cover
MMS	Modular modeling system
MSSA	Multichannel Singular Spectrum Analysis
NASA	National Aeronautics and Space Administration
NEMA	National Environment Management Authority
OCHA	Office of Coordination of Humanitarian Affairs
PCI	Precipitation Concentration Index
PET	Potential evapotranspiration
POP	Principal Oscillation Patterns
RCP	Representative Concentration Pathways
RS	Remote Sensing
SAI	Standard Anomaly Index
SHE	Hydrological system model
SMAR	Soil moisture accounting and routing
SPEI	Standard Precipitation-Evapotranspiration Index
SPI	Standard Precipitation Index
SSA	Singular Spectrum Analysis
SSMU	Site-specific modeling with uncertainty
SWAT	Soil and Water Assessment Tool

ABSTRACT

Globally, effective management of water resources is needed to provide sustainable water sources for human and ecosystem consumption. For the sustainability of water resources, careful planning is required for the management of catchments. One way to yield relevant information to support actionable policy is scenario analysis using hydrological modeling as a tool. This study investigated the sensitivity of Tropical catchments to changes in precipitation and evapotranspiration under different climatic conditions. The idea was to determine the extent to which flows would change given some incremental changes in rainfall and Potential evapotranspiration (PET). Six sub-catchments were considered and data from 1999-2016 (Malaba), 1980-2018 (Mpanga), 1990-2019 (Kabalega), 1980-2000 (Blue Nile), and 1980-2002 (El-diem & Ribb) were utilized. The AWBM and Hydrological Model focusing on Sub-Flow Variation (HMSV) were applied to data from each selected sub-catchment. Performance of AWBM in terms of Nash-Sutcliffe Efficiency (NSE) considering the full data period was 0.838 (Malaba), 0.686 (Kabalega), 0.676 (Mpanga), 0.812 (Blue Nile), 0.745 (El-Diem) and 0.56 (Ribb). Corresponding values for HMSV were 0.806 (Malaba), 0.748 (Kabalega), 0.620 (Mpanga), 0.806 (Blue Nile), 0.800 (El-Diem) and 0.520 (Ribb). Mean annual flows exhibited increasing trends in all sub-catchments except Kabalega. A positive trend ranged from 0.005-2.294m^3/s/year in magnitude. A negative trend in the flow of Kabalega was at a rate of -0.015m^3/s/year. All trends in flows were not significant since *p*-values were all above 0.05. The sensitivity of sub-catchments to increasing rainfall under constant PET ranged from 0.968m^3/s/year (Malaba) to 2.700m^3/s/year (Blue Nile) for every percentage increase in rainfall. The sensitivity of sub-catchments to increasing PET under constant rainfall ranged from -0.3603 m^3/s/year (Kabalega) to -1.288 m^3/s/year (Blue Nile) for every percentage increase in PET. Under simultaneous changes in rainfall totals and PET, the sensitivity of sub-catchments varied, ranging from 0.00821 m^3/s/year (Malaba) to 1.2218 m^3/s/year (Blue Nile) for every percentage increase in rainfall. Climate variability is characterized by both increases and decreases in flows depending on underlying factors. These results underscore the importance of careful planning of watershed management given factors like changes in climatic conditions that influence spatial and temporal variation in rainfall and PET.

Key Words: *Tropical catchments, HMSV, AWBM, rainfall, PET, and flow.*

CHAPTER ONE: INTRODUCTION

1.1 Background to the study

Globally, effective management of water resources is needed to provide sustainable water sources for human and ecosystem consumption that depend on surface and underground water (Donohue et al., 2011). Investigating progressions in water yield necessitates understanding both projected environmental variations and the reaction of catchments to hydrological changes (Dibaba et al., 2020, Banda et al., 2022). However, various scholars have been using climate sensitivity techniques to examine the effects of climate variability on watershed streamflow (Lv et al., 2019). Hydrological prediction is currently not well suited to projections of changing climatic conditions (van Dijk and Keenan, 2007, Al-Safi and Sarukkalige, 2017). Climate variation is presumed to be a big problem shortly after changing the hydrological system as well as hindering development and prosperity characterized by water scarcity, unpredictable rainfall, flooding, drought, etc (World Bank, 2021). In Africa, woods make up 23% of the land, and 10% of the continent total forest acreage was used for the production of commercial and subsistence crops between 1990 and 2010 (Tan and Hung, 2016). Africa has the second-highest annual net change in land cover of 0.36%, after South East Asia with 0.71% (Lambin et al., 2003).

For instance, over 20 years, natural forest cover in East Africa has decreased by around 13 million hectares, and surviving forests are fragmented and vulnerable (FAO, 2010).

Natural and human-made factors have caused total wetland coverage in Uganda (Lakes Kyoga & Victoria basins) to decrease by 26% and 53% respectively, after variations in land usage and its cover (Gabiri et al., 2020).

One of the geomorphic reactions to strengthening land use and cover types is expanded transportation of residue and storage at various periods (Poff et al., 2006). Though the slopes and along the channel influence the pattern of sediment load, these reactions are determined by the mixture of river and hillside water (Poff et al., 2006). Yet, the quantity and kind of soil have a significant impact on how resilient riverbanks are (Poff et al., 2006). Even while natural seasonal variation in discharge is often made worse by human alterations to sub-catchments, these effects can be changed by other human endeavors.

Human activities can result in a variety of alterations such as the rampant occurrence of soil erosion, deforestation, and overgrazing, all these hinder changes in the direction of the river and reduction of the volume of flow (Gregory, 2006). More specifically, the frequent occurrence of unpredictable meteorological conditions like heavy rainfall, overflows, droughts, and rising unpredictability of rainfall significantly hinders the governance of natural water resources (Nsubuga et al., 2014). Unpredictable rainfall consequences can be seen in an increased rate of rainfall runoff, and increased river deposit changes in river flow patterns, among other things (Nsubuga et al., 2014).

Elsewhere, large-scale changes in surface plant cover caused by land use patterns in northern China grasslands have profoundly impacted the ecosystem and local environment. To comprehend how different types of grassland affect ecosystem components responses to PET. Three normal-use designs in the mild steppe region were the subject of a review, and the discoveries uncovered that variety in the leaf region record fundamentally affects the size of the biological systems evapotranspiration (ET) and the cosmetics of its constituent parts under different prairie use designs (Li et al., 2015). The ability to maintain the ecosystem and stop the loss of biodiversity can be aided by our knowledge of the regional hydrological cycle and energy balance (Smith, 2020). This can be accomplished by working out the effects of changes in PET on changes in land use and land cover change (LULC) and the environment (Yang et al., 2012). The extent to which land surface affects PET assumes a significant part in the hydrology and energy balance (Jia et al., 2018). In addition to the complex interplay between land cover changes and hydrological systems, it is crucial to consider the role of evapotranspiration (ET) in the context of global water resource management. Evapotranspiration, the combined process of water evaporation from surfaces and transpiration from plants, plays a significant role in the water cycle and ecosystem dynamics. Variations in land cover, such as deforestation, land use changes, and urbanization, can significantly impact ET rates, altering local and regional hydrological patterns. Moreover, climate variability and change further influence ET dynamics, affecting water availability and ecosystem functioning.

It is known that other demographic factors, like population density, fertility, mortality, age and sex makeup of households as well as human migration have a significant impact on changes in land cover usage, as well as on large-scale planned resettlements like those in Indonesia and the Amazon (National Research Council, 2005). Subsequent studies revealed that the overall association is affected by several variables, such as land settlement rules, market forces, cultural and institutional effects, and the biophysical features of the environment (Geist et al., 2001).

Fluctuations in grassland usage might have an impact on the mechanisms that absorb carbon, through evaporation and transpiration. Changes in the vegetation, the initial soil structure, and the microclimate all have an impact on these processes. When the temperature is greater, plant cells that control the openings (stoma) through which water is expelled into the atmosphere open; when the temperature is lower, plant cells that control the openings close. Dryer air facilitates water evaporation more easily than more saturated air. To improve water use, watershed management, policy development, adoption of science-based management, and rational resource allocation are necessary (Li et al., 2017). This study therefore used flow, rainfall, and PET to investigate the sensitivity of Tropical catchments to changes in precipitation and evapotranspiration under different climatic conditions

1.2 Problem statement

Globally, the increasing frequency and intensity of extreme weather events exacerbate the vulnerability of communities and ecosystems to sudden disruptions, threatening lives, livelihoods, and infrastructure. At the national and regional levels, variations in precipitation patterns result in prolonged droughts in some areas and devastating floods in others, leading to water scarcity, food insecurity, economic losses, and social unrest.

Similarly, climate in Uganda is naturally variable and it is prone to flood and drought catastrophes where both have had detrimental socioeconomic effects (Hepworth and Gaulden, 2008). The government of Uganda has undertaken an initiative to preserve natural resources through the establishment of the National Environment Management Authority (NEMA) and Water Catchment Management Zones (WMZs) to regulate water resources. The Uganda 3rd National Development Plan also included the enactment of water resource management reforms and the promotion of catchment-based integrated water resource management, both of which would aid in protecting water resources and the environment (Katusiime and Schütt, 2020).

In addition, the Sustainable Development Goal (SDG: 15) emphasizes the conservation of forests, combatting desertification, halting biodiversity loss, and promoting sustainable land use practices (UNDP, 2023). However, it is very important to also appreciate the fact that there have been different scenarios of hydrological events unexpectedly like floods and drought, as a result, communities have lost property and their dear ones. It has damaged infrastructure for development and raised global human casualties (Desai et al., 2015). For instance, between 1960 and 2000, extreme temperatures and severe rain caused 5 million people to be displaced internationally (Marchiori et al., 2012). United Nations (UN) reported that nearly 6 million people were affected by floods in 2020 with about 1.5 million people evacuated from their homes (BBC, 2020). Furthermore, in 2010 Uganda experienced heavy landslides in Bududa, which left hundreds of people dead and others displaced. Recently, at least four people were killed by floods in October 2019, a situation that caused more than 2000 people to be evacuated, and about 51 community members were left dead due to floods (ACAPS, 2018). This has been mainly caused by changes in land usage and its cover through agriculture, bushland, exposed soil, and developed regions (Ngondo et al., 2021).

Several studies have been done in the region on changes in climatic conditions (Elshamy et al., 2009, Chelangat and Abebe, 2021). However, none of these research studies focused on the sensitivity of Tropical catchments to changing rainfall, and PET also understood the response of a catchment to rainfall. This can guide the stakeholders in making decisions on the status and the trend of climate variability and action to be taken properly. It is evident that while Uganda has taken steps towards environmental conservation and water management, there is a need for further research and a comprehensive understanding of catchment dynamics to address the ongoing challenges posed by climate variability management of water and its sustainability in Tropical catchments.

1.3 Main and specific objectives

1.3.1 Main objective

To investigate the sensitivity of Tropical catchments to changes in precipitation and evapotranspiration under different climatic conditions.

1.3.2 Specific objectives

i) To characterize changes in hydro-climatic conditions precipitation and evapotranspiration in Tropical catchments.

ii) To develop a hydrological model to ascertain catchment flow under varying rainfall totals and constant PET.

iii) To quantify the influence of PET on flow under constant rainfall.

iv) To assess the catchment response to concurrently changing rainfall and PET.

1.4 Research questions

i) What is the significance of changes in hydro-climatic conditions precipitation and evapotranspiration in Tropical catchments?

ii) What is the catchment response to flow under changing rainfall and constant PET?

iii) What is the catchment response to flow under changing PET and constant rainfall?

iv) How do changes in rainfall and PET affect the flow of the catchment?

1.5 Research justification

Although several studies have been conducted on changes in climatic conditions in the Tropics (Elshamy et al., 2009, Chelangat and Abebe, 2021), none of them have focused on the sensitivity of Tropical catchments to changes in precipitation and evapotranspiration under different climatic conditions over the study periods 1999-2016 (Malaba), 1980-2018 (Mpanga), 1990-2019 (Kabalega), 1980-2000 (Blue Nile) and 1980-2002 (El-diem & Ribb). Conducting such studies can guide the stakeholders in making effective decisions on the status and the trend of climate variability in the tropics.

Therefore, the purpose of this study was to investigate the sensitivity of Tropical catchments to changes in precipitation and evapotranspiration under different climatic conditions in sub-catchments of River Malaba, River Mpanga, River Kabalega, Blue Nile, Ribb, and El-Diem. The study utilized two lumped conceptual models: the HMSV (Onyutha, 2019b) and the AWBM (Podger, 2004). Semi-distributed models are based on sub-catchment units with various land use types where rainfall is applied and runoff volumes are estimated and routed. The model performance of HMSV and AWBM was done by calibration, validation, and for entire periods of the six sub-catchments.

1.6 Study significance

(i) The study can inform researchers on the prediction of the outcome of certain hydrological for better planning and decision-making on the sustainability of water shade management, land use management, and legitimate usage of the water resources of an area.

(ii) The findings of the study add to the prevailing information on changes in climatic conditions and thus aid in planning.

(iii) This research can guide the decision-makers and key stakeholders in preserving the green vegetation cover, developing catchment management plans, regulating the watershed, and predicting and preparing for future hydrological changes.

1.7 Scope of the study

1.7.1 Time

This research took 2 years from 2022-2023. The study involved collecting data related to rainfall, evapotranspiration, and temperature from the Uganda Metrological Authority under MWE.

1.7.2 Content

This study was restricted to investigating how sub-catchments in Tropical regions respond to changes in rainfall and PET. The findings are vital in anticipating future changes in climate variability.

1.7.3 Geographical coverage

This research focused on six Tropical sub-catchments, including River Malaba, River Mpanga, River Kabalega, Blue Nile, Ribb, and El-Diem located in Tropical regions.

1.8 Conceptual framework

Below is the conceptual framework showing the influence of precipitation, PET, and Catchment on flow in Tropical regions**.** Figure 1.1 above depicts that there is a direct relationship between independent variables (including precipitation, PET, and catchment characteristics) and flow (dependent variable). Precipitation augmented flow, while PET potentially reduced it; catchment features influenced water storage and release. Human activities and government policies acted as intervening variables, altering flow dynamics through urbanization, agriculture, and policy regulation. This holistic approach highlighted the interplay between natural processes, human actions, and governance in hydrological system management, offering insights into sustainable water resource policies.

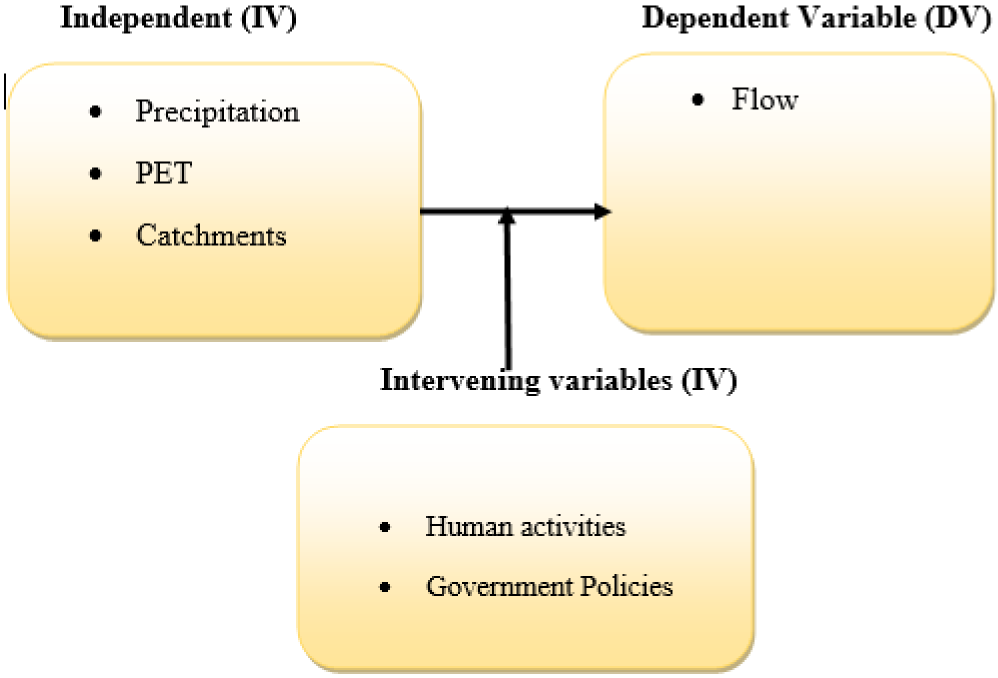


Figure 1.1: Showing the relationship between Precipitation, PET, Catchment characteristics, and Flow.

1.9 Summary of the chapter

This chapter introduced the research problem by giving the background of the study, problem statement, study objectives, research questions/hypotheses, significance of the study, and study scope. The next section (Ch.2) presents the review of literature that is related to the problem under investigation, by reviewing related research studies that have been undertaken by other researchers/authors.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter presents domestic and foreign literature. It includes a summary of concepts including hydrology, climate variability, techniques of analyzing change, methods of analyzing trends, and changes in rainfall. It also includes prior studies on the effects of land use changes in Tropical locations, numerous hydrological models that have been utilized, and past research on hydrological models used in Tropical regions. This chapter also presents two models AWBM and HMSV which were adopted while conducting this study.

2.2 Hydrology and human factors

Hydrology is the scientific study of the properties, distribution, and movement of water on and below the surface of the Earth (Gabriel and Chryst, 2015). It examines how water exists, flows, and spreads across the planet, and how its characteristics interact with the environment, especially affecting living organisms (Devia et al., 2015). It also considers how water influences its surroundings throughout the hydrological cycle. Urbanization and industrialization have changed hydrological systems through activities like deforestation, land use changes, and irrigation, impacting global river flows, soil patterns, and climate variability (Devia et al., 2015).

2.3 Changes in climatic conditions

Changes in climatic conditions were investigated by Mohammed et al. (2022) in the Upper Blue Nile Basin of Ethiopia. They aimed to understand variations and trends in rainfall and temperature extremes, crucial for managing water resources in Tropical areas. Using historical meteorological data, the authors analyzed trends in extreme weather events over a specific period.

Mohammed et al. (2022) utilized statistical methods to identify changes in frequency, intensity, and duration of extreme events like heavy rainfall, droughts, heatwaves, and cold spells. Results of the study revealed significant variability in rainfall and temperature extremes in the study period. Mohammed et al. (2022) observed a cumulative trend in heavy rainfall events, suggesting an advanced risk of floods and associated hazards. According to Mohammed et al. (2022), the findings of such a study can easily be absorbed by policymakers, water resource managers, and other key stakeholders in developing strategies to improve policymaking.

A study in the Sudan-Sahel Zone examined the effect of climate variability on environmental conditions as well as livelihoods in the region using a combination of satellite imagery, climate data, and socio-economic surveys (Mertz et al., 2012). The authors analyzed the historical climate trends and assessed their implications for land use, agricultural productivity, and water availability while focusing on the years 1950 to 2010. It is noted that this period was characterized by significant climate variability and increased vulnerability to environmental stressors (Mertz et al., 2012). It was found that the region experienced substantial shifts in temperature and rainfall patterns, leading to prolonged droughts, desertification, and decreased agricultural yields. Mertz et al. (2012) also identified various socio-economic factors that contributed to the vulnerability of local communities.

A study conducted in Rwanda examined the potential effects of climate variability on water resources in the Upper Akagera catchment of Rwanda to assess the current state of water resources, analyze climate variability trends, and project future water availability based on diverse climate variability situations (Ntakirutimana et al., 2021). The authors utilized a combination of data collection, analysis, and modeling techniques to assess the effect of climate variability on resources for water. Ntakirutimana et al. (2021) collected historical climate data and hydrological data to analyze trends and patterns. The study identified a noticeable rise in temperature and changes in rainfall patterns over the past few decades, indicating climate variability. The authors also observed a significant decline in water availability due to increased evapotranspiration rates and reduced rainfall, leading to potential water scarcity issues in the future. The findings of the study suggested a further decrease in water resources, with implications for agriculture, domestic water supply, and hydropower generation. The study also emphasized the urgency of implementing adaptive strategies of water management to curb down may help policymakers, decision-makers, and managers for water resources to develop effective strategies that bring about water security in the region (Ntakirutimana et al., 2021).

2.4 Methods for analysis of trends

The trend, which may be linear or non-linear, given a time series of similar temperatures, is the pace at which the variable changes over some time. The trend slope (m), yearly rainfall, and PET can be added after the trend magnitude or slope has been calculated (Theil, 1950, Sen, 1968). The significance of a linear variation of the variables and non-zero slope must be evaluated in the second step. The parametric linear regression test requires normally distributed data. The data need not be regularly distributed to use non-parametric approaches like the Mann-Kendall (MK) (Mann, 1945, Kendall, 1975) and Spearman Rho (SP) tests (Spearman, 1904, Lehmann, 1975).

2.5 Rainfall-runoff modeling

Understanding hydrologic processes and how they affect the hydrological cycle is improved by runoff modeling (Sitterson et al., 2018). Rainfall and runoff models are used to illustrate the effects of changes to vegetation, pervious surfaces, and meteorological events on water systems (Sitterson et al., 2018). An assortment of conditions that assist with computing how much rainfall that causes a runoff as a component of factors used to address the watershed is one more method for portraying a runoff model (Sitterson et al., 2018). Because of the intricate calculations and numerous interconnected components, surface runoff modeling can be difficult. The components of the model typically include the flowing formulae equation, the processes of the model, and the model output (Singh, 1995a). The modeling of the surface runoff requires a better understanding of the water shade area, yields, and its responses to the evaluation of availability, changes in water over the period, and projections (Sitterson et al., 2018).

There are numerous ways to classify models; the entirely different models may not fall into a single group because are made to achieve various goals (Singh., 1995). In this study, models are categorized into one of three broad types because each uniquely computes runoff way. The model structure has organized the categories into empirical, conceptual, and physical categories. Models are categorized and divided in various ways by researchers according to factors including input/output types, model simplicity, and spatial resolution. This study describes a different type based on the catchment area of the spatial interpretation of the models. This distinguishes between distributed, lumped, and semi-distributed models. The choice of rainfall-runoff model will rely on the modeling objective, such as comprehending the hydrological process and providing answers to specific queries, determining the frequency of runoff occurrences, or predicting runoff yield for management objectives (Sitterson et al., 2018).

To narrow the range of options and make sure the model is the best for the right purpose, it may be helpful to prioritize modeling and to determine the constraints on data accessibility, time, and budget.

Rain falls runoff models are many including the Nedbør-afstrømnings model (NAM), Hydrologiska byråns vattenbalansavdelning (HBV), Probability distribution model (PDM), rainfall-runoff Modeling System (PRMS) and the seven lumped models that is SACRAMENTO (SAC). Evaporation and stream (IHACRES), SIMHYD, Soil moisture accounting and routing (SMAR), Identification of unit hydrograph and component flows from rainfall, AWMB, TANK (Podger, 2004) and the HMSV (Onyutha, 2019b). All these models have been used because of the variety of applications and their availability at a free cost.

This model requires a mechanism to predict the future using the available data at any given period for ungauged catchments and into the future, to automate the potential implications of water cycle changes in the future.

2.6 Methods for analysis of variability in climate data

The analysis of climate variability is crucial when it comes to forecasting the behavior of several extreme weather events (Rehman et al., 2022). Smith et al. (2008) present an overview of climate data analysis tools and methods, including statistical techniques such as linear regression, correlation analysis, and principal component analysis.

Several methods have been utilized in analyzing climate variability.

The Empirical orthogonal function Analysis (EOF) is a method devised to uncover variations within a dataset (Martinson, 2018). In the realm of climate variability studies, EOF is widely utilized to explore potential spatial patterns of variability and their temporal evolution (NCAR, 2013). Some experts categorize EOF as a multivariate statistical technique (NCAR, 2013), and it stands as a key tool employed by meteorologists to elucidate climate variability (Attuabea et al., 2017).

Singular spectrum analysis (SSA) has gained broad application in identifying intermittent oscillations within geophysical and climatic time series data (Vautard et al., 1992). Specifically designed to extract signals from noisy time series, SSA has proven successful in analyzing geophysical data (Ghil et al., 2002, Macias et al., 2014).

Multichannel singular spectrum analysis (MSSA) was developed to analyze variability in nearby climatic stations (Walwer et al., 2016). As demonstrated by the authors, MSSA effectively models common seasonal signals in GPS position time series, enabling the analysis of spatial and temporal correlations among different time series (Gruszczynska et al., 2018, Ghil et al., 2002).

Principal oscillation patterns (POP) is a multivariate technique utilized to concurrently elucidate characteristic patterns and timescales within a vector time series (Von Storch et al., 1995). It serves as an investigative tool for objectively deriving space-time characteristics of a dataset (Xu and Von Storch, 1990). Principal Oscillation Patterns are adept at identifying 30-to-60-day oscillations within multi-year atmospheric general circulation model simulations (Xu and Von Storch, 1990, Hasselmann, 1988).

Li (2019) explored the application of machine learning techniques in climate data analysis. Various algorithms, such as support vector machines, random forests, and neural networks, and their use in climate variability analysis tasks, including pattern recognition, extreme event detection, and climate prediction were all discussed and provided insights into the strengths and limitations of machine learning approaches in this context (Li, 2019).

2.7 Water vapor and rainfall

Climate and weather are influenced by various processes, but studies often highlight the significance of rainfall in the water cycle (Acker et al., 2014). Rainfall notably impacts local weather in Tropical and temperate areas. The release of heat during cloud and rain formation affects both local and global atmospheric circulation (Acker et al., 2014). To enhance our understanding and predictions of weather and climate, it is essential to closely monitor and estimate rainfall in regions with low to medium latitudes. However, quantifying rainfall is challenging due to its variability in both time and location. Rain gauges provide only localized measurements, which are insufficient for broader analysis. While surface radar offers slightly better spatial coverage it is limited globally. Therefore, satellite remote sensing of rainfall has become indispensable (Smith et al., 2008).

In all ecosystems especially forests, rainfall delivers more water than the vegetation can utilize or the soils can retain, depending on the hydrologic cycle (Wraith et al., 1987). The extra water helps stream flow, which meets agricultural needs and urban needs far from the rainfall source. In the hydrologic cycle that occurs before rainfall reaches the soil, vegetation plays a significant role. The vegetation and the litter layer of the surface water are intercepted and evaporated (Wraith et al., 1987). The density and depth of root channels and the amount of organic residue integrated into the soil have an impact on how quickly water infiltrates into the soil, flows off the top, or percolates through to the water table (Smith et al., 2008).

2.8 Past studies on changes in rainfall in the Tropics

In a study conducted in Semi-Arid Eastern Kenya, Recha et al. (2016) assessed the effect of changing rainfall patterns among farmers from the Eastern parts of Kenya by use of a mixed-methods approach. The authors analyzed the collected data using statistical techniques and thematic analysis to provide a comprehensive understanding of the adaptation practices of farmers. Findings indicated that farmers in semi-arid eastern Kenya have been experiencing changes in rainfall patterns, with a reduction in total annual rainfall and an increment in the frequency of extreme weather events like droughts and heavy rains (Recha et al., 2016). The authors emphasized the importance of promoting and supporting the adoption of soil water management activities that make farmers resistant to changing rainfall patterns. The study suggested the need for policies and interventions that facilitate the dissemination of climate information, improve access to resources, and strengthen institutional support for sustainable agricultural practices. There is a need for policymakers, extension workers, and development practitioners working in similar contexts to utilize these findings to enhance agricultural resilience in semi-arid regions (Recha et al., 2016).

In Burundi, Lawin et al. (2018) explored variability in rainfall, temperature, and wind speed while using statistical techniques to analyze historical climatic data that was collected from different meteorological Centres in Burundi. The authors employed well-established methodologies such as the Mann-Kendall test and Sen's slope estimator to identify significant trends and quantify the magnitude of changes in rainfall, temperature, and wind speed. The findings of the study indicated notable trends and changes with a significant increment in temperature across Burundi, suggesting a warming trend. The study also identified variations in rainfall patterns, including both positive and negative trends in different regions of the country. Still, authors reported changes in wind speed, that have implications for various sectors such as agriculture and energy. Researchers, policymakers, and practitioners in Burundi and other parts of the world can benefit from these results (Lawin et al., 2018).

In their study conducted in Rwanda, Kazora et al. (2021) investigated the variations in rainfall over both time and space, exploring the factors influencing these changes. Utilizing rainfall data from CHIRPS and CRU spanning from 1981 to 2017, the authors applied various analytical methods, including Standardized Anomaly, Empirical Orthogonal Function, Pearson Correlation, Mann-Kendall, and Sen's Gradient Estimator. Their analysis revealed notable shifts in rainfall patterns across Rwanda. These findings are significant to policymakers and water managers to inform the development of climate adaptation and water management strategies in the country.

In another study conducted in Rwanda, Ntirenganya (2018) assessed rainfall variability in the country for small-scale farmers strategies for climate variability and determined the annual and seasonal trends of both rainfall and dry spells using 15 stations. By investigating the relationship between rainfall patterns and adaptation measures of the farmers, the study aimed to provide insights into effective coping strategies for sustainable agricultural practices in the face of changing climatic conditions in the region.

Ntirenganya (2018) employed statistical methods that included time series. We used GIS software to make maps with data. Looking at the rainfall and how many days it rained, we didn't see any clear pattern. Our study found that when there are long periods without rain, crops do not grow well because the plants get stressed. Seasonal dry spells also hurt crop production. But if farmers time their plowing and planting right, they can get good yields by using the rainwater efficiently. We found that small-scale farmers are doing different things to deal with these changes, like growing different crops, collecting rainwater, taking care of the soil, and using better farming methods. This study highlighted the importance of irrigation in meeting crop water needs for farmers across different regions of the country. Therefore, expanding irrigated areas would lead to higher total crop yields (Ntirenganya, 2018).

In Tanzania, Massawe and Xiao (2021) investigated the variability of rainfall patterns during the late summer to provide information on the temporal and spatial distribution of rainfall, which is crucial for agriculture, water resource management, and overall socio-economic development. The authors employed a comprehensive analysis of observed rainfall data from multiple sources, including ground-based stations and satellite measurements. The authors analyzed rainfall variability by use of various statistical and data analysis techniques. Massawe and Xiao (2021) found considerable variability in rainfall patterns during the late austral summer, observed both inter-annual and intra-seasonal variations in rainfall amounts, revealed the existence of different rainfall regimes across the country, and showed a north-south gradient in rainfall, with higher amounts recorded in the northern regions compared to the southern parts of the country.

Findings indicated a need to incorporate long-term climate projections and adaptation strategies to mitigate the potential impacts of changing rainfall patterns.

A study titled “On Tanzania’s Rainfall Climatology, Variability, and Future Projection” by Borhara et al. (2020) explored climatology, variability, and future projections of rainfall in Tanzania by utilizing a combination of observational data and climate model simulations to examine historical trends and make projections for the future (Borhara et al., 2020). The authors employed statistical techniques to analyze the spatial and temporal patterns of rainfall in Tanzania over a specific period. The findings of the study revealed that Tanzania experiences considerable spatial and temporal variability in rainfall, with distinct wet and dry seasons across the country. Borhara et al. (2020) projected future rainfall patterns under different emission scenarios, providing valuable information about potential climate impacts in Tanzania. These findings confirm that understanding the future rainfall trends and variability is crucial for policymakers, stakeholders, and local communities to develop effective strategies for climate change adaptation and sustainable development (Borhara et al., 2020).

In Uganda, Jury (2018) investigated rainfall variability and explored its predictability to enhance the understanding of climate dynamics in the country to provide insights into potential methods for rainfall prediction. Jury (2018) employed a theoretical and applied climatology approach to analyze the rainfall patterns. The author utilized historical rainfall data and employed statistical and modeling techniques to identify trends and patterns in rainfall variability. The study examined both inter-annual and intra-seasonal variability and took into account various factors that influence the climate system of Uganda. The author identified patterns and trends and explored the potential drivers of rainfall fluctuations in the region. Furthermore, the study highlighted challenges associated with rainfall prediction in Uganda and suggested possible strategies for improving prediction accuracy (Jury, 2018). Thus, studying historical rainfall patterns and identifying potential predictors, contribute to the development of reliable prediction models that can assist in effective water resource management and agricultural planning in Uganda in particular and other tropics in general.

Kilama et al. (2021) also examined the variations and trends of rainfall, temperature, and river flow in the Sipi sub-catchment in eastern Uganda by utilizing long-term climate data to assess changes over time and provide an understanding of the hydrological dynamics in the region. The authors employed statistical techniques and trend analysis to identify long-term trends and patterns. The study pointed out the significance of monitoring and understanding climate variability, particularly the Sipi sub-catchment (Kilama et al., 2021). The study emphasized the need for adaptation strategies to mitigate the potential risks associated with changing climate patterns and their influence on water availability. Investigating the interactions between rainfall, temperature, and river flow, researchers were in the position to contribute to the knowledge of climate variability impacts on local water resources (Kilama et al., 2021).

Owoyesigire et al. (2016) examined trends in rainfall and temperature from the cattle corridor of Uganda to assess the potential impact on agricultural activities, particularly cattle rearing. The study employed statistical analysis methods to analyze historical climatic data, focusing on rainfall and temperature trends. Results revealed notable trends in rainfall and temperature variability over the examined period. The results of this study ought to be utilized by policymakers, researchers, and key agricultural stakeholders to develop effective strategies and interventions for climate resilience and sustainable development in the cattle corridor and similar agro-pastoral regions.

2.9 Past studies on changes in potential evapotranspiration in the Tropics

In their study, Obada et al. (2017) focused on the most recent variability of annual PET for six synoptic centers in Benin to quantify future changes in PET under 3 different projected periods (2011-2040; 2041-2070; and 2071-2100) in comparison with the referenced period (1981-2010). Obada et al. (2017) employed the Penman-Monteith method, a widely applied approach to assess PET, that integrates numerous meteorological parameters like temperature, humidity, wind speed, and solar radiation. The findings of this study showed a high variability of PET in all centers during the baseline period with an interchanging deficit and excess periods. These findings suggested a possible increment in demand for water regarding agricultural activities, and other water-dependent sectors in Benin. There is therefore a need to adopt measures that can enable community members in such regions to cope with changing climatic conditions (Obada et al., 2017).

Shilenje et al. (2015) conducted a study in Kenya and focused on the rainfall and PET regimes in Murang’a County. Shilenje et al. (2015) employed the Penman equation, a widely used method for estimating potential evaporation, to calculate the evaporation rates in Muranga County. Meteorological data was collected and analyzed to derive the required input parameters for the Penman equation (Shilenje et al., 2015). The utilized climate models yielded 3 different variations implying some level of uncertainty for future agricultural production. Their study suggested a rigorous study about the individual effect of each parameter on PET in similar environments (Shilenje et al., 2015).

A study conducted in Rwanda, investigated potential impacts of climate variability on rainfall, air temperature, and PET in Rwanda (Haggag et al., 2016). It utilized climate data from 1964-2010. This data was collected from multiple sources, including observations and climate model outputs. Climate projections for the future (2010-2099) based on three general circulation models and two emission scenarios were used for climate projections. The findings of this study indicated a warming trend over the past forty years and rainfall records on the other hand showed no significant trend in the considered period and PET was observed with an increasing trend. Climate projections indicated a pattern towards warmer and wetter climatic conditions in Rwanda. Generally, the findings of this study have significant implications for several sectors, including water and agriculture, infrastructure planning, etc. For instance, the projected increase in temperature and potential water stress could adversely impact agricultural productivity, posing challenges to food security. More efforts ought to be geared toward addressing the changing rainfall patterns and increased evapotranspiration in the country (Haggag et al., 2016).

2.10 Past studies on changes in rainfall and PET in the Tropics

Yagoub et al. (2017) applied a Standard Precipitation-Evapotranspiration Index (SPEI) to explore possible drought events in Sudan and South Sudan over the last 53 years. SPEI combines both rainfall and evapotranspiration data. Findings indicated that temperature is increasing in Sudan, but rainfall is dramatically decreasing. There was an opposite scenario where temperature had a declining trend when rainfall was increasing in South Sudan. Findings further indicated that there was an extensive seasonal and spatial changeability in drought intensity. On the other hand, this study had no intention of forecasting drought in the two countries of study (Yagoub et al., 2017). This study called for a need to look into drought patterns in both countries to aid the development of effective drought monitoring and management strategies (Yagoub et al., 2017).

Omay et al. (2023) investigated spatial patterns for trends and variability in rainfall patterns in the Eastern Africa region. The study applied the Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS v2.0) and a National Oceanic and Atmospheric Administration (NOAA) gridded temperature. PET and water balance were calculated to determine rainfall cessation dates (Omay et al., 2023). In Kenya, early rainfall cessation over more than 30 counties was observed, in Upper Nile, and 20-40 days of early onset dates were observed. In Khartoum and southern parts of Sudan, 20-40 days of delayed rainfall onset was also observed. There was no observed sign of cessation before November in most parts of Uganda and the Nyanza region in Kenya. However, the two regions observed rainfall onset by March (Omay et al., 2023). The findings of the study suggested that the observed changes in rainfall patterns could have implications for different sectors in the region (Omay et al., 2023).

A study conducted in Southern Ethiopia investigated the changes in seasonal and annual rainfall and temperature data using time series analysis for the period 1983-2016 to understand the historical climate patterns and changes in the region (Belay et al., 2021). The authors employed the Standard Anomaly Index (SAI), Coefficient of Variation (CV), Precipitation Concentration Index (PCI), and Standard Precipitation Index (SPI) to assess variations in rainfall in the region. Findings showed that the region went through a significant rainfall variability a situation that led to prolonged periods of drought and flood events. The authors of this study suggested further research and monitoring efforts to identify the evolving climate dynamics of Southern Ethiopia and design targeted interventions for sustainable development (Belay et al., 2021).

In their study, Mahtsente et al. (2020) investigated the long-term variability in PET, water availability, and drought conditions in the Awash River Basin of Ethiopia. PET and water availability were estimated from 1995 to 2009 and two future scenarios (2050s and 2070s). That is, Mahtsente et al. (2020) analyzed the historical climate data and compared it with future scenarios to identify potential changes in water availability and drought severity. The findings of this study indicated that the ARB is projected to experience an increase in PET under all climate scenarios, suggesting higher evaporation rates and potential water stress. Overall, the findings of this study indicated the presence of water shortage and drought in the region, meaning that a fundamental consideration in terms of climate mitigation strategies should be implemented especially in the Lower and Middle parts of ARB (Mahtsente et al., 2020).

In Ethiopia, another study conducted by Geleta et al. (2020) focused on the evaluation, modeling, and projection of PET under climate scenarios in the Kesem sub-basin of the ARB. The study aimed to assess different PET models and their applicability in the study area. The authors employed various PET models and compared their performance in simulating evapotranspiration processes in the Kesem sub-basin. The authors collected climatic data, including temperature, humidity, solar radiation, and wind speed, from meteorological stations in the study area and compared different PET estimation methods, such as the Penman-Monteith equation, Hargreaves-Samani method, and Thorn Thwaite method, among others. Findings revealed the performance of the selected PET models, highlighting their strengths and weaknesses in accurately estimating PET (Geleta et al., 2020). Such studies are crucial because the understanding of PET patterns and variations is needed by key stakeholders, especially in regions where water scarcity is a significant concern.

2.11 Past studies on changes in land use/land cover in the tropics

Biro et al. (2013) analyzed LULC changes in North Sudan to assess their impact on soil properties. The study utilized remote sensing data (satellite imagery and Geographic Information System (GIS) techniques) to analyze LULC changes over a specific period. Biro et al. (2013) also collected soil samples from different land use types, including croplands, forests, and grasslands, to assess the impact of LCC on various soil properties.

Biro et al. (2013) conducted laboratory analyses on the collected soil samples to assess several soil properties, including soil organic carbon content, pH levels, nutrient availability, and soil compaction. The findings indicated a strong correlation between LUC and soil degradation. Findings demonstrated that the alteration of forests and grasslands into farming land yielded reduced soil carbon content, increased soil compaction, and altered nutrient availability. Overall, the findings of this study confirm good practices of sustainable land management in mitigating soil degradation, providing a basis for informed decision-making and policy formulation (Biro et al., 2013).

Gudo et al. (2022) conducted a land use land cover (LULC) study of 17 years (2000–2017) in South Sudan. In their study, Gudo et al. (2022) investigated spatiotemporal dynamics of LULC changes to discover the patterns and trends of LULC in Jubek State. The authors utilized Remote Sensing (RS), Geographic Information System (GIS), Landsat TM, Landsat ETM+, and Landsat 8 OLI methods. Quantitative and spatiotemporal findings indicated that build-up areas significantly increased most especially from 2009-2017. The findings of this study indicated that ever since 1995, Juba has been a desirable place for settlement of the people. The implementation of a good strategy like LULC transformation was commended by authors because Jubek State/Juba is rich in natural resources needed by the people (Gudo et al., 2022).

A study in Uganda investigated LULC changes that occurred in the L. Victoria basin (LVB) over 30 years from 1985-2014 (Mugo et al., 2020). The authors conducted the study to acquire knowledge on spatial and temporal patterns of LULC changes within

LVB, which is a crucial freshwater resource and ecologically sensitive area. Mugo et al. (2020) assessed LULC changes in the study period while utilizing Landsat images and field data obtained from the L. Victoria basin. By analyzing satellite imagery from multiple time points, authors generated LULC maps that allowed the identification and quantification of changes in different land categories. The findings of this study demonstrated that LVB has gone through extreme changes regarding LULC mainly as a result of human activities (Mugo et al., 2020). The authors concluded by targeting, highlighting, and monitoring small-scale, community-led efforts to restore degraded and fragmented areas in the LVB.

Another study conducted in the LVB utilized data and information from the natural resources and climate components to examine the impact of LULC changes on climate variability (Kashaigili et al., 2015). The authors of the study conducted another analysis while utilizing the Mann-Kendal (MK) test, Linear regression, and moving averages with the intention of revealing patterns of change and trends in annual and seasonal rainfall and temperature (Kashaigili et al., 2015). The findings of this study revealed that LVB has changed over time due to factors like land cover manipulations and land use change coupled with climate variability (Kashaigili et al., 2015). Crop cultivation and settlement expansion were found to be the main types of land use that have even overtaken grazing lands. Kashaigili et al. (2015) concluded that integrating crop residues into ruminant feeding systems is a possible way to curb rangeland degradation.

A study conducted in Burundi by Geo-Informatics utilized Landsat satellite imagery from different periods to capture historical patterns of LULC changes (Ntakirutimana and Vansarochana, 2021). The authors utilized the CA-Markov Model to simulate and predict future LULC changes based on historical data. The findings of the study indicated moderate agreement of 75% and the same trends of LULC changes. Whereas tree cover, grassland, and shrub-land were found to decrease by 11.5km^2, agriculture and built-up area were found to increase by 30km^2 and 6km^2 respectively by 2057 (Ntakirutimana and Vansarochana, 2021). These study findings have positive effects in terms of planning for urban areas and managing the environment in Burundi and other regions facing similar challenges (Ntakirutimana and Vansarochana, 2021).

Gedefaw et al., (2023) investigated the influence of LULC changes on the water resources in Ethiopia. The authors utilized several methods like the MK test, and Sen's slope estimator test to analyze trends in the Nile River basin. On the other hand, LULC change was assessed by use of the TM and ETM+ from 2012 to 2022 (Gedefaw et al., 2023). The findings of the study indicated that forestland and shrub-land decreased by 5.2% and 2.4% respectively. The significant changes in LULC could be a result of man-made activities in the basin. The findings of the study benefit key stakeholders in coming up with informed decisions regarding LULC planning to ensure long-term water security and ecosystem sustainability (Gedefaw et al., 2023).

A study in the tropics conducted by Bullock et al. (2021) revealed that faster population growth rates put pressure on the conversion of nine different land cover classes in

Ethiopia, Uganda, Kenya, Rwanda, Malawi, Tanzania, and Zambia between 1998 and 2017. In East Africa, cropland increased by 18,154,000 (or 1,580,000 ha), or 34.8%, according to the research. Their findings showed that the population is expanding quickly and settling in new places, with a 43.5% increase in settlement area over 30 years. The findings revealed, both physically and statistically, the locations and ecoregions most affected by 30 years decades of human growth. More specifically, research on land-cover changes in West Africa (Herrmann et al., 2020) revealed that agricultural expansion was the most dominating trajectory of land-cover change, resulting in the extinction of savanna and forests. Estimates of deforestation for Tropical locations, particularly in West Africa, are uncommon and ensure (Lambin et al., 2003).

East Africans rely largely on the land for their subsistence, and each household now owns less land than before (Maitima et al., 2009). Increasing pressure land use has influenced activities like overgrazing, and conversion of natural forests into agricultural farms and habitants (Maitima et al., 2009). The forest was decreasing at a rate of 1% annually in the period between 1990 and 2015 in East Africa yet the population is increasing at the average rate of 2% annually. However, there has been a program to reinstate all types of forest in the Tropical of East Africa (Frost, 2001). LULC compromises the provision of human consumables food and fiber for human consumption as well as reducing negative effects on the water quantity, and quality of among others the ecosystem (Gutman et al., 2004).

2.12 Importance of land use changes to hydrology

One significant human intervention that affects the usage of both surface and groundwater in its quantity is land use change (Dwarakish and Ganasri, 2015). Understanding the model link between various hydrological systems and their behavior concerning alterations caused by humans is crucial (Dwarakish and Ganasri, 2015). The importance of assessing the effects of change in land cover on stream flow is because stream flow has control over other abiotic and biotic elements. Stream flow shapes the physical structure of the bed, banks, and floodplain of the stream affecting the habitat and functioning of aquatic ecosystems (DeFries and Eshleman, 2004). Lessening the raindrop effect comparable to the forest may affect the water cycle as infiltration, groundwater recharge, base flow, and runoff (Woldesenbet et al., 2020). Its root fiber systems, which promote infiltration, retain the soil in place, and lessen the severity of soil erosion, are the significant variables influencing that lead to movement of soil and sediment output (Shikangalah et al., 2016).

Together with climate change, the usage of land is one of the changes of landscapes that is most obvious in the world. As stated by Defries and Eshleman, (2004), the main problem in current hydrological findings is determining the effects of various environmental changes. Changes in the usage of land have played a big role in the water budget and hydrology of river catchments.

2.13 Impacts of land use changes on hydrology in the Tropics

The main factors that affect land use change include rapid population growth, urbanization, agricultural intensification, and an increase in surface mining are some of the key causes affecting LU changes in the West. In 1990 and 2010 over 32 million acres of forest in West and Central Africa were converted to various land (Braimoh and Vlek, 2005, FAO, 2010). Changes in land use can affect the hydrological cycle components distribution of rainfall, which can hurt the environment and socioeconomic well-being of people.

The water cycle is significantly impacted by LULC because it changes ET, soil water storage, and the ability of vegetation to collect rainfall (Mao and Cherkauer, 2009). The hydrologic budget, which combines the two sub-processes of evaporation and transpiration, includes ET as one of its essential components (Matheny et al., 2017). Open water, marshes, bare soil, snow cover, etc, all lose water by evaporation, whereas living plants lose water through transpiration (Matheny et al., 2017). Consequently, the peculiarities of the ground surface affect ET. According to studies, the key factors influencing ET in a watershed include changes in land use, crop variety, crop rotation, and land cover. According to Zhang and Schilling, (2006), there was a decrease in ET in the Upper Mississippi River between the 1940s and 2003 because of the shift of land from perennial vegetation to seasonal row crops. According to Baker and Miller, (2013), a decline in forest area also resulted in a drop in ET. Because of their thick roots, low albedo, and water-interception abilities, forests encourage higher ET (van Dijk and Keenan, 2007).

Changes in LULC impact surface roughness and vegetation cover, which modify the timing and quantity of groundwater and discharge of surface runoff, affecting stream flow and the size and frequency of floods (Neelam, 2018). More surface runoff results from changes in land use, including urbanization and agricultural operations (Tong and Chen, 2002, Ding et al., 2015). Large paved landscape features in urban settings increase the number of impervious surfaces. Less rainfall can therefore penetrate the soil profile, resulting in more surface runoff (Mishra and Singh, 2010, Angeler and Allen, 2016, Lambrinos and Haegele, 2005). Similar outcomes were demonstrated in the Cedar River watershed, where increased surface runoff due to anticipated urban growth was forecast (Wu, 2013). Intense agricultural practices can lessen surface roughness (Guzha, 2004), which results in less soil pore space available for water storage and reduced interceptions. According to Baker and Miller (2013), increasing surface runoff was caused by the conversion of forest areas to agricultural land. In the semi-arid Zanjan rood basin in Iran. Lu et al. (2015) demonstrated that a loss in grassland and an increase in agricultural land reduced base flow and groundwater recharge. It was also noted that the upper San Pedro watershed in Arizona saw a lower percolation rate and reduced base flow because of the conversion of grassland to woods (Nieto et al., 2011). According to Schilling et al. (2014), the Raccoon River basin in Iowa had less flooding when agriculture was converted to grassland.

2.14. Application of models for hydrological changes

2.14.1 Main categories of model

Hydrological models are used primarily in the prediction of hydrological events and the understanding of hydrological processes. There are many categories of models used in hydrological changes including lumped conceptual models, semi-distributed, and distributed.

2.14.1.1 Lumped conceptual models

Lumped conceptual models are commonly employed in modeling for rainfall-runoff simulation due to their improved ability to predict runoff utilizing simple processes and their low data demand (Westerberg and Halldin, 2010). Lumped conceptual models are simplified representations of hydrological systems that aggregate multiple components into a single entity and they are commonly used to understand and predict hydrological changes (Jain and Sudheer, 2008). However many conceptual models use simplified representations of the hydrological processes, they are often used when data availability is limited (Nash and Sutcliffe, 1970a). Below are some of the lumped conceptual models for hydrological changes: -

(i) Rainfall-runoff models

Rainfall-runoff model is a hydrological tool used to simulate the transformation of rainfall into streamflow (Singh, 2016, Todini, 1996). It is a mathematical model describing the rainfall-runoff relations of a catchment area, drainage basin, or watershed (Trivedi et al., 2021). Rainfall-runoff models focus on the transformation of rainfall into runoff by incorporating various physical and mathematical equations to estimate the runoff generated by rainfall events (Singh, 2016, Chiew et al., 2014, Todini, 1996). It should be noted that various algorithms and equations, such as the Soil Conservation Service Curve Number method are used to simulate runoff response (Chiew et al., 2014) and these models are based on the principle of mass balance (Singh, 2016, Todini, 1996).

(ii) Hydrologiska byråns vattenbalansavdelning model

The HBV model is a hydrological model developed by the Swedish Meteorological and Hydrological Institute (SMHI) and it is widely used for simulating and analyzing the water balance in various regions (Lindström et al., 1997). It is a conceptual rainfall-runoff model that simulates the hydrological processes in a catchment with its components for soil moisture, groundwater, and surface runoff, allowing for the analysis of various hydrological changes (Lindström et al., 1997, Bergström, 1995). The HBV has been applied in various research and practical applications related to hydrology and water resources management such as streamflow forecasting, water resources management, climate change impact assessment, water quality analysis, and ecosystem studies among others (Bergström, 1995, Lindström et al., 2010).

(iii) Conceptual groundwater models

These are simplified representations of the subsurface hydrogeological system used to understand and predict the behavior of groundwater flow and contaminant transport by incorporating various elements such as aquifers, aquitards, recharge areas, wells, and other features to simulate the flow and movement of groundwater (Anderson et al., 2015, Neuman, 2005, Anderson and Woessner, 1992). Conceptual groundwater models rely on conceptualization and assumptions to simplify complex processes and parameters. They represent the behavior of groundwater systems using simplified equations that describe the movement and storage of water. These models consider inputs such as recharge from rainfall and losses due to evapotranspiration, as well as interactions with surface water bodies and other hydrological features (Neuman, 2005, Anderson and Woessner, 1992).

(iv) The Stanford watershed model (SWM)

This is a hydrological model developed by Stanford University to simulate water flow and quality in river basins (Hutton et al., 2018, Loftis and Arnold, 1986). The SWM is used for water resources management and environmental studies as it incorporates various components such as rainfall, evapotranspiration, infiltration, runoff, and pollutant transport (Hutton et al., 2018, Schmitz and Rodriguez-Iturbe, 1992, Linsley et al., 1982). The model is a widely used tool for studying the impact of land use changes, climate variability, and water management strategies on hydrological processes through the utilization of digital elevation data, land cover information, and soil properties to simulate the movement of water and contaminants through the landscape (Linsley et al., 1982, Donigian et al., 2018).

2.14.1.2 Semi-distributed models

(i) Soil and water assessment tool (SWAT) model

This is a semi-distributed hydrological model developed by the United States Department of Agriculture, a process-based, spatially distributed model that integrates hydrological and water quality processes within agricultural watersheds and it is commonly used for assessing water resources and predicting the impacts of land management practices on hydrological processes (Arnold et al., 1998, Neitsch et al., 2011a, Arnold et al., 2012). The model divides a watershed into sub-basins and further discretizes them into hydrological response units and it is a widely used hydrological model that integrates various components such as hydrology, climate, land use, and agriculture to simulate water balance and assess the impacts of land management practices on hydrological processes (Gassman et al., 2007). It has been applied to study hydrological changes in various regions through the simulation of water flow, sediment transport, and nutrient cycling within river basins (Arnold et al., 1998, Gassman et al., 2007).

(ii) Variable infiltration capacity (VIC) model

The VIC model was developed by the University of Washington and it is a macroscale hydrological model that simulates the spatial and temporal variability of water fluxes and storages within a river basin (Liang et al., 1994). It is a widely used semi-distributed hydrological model that simulates the water balance at the grid cell level, accounting for spatial variations in soil moisture, infiltration, and runoff (Liang et al., 1994, Nijssen et al., 2001). The model has also been used for studying hydrological changes in various regions because it incorporates various components, such as rainfall, evapotranspiration, snow accumulation and melt, soil moisture, and streamflow routing, to simulate the water balance and hydrological behavior of a region (Liang et al., 1994, Li et al., 2008, Hamman et al., 2016, Mao and Lettenmaier, 2018).

(iii) The Tank model/linear reservoir model

This is a hydrological concept used to simulate the flow of water through a system (Singh, 1995b). That is, a tank model represents a hydrological system as a series of interconnected storage tanks and each tank represents a component such as soil moisture, groundwater, or surface water, and the flow between tanks represents hydrological processes (Kirchner, 2009). Based on this model, every tank represents a portion of the system where water is stored and released at a certain rate and the flow between tanks is determined by the storage capacity and the outflow characteristics of each tank (Singh, 1995b, Nash and Sutcliffe, 1970b). According to Nash and Sutcliffe (1970b), the Tank model assumes linearity because the outflow is proportional to the storage within each tank. The model provides a practical approach to simulate the response of a system to different inputs and evaluate the impact of various scenarios on water availability, runoff, and other hydrological variables (Beven, 1984, Abbaspour et al., 2007).

(iv) Hydrological model focusing on sub-flow

The structure Identification of this modal relies on two Primary input variables which include precipitation (P) and PET. Precipitation serves multiple purposes within the model framework, including meeting evapotranspiration needs, replenishing soil moisture, and generating runoff when in excess. Runoff is further divided into baseflow (Q_{bf}), interflow (Q_{if}), and overland flow (Q_{of}) components (Onyutha, 2019b).

Upon satisfying evaporation demands using meteorological inputs, the model computes these runoff components as linear or exponential functions of soil moisture storage. The resulting simulated total runoff (Q_{sim}) constitutes the sum of these flow components. The subsequent mathematical equations detail how the model integrates actual evapotranspiration (E_{act}) and soil moisture (S) to generate its outputs.

(v) Australian water balance model

The AWBM serves as a comprehensive tool for catchment water balance assessment, offering both daily and hourly resolution for runoff calculations (Boughton, 2004). It is one of the Rainfall Runoff Library (RRL) that is designed to simulate catchment runoff by using daily rainfall and evapotranspiration data (Trivedi et al., 2021). The daily iteration finds utility in water yield and management investigations, while the hourly version is instrumental in design flood estimation endeavors. This paper provides a thorough account of the evolution of AWBM, tracing back to its foundational elements such as saturation overland flow modeling. Notably, the AWBM distinguishes itself through tailored calibration techniques aligned with its structural intricacies. These methodologies encompass graphical analyses of rainfall-runoff relationships, multiple linear regression, and an automated self-calibration mechanism.

Demonstrations of the model efficiency span diverse contexts, including daily streamflow simulations across 19 catchments nationwide and hourly analyses for flood assessments in Victoria. Furthermore, the paper elucidates a protocol for extending the applicability of the model to ungauged catchments, exemplified by its utilization across the aforementioned 19 catchments in water yield studies.

The narrative encapsulates various research endeavors where the AWBM has been instrumental, underscoring its versatility and robustness across multifaceted research programs. Under the leadership of Walter Boughton, a study was conducted to assess a pioneering calibration technique for the AWBM in coastal Queensland, Australia (Boughton, 2009). This method involved transferring calibrated parameter values across 18 catchments and adjusting input rainfall and evaporation using linear scaling, while also considering constraints on surface storage capacity. Results demonstrated highly accurate runoff estimation, with just a 5.5% average error and an impressive 94% of estimates within 15% of actual runoff. Furthermore, averaging calibrated parameters led to even better performance, with an average error of 5.3% and a maximum error of 15.8%, highlighting the method, effectiveness and in precisely estimating runoff, even in ungauged catchments (Boughton, 2009).

2.14.1.3 Distributed models

(i) Distributed hydrology soil vegetation (DHSV) model

This is a distributed, process-based hydrological model that simulates the interactions between rainfall, vegetation, soil, and terrain properties (Wigmosta et al., 1994, Wigmosta et al., 2002, Nearing and Jetten, 2017). The model also simulates processes such as snow accumulation and melt, evapotranspiration, and runoff generation, accounting for spatial variability. It is capable of simulating hydrological processes at fine spatial and temporal resolutions, making it suitable for studying hydrological changes in small-scale catchments (Wigmosta et al., 1994). The DHSV model incorporates various components such as rainfall, evapotranspiration, infiltration, runoff generation, and groundwater flow to provide a comprehensive representation of the water cycle (Nearing and Jetten, 2017). The model is also widely used in hydrological research, water resources management, and environmental studies (Wigmosta et al., 2002).

(ii) MIKE surface water hydrology (MIKE SHE) model

MIKE SHE model is a fully distributed hydrological model that simulates water flow, infiltration, evapotranspiration, and groundwater dynamics, allowing for the assessment of hydrological changes and their impacts on water resources (Refsgaard and Storm, 1995, Beven and Kirkby, 1979). MIKE SHE model is physically based, that is, the model is a software tool developed by DHI Group for integrated catchment and river basin modeling (Nossent and Willems, 2014). According to Jensen et al. (2005), these components are interconnected to provide a comprehensive representation of the hydrological cycle and its interactions. It is widely used for various hydrological applications, such as water resources management, flood forecasting, and environmental impact assessment through the integration of surface water and groundwater components (Refsgaard and Storm, 1995, Nossent and Willems, 2014).

(iii) Swat-modflow model

This model is a combined hydrological modeling system that integrates the Soil and Water assessment tool (SWAT) with the modflow groundwater model to study hydrological changes and their interactions between surface water and groundwater systems (Nanduri et al., 2008, Neitsch et al., 2011b, Wu et al., 2010). This implies that the model is a coupled hydrological and groundwater model that combines the SWAT with the modflow groundwater model (Neitsch et al., 2011b). The swat-modflow model is commonly used for the analysis of water availability, water quality, and groundwater-surface water interactions in a comprehensive manner (Neitsch et al., 2002, Neitsch et al., 2011b, Wu et al., 2010).

Table 2.1: Types of models

Model Category	Specific Model	Major Fields of Application	Advantages	Special Requirements and Problems
Hydraulic (hydrodynamic) models with distributed	Full Saint - Venant equation (dynamic wave model)	Water level and f1ow computation in any type of river or canal, even those with significant backwater	The most adequate description of gradually varied stream flow in	A large amount of quality data on the channel and flood plain geometry roughness etc.

parameters	Diffusion wave model	effects (subcritical flow) The basis for investigation of sediment transport, water quality, the effort of planned system changes hydraulic structures, etc.	any type of river, even for changing system conditions Most applicable and prototype characteristics are identified	High-capacity computers required Extended efforts in programming and program operation
Hydrologic conceptual) models with lumped parameters	Kinematic wave model special solution of the above-listed model (linearized) lag and route model Muskingum model multilinear model e.g nonlinear threshold model	Stream flow comparison in rivers without backwater effect (esp., for supercritical flows Real-time hydrological forecasting (except in backwater-affected reaches)	Adequate description of flows for the listed field of application A small amount of input data for model calibration Easy to handle and operatic on a small computer Model parameters have physical significance and are related to prototype characteristic	Significant simulation errors in case of applications beyond the given limits Parameters are not identical to prototype characteristics No application for predictions in case of planned system changes

Table 2.1 provides a detailed explanation of different types of models. Hydraulic models, like the Full Saint-Venant and Diffusion Wave, are ideal for detailed water level and flow computations in rivers and canals, including those with backwater effects, as well as for studying sediment transport and water quality. However, they require extensive data, powerful computers, and significant programming. In contrast, hydrologic models with

lumped parameters, such as the Kinematic Wave and Muskingum models, are suitable for stream flow comparisons and real-time forecasting in simpler conditions without backwater effects. These models are easier to use, need less data, and can run on small computers, but they can be inaccurate outside their intended applications and cannot predict system changes

2.14.2 Hydrological change

Hydrological change refers to any alteration in the water cycle of a particular area caused by natural or human-induced factors (Gleick, 2003). This can include changes in the quantity, quality, and timing of water flow in rivers, lakes, and groundwater systems. Hydrological changes can have significant impacts on ecosystems, agriculture, human health, and infrastructure. Understanding and managing these changes is crucial for ensuring water security and sustainable development. Some examples of hydrological changes may include: - changes in rainfall patterns, such as increased rainfall or drought conditions; alterations to land use, such as deforestation or urbanization, which can affect water runoff and infiltration; climate change, which can cause changes in temperature, snowpack, and glacier melt rates, and water management practices, such as the construction of dams and reservoirs, which can alter water flow and storage (Gleick, 2003, Vorosmarty et al., 2010, IPCC, 2014) among others

2.14.3 Computation of PET

PET is the theoretical maximum rate at which water could evaporate from a surface under ideal conditions, assuming an adequate supply of water. It represents the combined processes of evaporation from soil and water surfaces, as well as transpiration from vegetation, given sufficient moisture availability. PET serves as a useful indicator of the evaporative demand of the atmosphere and is often used in water resource management and agriculture to estimate irrigation requirements and assess water balance. The FAO Penman-Monteith method is a widely accepted approach for calculating Potential evapotranspiration. The formula for estimating PET using this method is as follows

$$\mathrm{PET} = \frac{0.408 \times \Delta \times (R_n - G) + \gamma \times \frac{900}{T + 273} \times U_2 \times (e_\alpha - e_a)}{B + \gamma(1 + 0.34 \times U_2)} \tag{2.1}$$

Where

PET= Potential evapotranspiration (mm/day)

R_n = Net Radiation at the crop surface (MJ/M^2/day)

G= Soil Heat Flux density (MJ/M^2/day)

T=Mean daily air temperature at 2-meter height (^{0}C)

U_2= Wind speed at 2-meter height (m/s)

e_∞= Saturation Vapor Pressure (kpa)

e_α= Actual vapor pressure (kpa)

$\triangle$= Slope of vapor pressure curve (kpa/^{0}C)

Υ=Psychometric constant (kph/^{0}c)

This formula considers various meteorological parameters, such as net radiation, air temperature, wind speed, and vapor pressure, to estimate the Potential evapotranspiration rate. It provides a comprehensive assessment of the evaporative demand of the atmosphere and is widely used in agricultural and hydrological applications.

2.14.4 Past Studies on hydrological models in the Tropical region

Onyutha (2019a) tested the HMSV framework using hydro-meteorological data from the Blue Nile Basin in Ethiopia. When compared to the five widely recognized hydrological models (AWBM, IHACRES, SACRAMENTO, SIMHYD, and TANK), HMSV performed favorably, particularly in reproducing both high and low flow quantiles. The combination of flow separation and step-wise calibration against sub-flows enhances the understanding of the system of the modeler, enabling them to identify areas that require more attention in the modeling process to achieve meaningful simulation results, especially for extreme events.

Mubialiwo et al. (2021) compared six hydrological models using limited data from River Kafu (1952-1981). They found AWBM excelled in normal conditions, while HMSV stood out in capturing extreme events, vital for flood and drought risk assessment. SACRAMENTO struggled, underlining the importance of accounting for model uncertainty in water resources planning.

Chalangat et al., 2021 carried out research on the Wambabya River catchment from 2010 on changes in upstream which altered rainfall patterns and raised temperatures, increasing evapotranspiration, and decreasing river inflows. This affected power generation at Kabalega dam, prompting the study to devise reservoir operation strategies using the

AWBM. Calibration and validation from 1990–2019 showed good model performance. Further optimization with the Hydrologic Engineering Center Reservoir System Simulation model improved power supply and reduced spill flows, recommending these strategies for maximizing Kabalega reservoir benefits.

In a quantitative assessment of uncertainty that was conducted in connection with the calibration of AWBM for both gauged and ungauged catchment cases, the performance of the AWBM model was found to be dominated mainly by the selection of appropriate rainfall data followed by the selection of an appropriate calibration data length and optimization algorithm (Haque et al., 2014).

In South Africa, Mooi River catchment, a framework for incorporating rainfall uncertainties in catchment modeling was presented and applied to a daily streamflow simulation using the AWBM model and it was found to double the proportion of observed flows within the 5-95 percentile bounds from an average of 25%-52% in validation, indicating that rainfall input uncertainty is indeed highly significant, indicating that the framework is potential for practical use (Ndiritu, 2013).

A study conducted in Australia to develop regionalization relationships to be estimated for ungauged catchments indicated that by using only easily identifiable characteristics of an ungauged catchment, suitable estimates of the unknown AWBM parameter values can be obtained allowing reasonable rainfall-runoff models to be developed (Gibbs et al., 2008). Authors assert that the relationships developed in their work were specific to

Australian catchments but the methods applied can be easily adapted to develop such relationships in other tropics (Gibbs et al., 2008).

In her study to test the performance of six conceptual models (such as HMSV and AWBM among others) using hydro-meteorological data from River Kafu, (Amollo, 2020) found that all the six models performed better on high flow and low flow but HMSV found with a particular calibration framework to capture extreme hydrological conditions.

When the two models were calibrated in the Impact Assessment of Climate Change on Hydrological Extremes of River Rwizi Catchment, in the AWBM, mean projections of Ten year return period were found to decrease; and in the HMSV, mean projections were found to increase (Baraza, 2019).

In their study, Nambi et al. (2014) evaluated hydrological models in a Tropical rainforest catchment and examined the performance of different models in simulating hydrological processes such as streamflow and rainfall-runoff relationships (Nambi et al., 2014). Through a comprehensive analysis, the authors compared the models' performance in capturing streamflow patterns and water balance components. The study highlighted the challenges and limitations of hydrological modeling in such complex ecosystems. According to Nambi et al. (2014), there is a need for accurate and reliable hydrological models to address the unique characteristics of rainforest ecosystems.

In their “evaluation of hydrological models for simulating streamflow in a Tropical catchment,” Singh et al. (2012) assessed the performance of hydrological models in simulating streamflow within a Tropical catchment. Their study focused on evaluating the accuracy of various models and their ability to replicate observed streamflow data. The study demonstrated the importance of selecting appropriate models for Tropical regions, where hydrological processes can exhibit significant spatial and temporal variability (Singh et al., 2012). Through their evaluation, Singh Singh et al. (2012) provide valuable insights into the strengths and limitations of different modeling approaches in capturing streamflow dynamics in Tropical catchments.

Lim et al. (2016) conducted a comparative analysis of hydrological models used for streamflow simulation in a Tropical watershed. These researchers aimed to assess the performance of different models in capturing the hydrological processes specific to the Tropical context. Various models, including physically based and data-driven approaches were evaluated using observed streamflow data (Lim et al., 2016). The study found that the performance of the models varied in terms of their ability to reproduce streamflow patterns accurately. According to their study, factors such as watershed characteristics, model complexity, and calibration methods were identified as influential factors affecting model performance (Lim et al., 2016).

In their study entitled “Performance evaluation of hydrological models in a Tropical catchment with sparse data” Suribabu, Srinivas, and Kothyari aimed to evaluate the performance of hydrological models in a Tropical catchment characterized by sparse data availability (Suribabu et al., 2017). To evaluate the models, the authors compared observed streamflow data with simulated streamflow generated by the selected models. Various statistical measures, such as Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percent Bias (PBIAS), were utilized to quantify the models' performance. The study considers multiple evaluation criteria to provide a comprehensive assessment of the models' accuracy and reliability. The study confirmed the need for robust hydrological models that can account for the challenges posed by sparse data in Tropical catchments (Suribabu et al., 2017).

Obropta et al. (2019) evaluated hydrological models to assess their performance in simulating streamflow in Tropical watersheds with limited data availability. Obropta et al. (2019) recognized the challenge of data scarcity in these regions and aimed to identify suitable modeling approaches for accurate streamflow predictions (Obropta et al., 2019). The findings of the study indicated that all three models were capable of simulating streamflow in Tropical watersheds to some extent. According to Obropta et al. (2019), the SWAT model demonstrated the highest level of accuracy in capturing the streamflow patterns, followed by HEC-HMS and SCS-CN. The superior performance of SWAT, the researchers noted, is due to its ability to consider more detailed hydrological processes and land characteristics. The findings of the study indicated the importance of incorporating local data to improve the accuracy of streamflow simulations in data-scarce Tropical watersheds (Obropta et al., 2019).

2.15 Policy implications issues related to catchment sensitivity

In the context of Uganda, the policies and Vision 2040 emphasize sustainable development and environmental conservation, understanding hydrological processes and climate variability is paramount. Rapid urbanization and industrialization, as highlighted by Gabriel and Chryst (2015) and Devia et al. (2015), have led to significant changes in hydrological systems, impacting water availability and quality. Similarly, Mohammed et al. (2022) emphasize the importance of managing extreme weather events, such as heavy rainfall and droughts, to mitigate flood risks and ensure water security in Tropical regions like Uganda. The climate resilience and disaster risk reduction as outlined in its National Climate Change Policy and Vision 2040 align with the focus of Uganda.

Moreover, studies by Mertz et al. (2012) and Ntakirutimana et al. (2021) underscore the vulnerability of East African regions, including Uganda, to climate variability and its implications for livelihoods and water resources. The observed shifts in temperature and rainfall patterns, as well as declining water availability, necessitate adaptive water management strategies to ensure sustainability. These findings are crucial for informing policy and decision-making by stakeholders, including policymakers, water resource managers, and local communities, to develop effective strategies for water management and conservation in Uganda. By integrating these research findings into policy frameworks, Uganda can enhance its resilience to climate change and work towards achieving its development goals outlined in Vision 2040, particularly in ensuring water security and environmental sustainability.

2.16 Chapter Summary

This chapter provided a comprehensive review of relevant literature aligned with the study variables and objectives, focusing on past research studies conducted by other scholars. It underscores the significance of investigating flow, rainfall, and PET that influence climatic conditions, particularly in the tropics, which is a critical concern for policymakers and researchers. Notably, Onyutha (2019a) introduced HMSV, demonstrating its superiority over traditional models in the Blue Nile Basin. Additionally, a study led by Boughton (2004) evaluated a novel calibration technique for AWBM in coastal Queensland, showcasing highly accurate runoff estimation. The subsequent chapter detailed the materials and methods employed in this study.

CHAPTER THREE: MATERIALS AND METHODS

3.1 Introduction

This section contains the materials and methods used in this research. The selected sub-catchments include: - Mpanga, Kabalega, Blue Nile, El-Diem, Malaba and Ribb. Ethical considerations for this research, the data used for the sub-catchments, methods of modeling computing trend, variability, model build-up calibration, validation, scenario analyses, and sensitivity analysis are presented in this section.

3.1.1 Ethical considerations

This study adhered to the highest ethical standards during research, ensuring the acknowledgment of data sources and privacy throughout all stages of the research process. Using data from previous research studies and exclusively relying on open-access models for this study raises several ethical considerations. These include ensuring proper attribution to the sources of the data, confirming that informed consent was obtained from the owners, data used for the sub-catchments, methods of modeling computing trend, variability, model build-up calibration, validation, scenario analyses, and sensitivity analysis are presented in this section. Respecting privacy and confidentiality, and evaluating the integrity and quality of the data.

3.2 Description of the study area

This research focused on areas in the Tropical region (areas that lie between the Tropical of Cancer and the Tropical of Capricorn). Selected catchments in the Nile basin and included Blue Nile, Kabalega, Malaba, Mpanga, Ribb, and El-Diem sub-catchments. The geographical maps and location of the study sub-catchments are indicated in Fig. 3.2 and Fig.3.3.

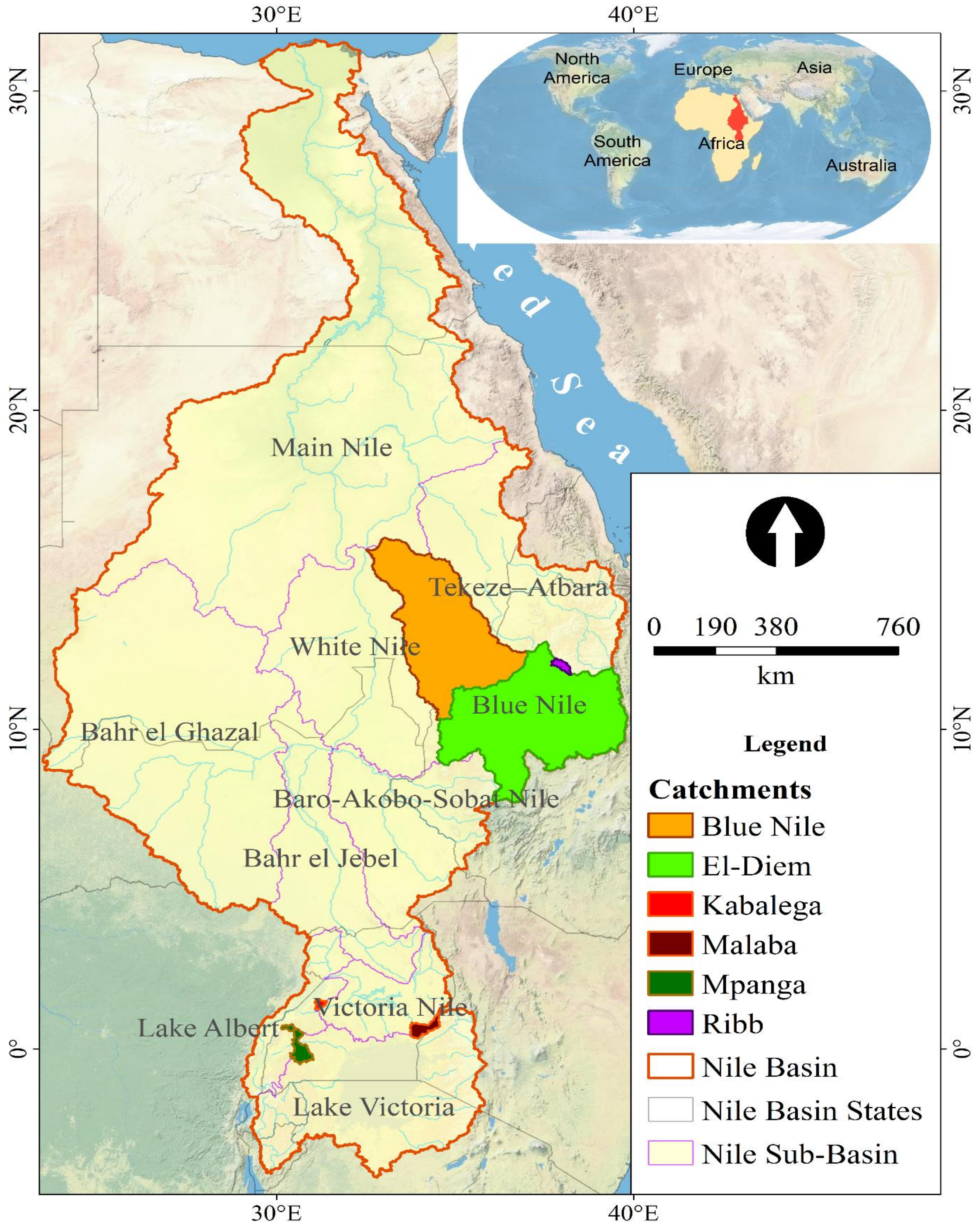


Figure 3.2: Selected sub-catchment areas in the Tropical region (Source: Primary data)

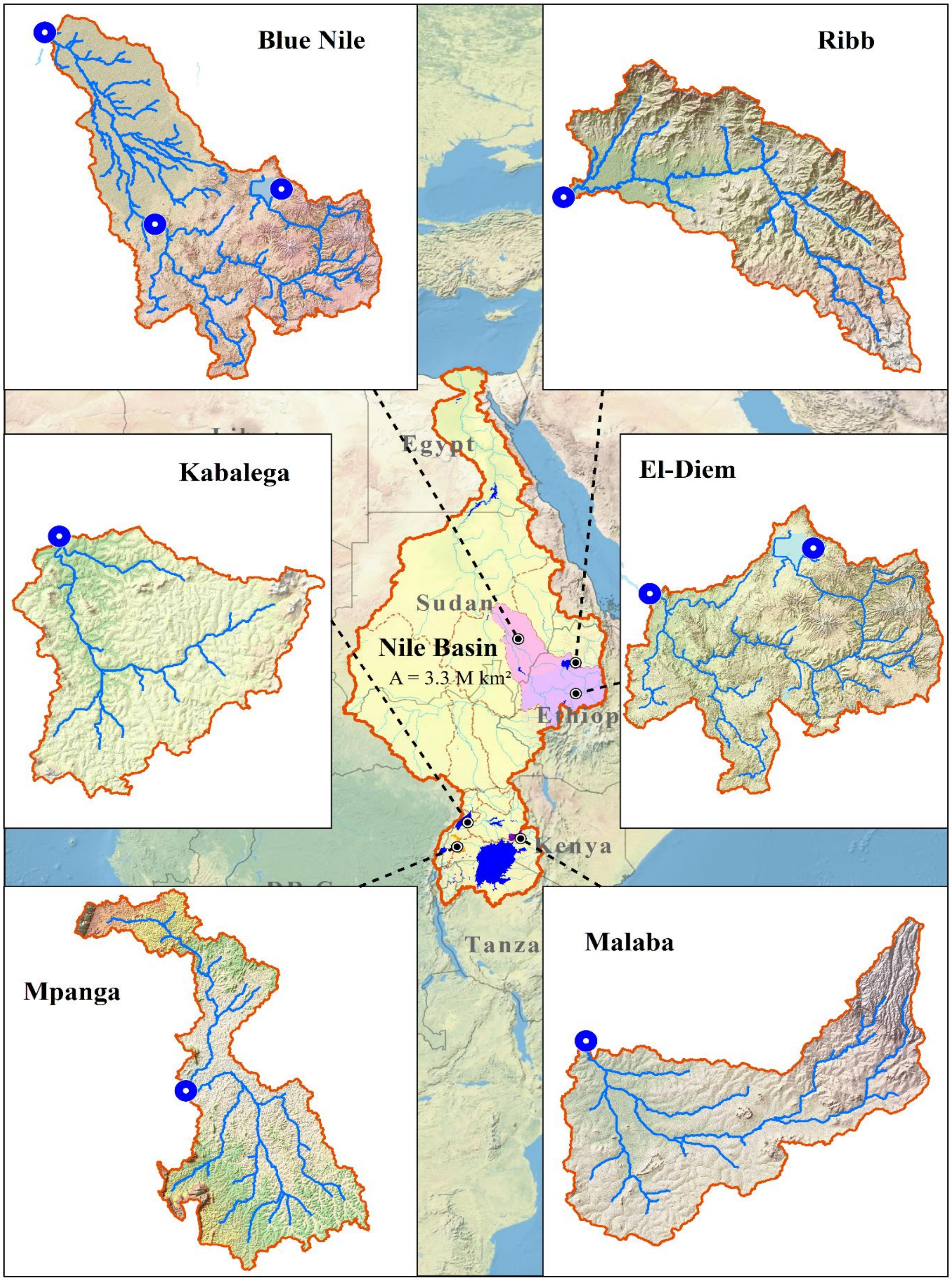


Figure 3.3: Nile basin (Mpanga, Malaba, Blue Nile, Ribb, El-Diem, and Kabalega) sub-catchment areas (Source: Primary data)

3.2.1 Malaba sub-catchment

Figure 3.4 indicates the Malaba Sub-catchment which is shared by both Uganda and Kenya with an approximate population of four million with a catchment covering a total of 3500 km^2 (Malaba-Malakisi catchment) which stretches from Mt. Elgon-Lwakhakha-Malakisi, Malaba-Manafwa and Mpologoma. It is transboundary on the border of Uganda and Kenya (about 69% or 2395 km^2 and 31% or 2395 km^2 respectively) and it originates from the slopes of Mount Elgon which drains to Kyoga. Malaba sub-catchment is later joined by the Lumbaka/Kibimba tributary, which originates in the Mpologoma catchment between latitude 0^0 19' N and longitudes 33^0 37' E and 34^0 37'. Around 27^{o}C is the mean annual temperature in the catchment. The soil of the catchment area is composed of PETric, plinthosal, gleysal, and other types of soil like lixicferrasol, acricferrasol, and nitsol (Bernard et al., 2013). Approximately 85% population uses the land for substance farming depending on rainfall beyond Mt Elgon the land all affected by changes in land use.

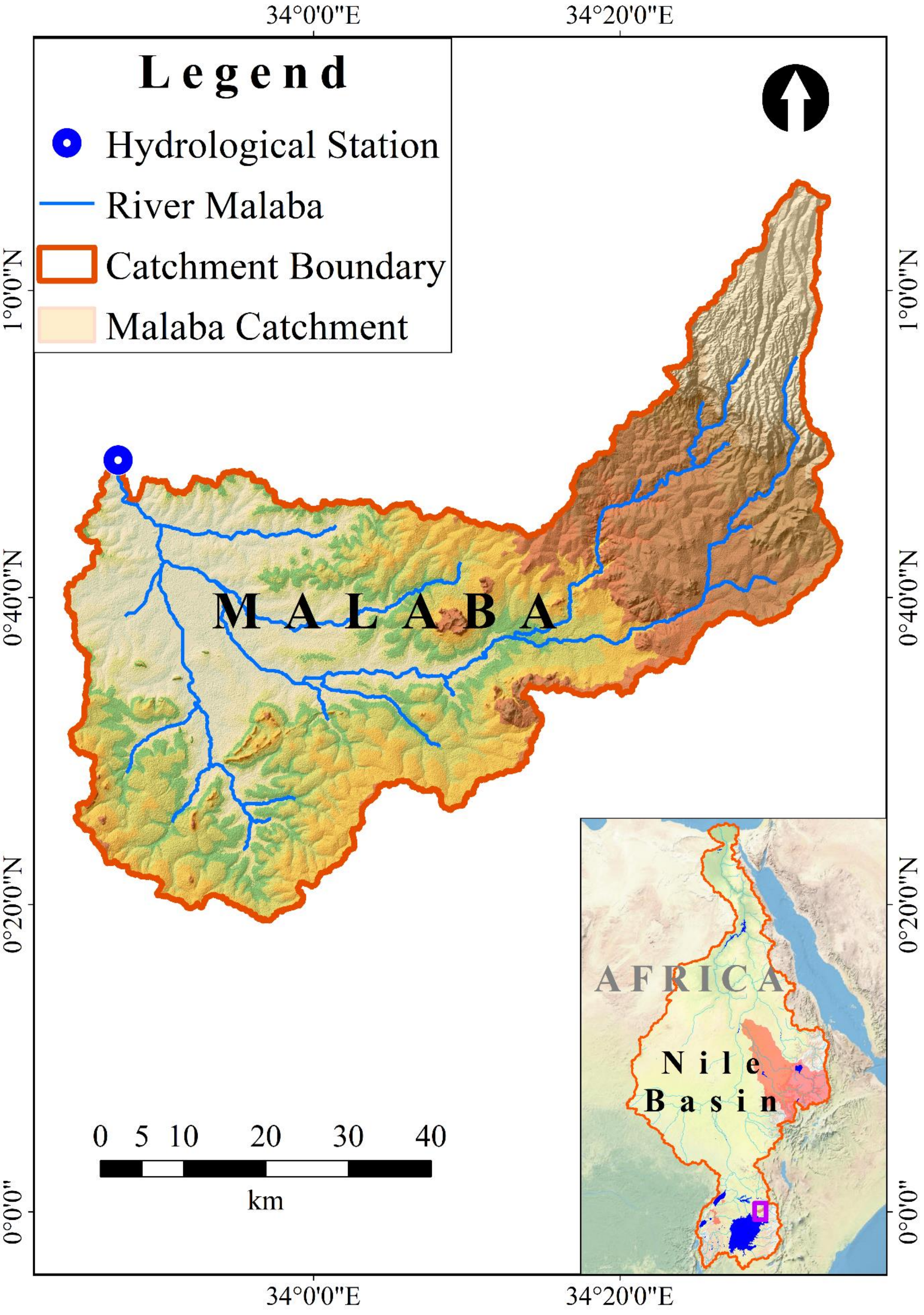


Figure 3.4: Malaba Sub-catchment area (Source: Primary data)

3.2.2 Ribb sub-catchment

River Ribb Sub-catchment in Fig. 3.5 has a total area of 1592 km^2. It originates from Guna Mountains at an elevation of 4000m above sea level. The hydrological station of the outlet location of River Ribb is located at Long=37.73^o and Lat=12.00^o. The Ribb catchment is within the Blue Nile basin, it flows to Lake Tana at an elevation of 1787m above sea level. The average temperature of the sub-catchment in the upper part is 27^{o}c, and the lowest temperature is 0^{o}c around December. The temperature around Lake Tana increases with average annual maximum and minimum values of 35^o and 11^{o}c respectively. The rainfall in the catchment was about 1300mm between 1988-2015 with 80% received in June and September and due to population increase, excessive grazing, and other agricultural operations, the land in the watershed is degraded (Mulatu et al., 2018).

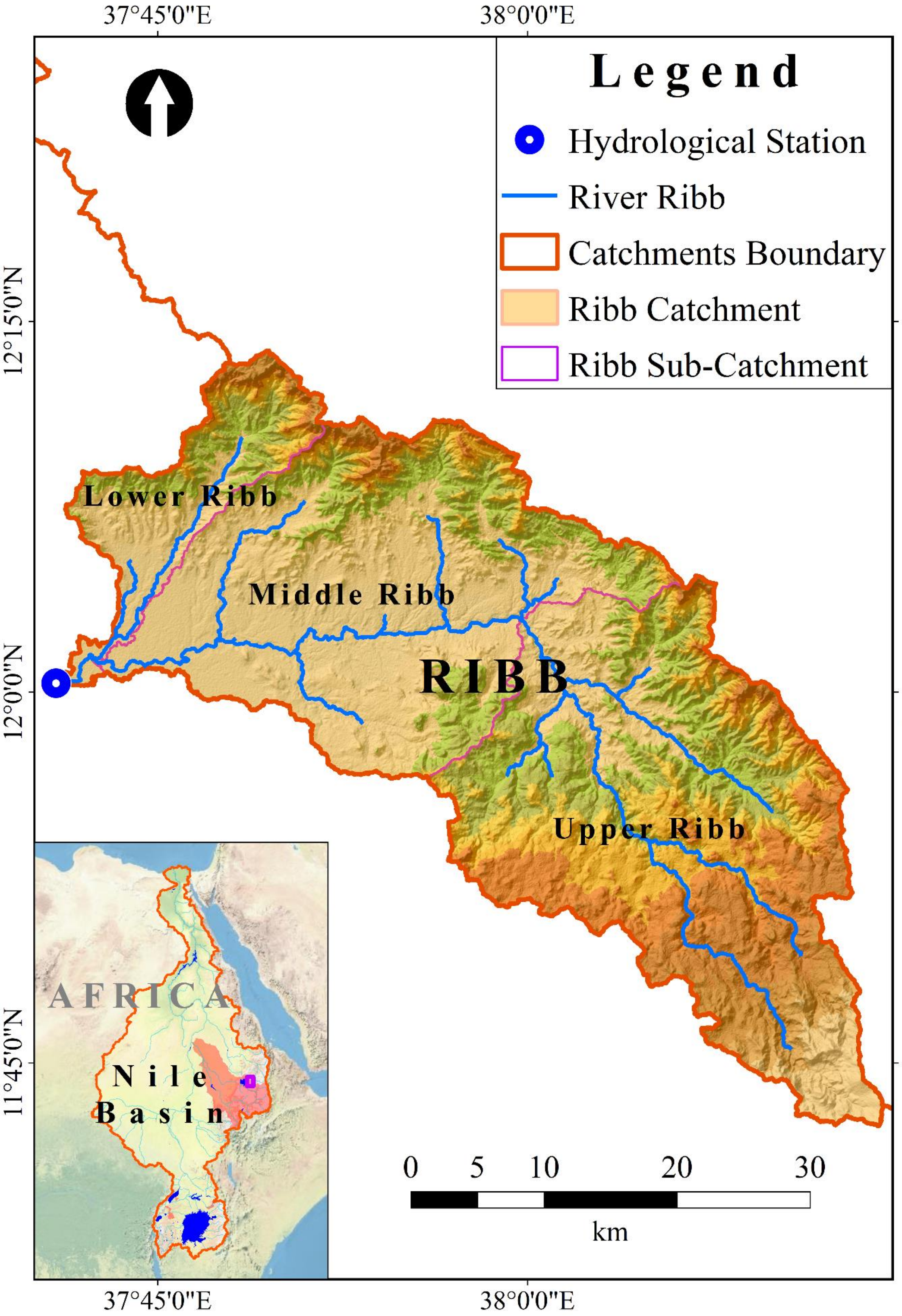


Figure 3.5: Ribb sub-catchment area (Source: Primary data)

3.2.3 Kabalega river sub-catchment

River Wambabya is located in the Lake Albert Basin in the watershed where the Kabalega reservoir is situated as seen in Fig. 3.6. Its drainage basin is about 795km^2, with elevations ranging from 634m - 1441m above mean sea level, between 1° 13′ and 1° 33′ N and 31° 3′ and 31° 24′ E. The centroid of the reservoir is situated at 1° 32′ N and 31° 6′ E. The research area experiences substantial variability in yearly rainfall, with a high average of 800mm over Eastern Lake Albert and a high of 1,200mm over the western parts (WWF, 2006). Rain occurs in two seasons with the Primary one lasting from August through November. Subsistence agriculture is practiced in the catchment, crops such as Cassava are grown in the area, and there is livestock grazing in the catchment wildlife reserve. Grazed in the catchment are goats and cattle, and there is subsistence farming and commercial fishing.

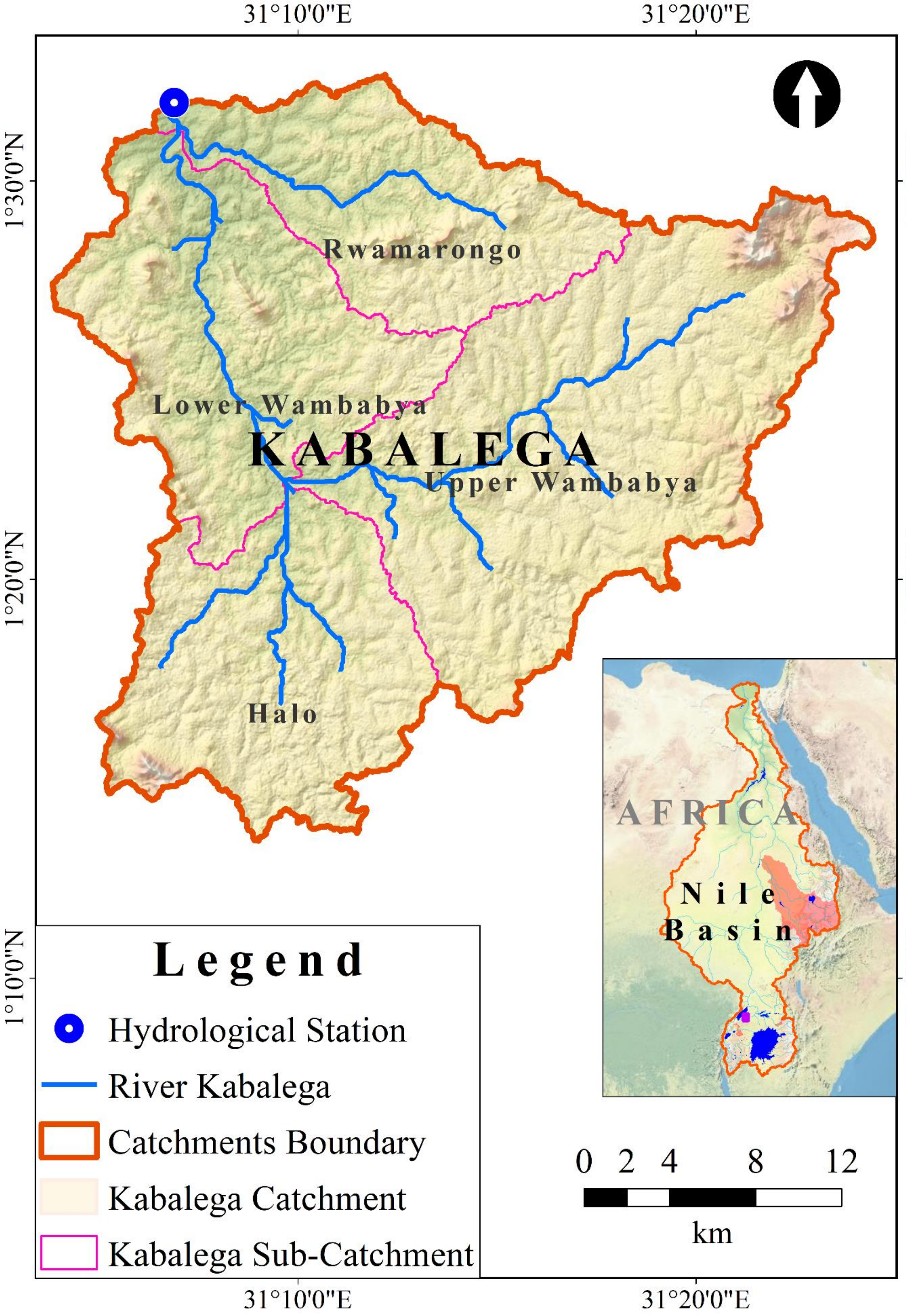


Figure 3.6: Kabalega sub-catchment (Source: Primary data)

3.2.4 River Mpanga sub-catchments

River Mpanga originates from the foothills of Mount Rwenzori and flows through the southwest region of Uganda in East Africa. Before emptying into Lake George, River Mpanga passes through the Kabarole, Kyenjojo, and Kamwenge districts. The upper Mpanga, Middle Mpanga, Lower Mpanga, and Rushango as seen in Fig.3.7 are sub-catchments of the Mpanga River basin, each having drainage areas of 384,1174,477, and 3170km^2, respectively. Lake George, which spans 5205 km^2, is located above the River Mpanga. The hydrological stations for the sub-catchment are located on the Kampala-Fort Portal and Fort Portal-Ibanda roads, respectively, at 401 and 1484km^2.

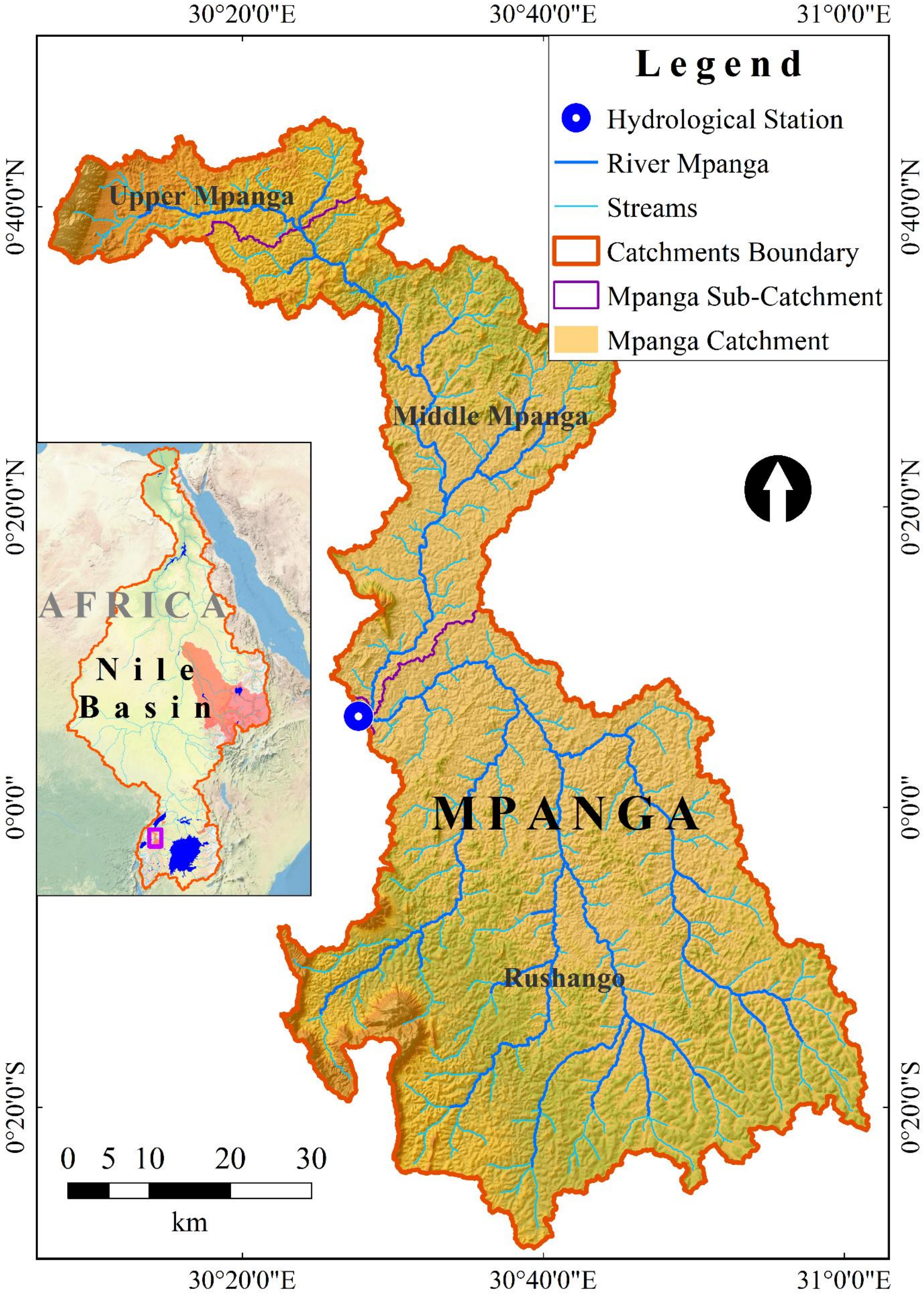


Figure 3.7: Mpanga sub-catchment (Source: Primary data)

3.2.5 River El-Diem sub-catchment

The higher region of the Blue Nile basin, as shown in Fig. 3.8, is known as El-Diem. The outlet is located at Long=34.93^o and Lat=11.24^o. It is a 176,000 km^2 catchment area that covers around 17% of Ethiopia. It is originally from Lake Tana which is located near Bahir Dar at an elevation of 1830m above sea level. It has numerous tributaries that join the mainstream in Ethiopian central and southern highlands before flowing into the lowlands of the county near El-Diem. The upper Blue Nile in Ethiopia is a section of the Blue Nile, which has coordinates of 34^o 30' and 39^o 45'E in the east and 7^{o}45' and 12^o 45'N in the northern part. The elevation ranges from 4000m at the headwaters in the Ethiopian highlands to 480m close to downstream at the Sudanese border, with the upper Blue Nile approximate length being 940km. The basin has terrain distinguished by highlands and hills. Around 7% of the upper blue basin is comprised of flow from Lake Tana, with 80% of that flow occurring between June and September and the remaining 7% occurring in the southern tributaries between March and May (Samy et al., 2019).

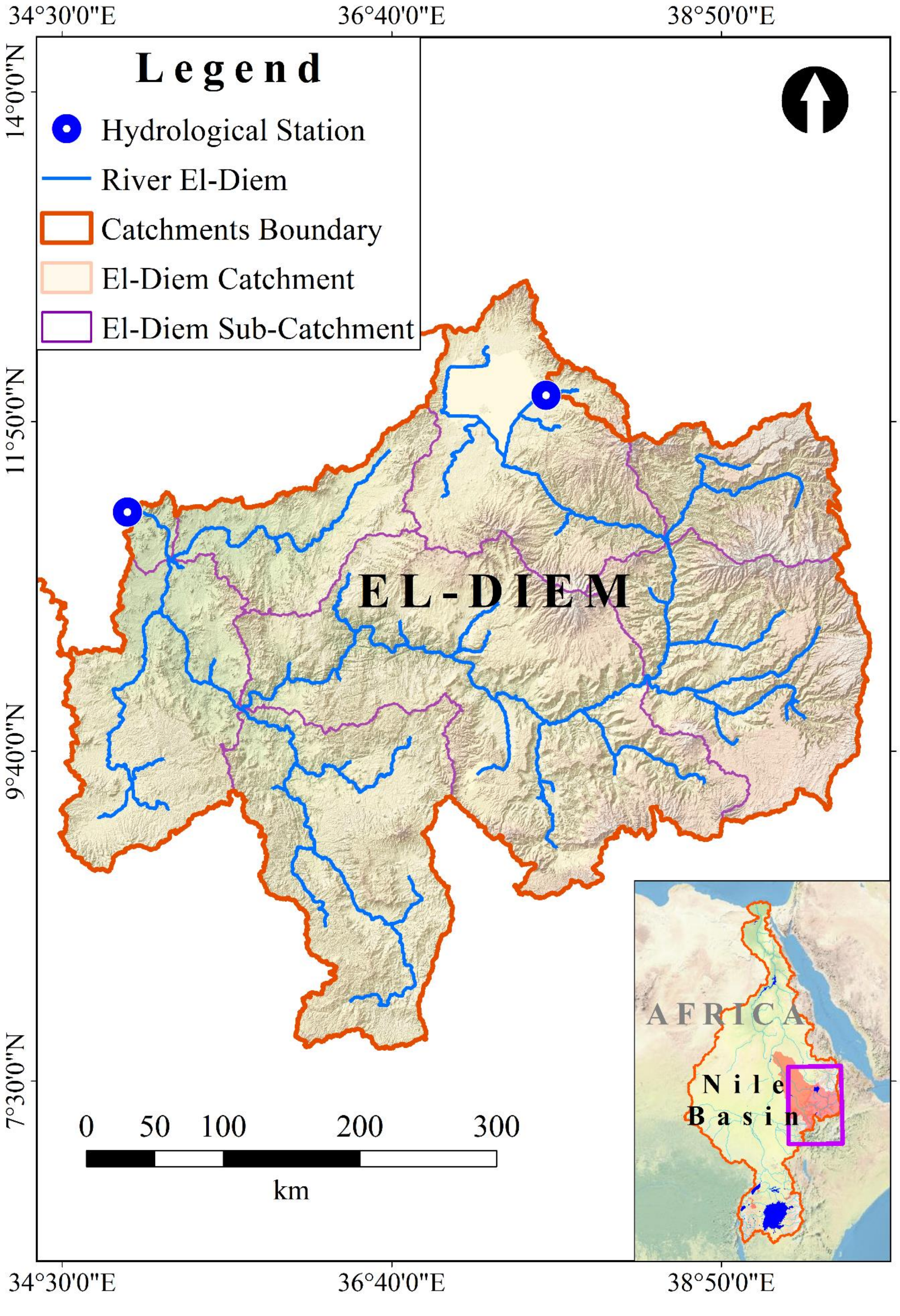


Figure 3.8: El-Diem Sub-Catchment (Source: Primary data)

3.2.6 Blue Nile sub-catchment

The source of the Blue Nile is Little Abbya which is found in the highlands of Ethiopia and flows to Lake Tana, which discharges to the Blue Nile, covering a distance of 900km^2 down through the highlands of Sudan. The contribution of the Blue Nile is about 60%, (Sutcliffe and Parks,1999) with a catchment area of 325,000km^2 as seen in Fig. 3.9. Its outlet of the Blue Nile basin is at Khartoum located at Long=32^o and Lat=16^o. From the borders of Sudan and Ethiopia, the Blue Nile flows north from humid to semi-arid conditions with little additional flow north of Roseire. The seasonal rainfall in the sub-catchment is characterized by a high pattern most of the rain falling from June to September. The basin receives rainfall varying from 1000mm in the northeast region ranging from 1450-2100mm over the southwestern part of the basin. The range of average evapotranspiration in the sub-basin is 1765mm with soil erosion being a major problem in the basin (Conway and Hulme, 1993).

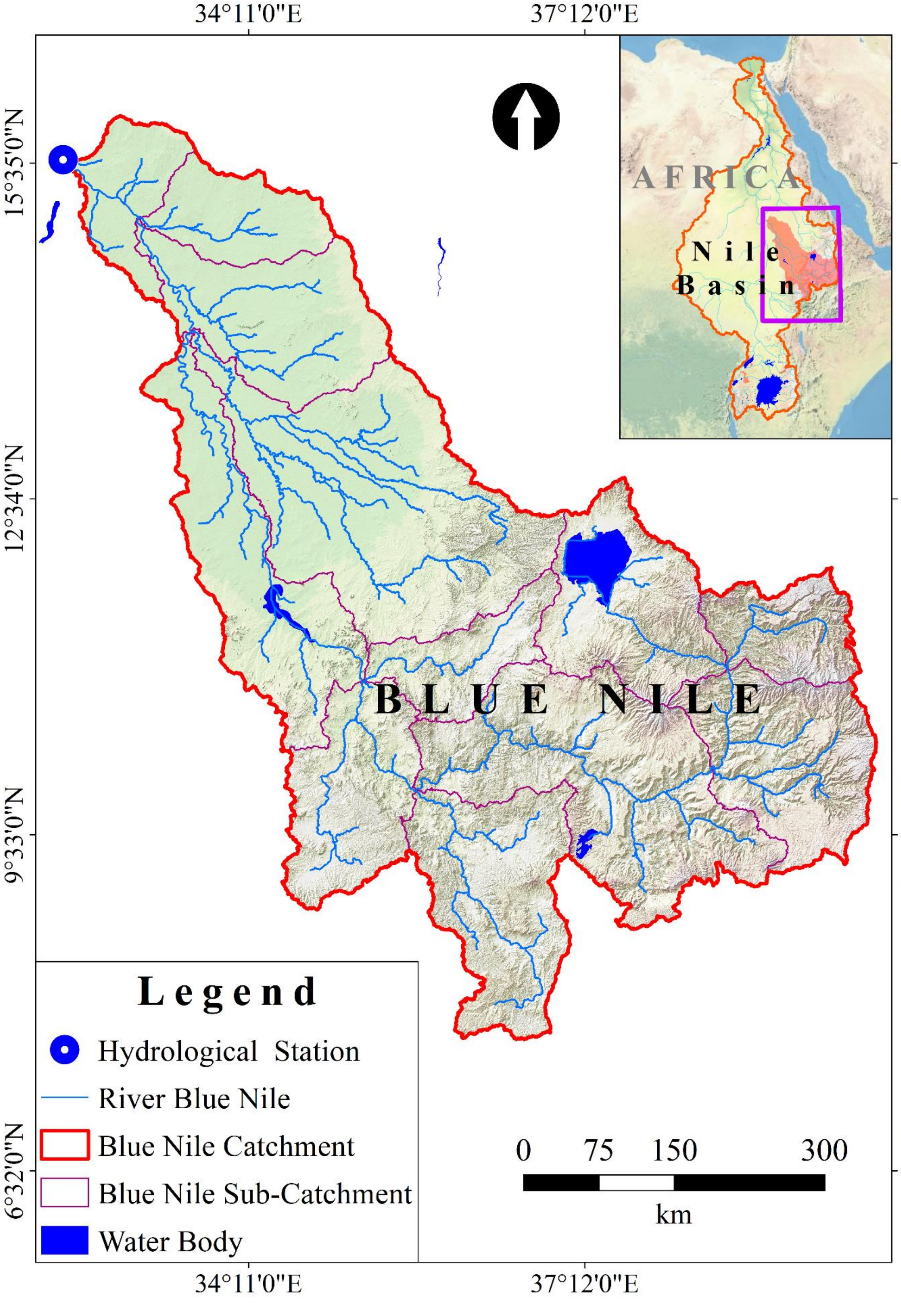


Figure 3.9: Blue Nile catchment (Source: Primary data)

3.3 Data for the study

3.3.1 Rainfall and potential evapotranspiration

For quality control daily rainfall and PET were obtained from various sources as summarized in Table 3.2 which has data already published.

Table 3.2: Indicating catchment and its source of data

S/N	Catchment	Source of rainfall and PET
1	Blue Nile	Onyutha (2016)
2	El- Diem	Onyutha (2016)
3	Ribb	Onyutha (2016)
4	Mpanga	Onyutha et al. (2021)
5	Kabalega	Chelangat and Abebe (2021)
6	Malaba	Mubialiwo et al. (2021)

This data can be found in Onyutha (2016); Onyutha (2021); Onyutha et al. (2021); Chelangat and Abebe (2021); Mubialiwo et al. (2021).

3.4. Methods

3.4.1 Rainfall-runoff modeling

There are two types of models used in this research, the AWMB, which was obtained from http://www.toolkit.net.au/ (Podger 2004), and HMSV (Onyutha, 2019b) obtained from https://sites.google.com/site/conyutha/tools-to-download. All these models have been used because of the variety of applications and they are freely available. More so, no research has used these models in the Tropical region to characterize changes in hydro-climatic conditions in Tropical catchments: - to simulate the hydrological model under changing rainfall totals and constant PET; to simulate the hydrological model under changing PET and constant rainfall; and to simulate the hydrological model under simultaneous changes in rainfall totals and PET.

3.4.2. Characterization of changes in hydro-climatic conditions

The characterization of changes in hydro-climatic conditions flow, rainfall, and PET in six sub-catchments were all computed at both mean values and at annual maxima. This helped in the understanding of minimum and maximum values of flow, rainfall, and PET. Temperatures are on the rise due to greenhouse gasses, Tropical storms are becoming more frequent, and drought becoming extreme across the globe (UNEP, 2020).

The characterization of changes in hydro-climatic conditions involves a comprehensive analysis of various meteorological and hydrological parameters over time. This included examining historical data on precipitation patterns, and temperature fluctuations of the catchments within Tropical catchments. Additionally, it involves assessing trends and variations in hydrological indicators such as streamflow, Spatial and temporal analyses are typically conducted to identify patterns, anomalies, and potential drivers of change, including natural variability and anthropogenic influences such as land use changes or climate change. Furthermore, statistical methods, modeling techniques, and data visualization tools are utilized to synthesize and interpret the complex interactions between climate and hydrology within the Tropical catchment context. The ultimate goal is to provide a detailed understanding of how hydro-climatic conditions have evolved and to inform future projections and adaptation strategies for sustainable water resources.

3.5 Trend analysis

The slope (*m*) of the trend was computed using (Theil, 1950, Sen, 1968).

$$m = \text{Median}\left(\frac{x_j - x_i}{j - i}\right), \quad \forall\, i < j \tag{3.1}$$

The null hypothesis H_0 (no trend) was tested using the method of (Onyutha 2021). For a given variable *Y* of sample size *n*, we can re-scale *X* into series d_x in terms of

$$d_{y,i} = n - w_{y,i} - 2t_{y,i} \qquad \text{for} \quad 1 \le I \le n \tag{3.2}$$

where, $t_{y,\ i}$ is the number of times the i^{th} observation exceeds other data points in *Y*. Furthermore, WY, I denote the number of times the i^{th} data point appears within *Y*.

The trend statistic *T* was given by (Onyutha 2021)

$$T = \sum_{j=1}^{n} \sum_{i=1}^{j} e_{y,i} \tag{3.3}$$

where

$$e_{y,i} = d_{y,i} \times \sqrt{\frac{(n-1)}{\sum_{i=1}^{n} \left(d_{y,i}\right)^2}} \qquad \text{for} \quad 1 \le i \le n. \tag{3.4}$$

The mean of *T* is zero and for large *n* the distribution of *T* is approximately normal with the variance of *T* or given by (Onyutha 2021)

$$V\left(T\right)=\frac{n\left(n^{2}-1\right)}{12}. \tag{3.5}$$

To take into account the effect of persistent on-trend results, $V(T)$ was corrected to become $V^{q}\left(T\right)$ such that (Onyutha 2021)

$$V^{q}\left(T\right)=V\left(T\right)\times\beta\times n^{\gamma} \tag{3.6}$$

where

$$\beta=1.4784H^{4}+0.5094H^{3}-3.9455H^{2}+0.8312H+1.4174 \tag{3.7}$$

$$\gamma=-0.4512H^{4}-0.4057H^{3}+1.9193H^{2}+4.237H-0.6144 \tag{3.8}$$

And H is the sample Hurst exponent. The standardized test statistic Z which follows the standard normal distribution with a mean (variance) of zero (one) is given by (Onyutha, 2021).

$$Z=\frac{T}{\sqrt{V^{q}\left(T\right)}} \tag{3.9}$$

Consider $Z_{\alpha/2}$ as the standard normal variate at the selected α. The H_0 (no trend) is rejected $\left|Z\right|>\left|Z_{\alpha/2}\right|$, Otherwise, the H_0 is not rejected at α. In this study, α was taken as 0.05 and this corresponded to a Z value of 1.96.

The trend test was applied to the mean values and annual maxima of rainfall, PET, and flow for the various catchments.

3.5.1 Variability analysis

Using a range of 10-20 years, the H_o (null hypothesis) was put to the test. The standardized trend statistic Z may be calculated based on the time slice shifted from the beginning to the conclusion of the series in an overlapping manner if a variable Y contains a subset y from the U^{th} to the V^{th} value of Y. Let a term and in the situations where t is odd and even respectively, for a given value of t. You may calculate sub-trends using.

$$Z_i^{(t)} = f\left(x \subset X \mid x_u \le x \le x_v\right) \quad \text{for } i = 1,\ 2,\ ....,\ n \tag{3.10}$$

where Z_i is the i^{th} value of Z, and the terms u and v are all based on I and can be given by:

$$\left.\begin{array}{l} \text{if } i < \lambda, \quad u = 1,\ \ v = t + i - \lambda - 1 \\ \text{if } i \ge \lambda \ \text{ and } i \le (n - \lambda), \quad u = i - \lambda + 1,\ \ v = i + \lambda \\ \text{if } i > (n - \lambda) \ \text{ and } i \le n,\ \ u = i - \lambda + 1,\ \ v = n \end{array}\right\} \tag{3.11}$$

When visualizing Zj against the matching j^{th} data year, confidence interval limits (CILs) on the variability may be created using Z/2 to evaluate the H_0 (natural randomness).

If the values of the sub-trends do not deviate from the CILs, the H_0 (natural randomness) is not rejected. If Z values fall outside of the CILs, the H_0 (natural randomness) hypothesis is, nevertheless, rejected. The mean values and annual maximums of rainfall, PET, and river flows for several catchments were used to assess the H_0 (natural randomness).

3.5.2 Hydrological modelling

3.5.2.1 Model build-up

This study considered two known models, including HMSV (Onyutha 2019) and AWBM (Podger, 2004). Files for the sub-catchments containing observed flow, temperature, and ET were all converted into required formats. AWBM files were converted to evap. tts, Q obs. tts and Rainfall. tts formats. A model warm-up period of one year was considered. Inputs into HMSV were in MS Excel formats. HMSV allows step-wise calibration of parameters of sub-flows, that is, base flow, interflow, and overflow.

3.5.2.2 Calibration

The parameters of the model were calibrated until the output of the model gave a good match with the observed data. For both models, automatic calibration was used. Calibration was done using daily time series. The calibration periods for Blue Nile, Ribb, El-Diem, Kabalega, Malaba, and Mpanga were 1966-1987, 1980-1994, 1980-1994, 1990-2008, 1999-2010, and 2000-2011 respectively and 60% of the data period was used for calibration.

3.5.2.3 Validation

Data not used during calibration was considered for validation. This idea is to determine if the model can be valid over a period. Data not considered for calibration model performance was also assessed using NSE. The validation period for Blue Nile, Ribb, El-

Diem, Kabalega, Malaba, and Mpanga were 1988-2000, 1995-2002, 1995-2002, 2009-2019, 2011-2016, and 2012-2018 respectively and 30% of the data period was used for validation.

3.5.2.4 Nash-Sutcliffe Efficiency (NSE)

NSE is the most commonly applied objective function due to its simplicity and robustness for model calibration (Nash and Sutcliffe, 1970b).

$$NSE = 1 - \frac{Q_o - Q_m}{Q_o - Q_a} \tag{3.12}$$

Where Q_o, Q_m, and Q_a denote observed, modelled and mean flow, respectively.

It minimizes the root mean square error between modeled and observed stream flows (Arsenault et al., 2018). Negative values indicate that the mean is a better predictor than the model, meaning the model performs very poorly. Interpretations of NSE values include:

NSE > 0.75: Excellent model,

0.36 < NSE ≤ 0.75: Satisfactory model,

0 < NSE ≤ 0.36: Unsatisfactory model, and

NSE ≤ 0: The model performs worse than using the mean of observed data.

3.5.2.4 Scenario analyses

In this research scenario analysis was done following the research objectives which: to characterize changes in hydro-climatic conditions precipitation and evapotranspiration in

Tropical catchments. ii) to develop a hydrological model to ascertain catchment flow under varying rainfall totals and constant PET. iii) To quantify the influence of PET on flow under constant rainfall. iv) To assess the catchment response to concurrently changing rainfall and PET. The optimal parameters were kept constant during the simulation to investigate the sensitivity of the catchments. This was done to determine the response of the flow of the river to different PET rates of 0%, 2.5%, 5%, 7.5%,10%, 12.5%, 15%, 17.5%, and 20% and various rainfall intensities including 0%, 2.5%, 5%, 7.5%, 10%, 12.5%, 15%, 17.5% and 20%. Each time the model was run, changes in the resulting flow were noted.

3.6 Chapter summary

This chapter presented materials and methods that were adopted while conducting this study. This chapter focused on presenting data used for the sub-catchment, methods of modeling computing trends, variability, model build-up calibration, validation, and scenario analyses. The next chapter of this study presents the findings and their discussion.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction

This section contains results, interpretation, and discussion of results. These results are organized under various sub-sections to cover specific objectives 1, 2, 3, and 4.

4.2 Model performance

Table 4.3 shows the performance of the models for studied Tropical sub-catchments by computing NSE for calibration, validation, and the entire data period. Model performance of HMSV and AWBM was done by calibration, validation, and for entire periods of the six sub-catchments as indicated in Table 4.3. AWBM performed well in Malaba, Mpanga, and Blue Nile whereas HMSV performed better in Kabalega, Ribb, and El-Diem

Table 4.3: Model Performance for the calibration, validation & entire data period

S/N	Catchment	Model	Calibration	Validation	Entire period
1	Malaba	HMSV	0.794	0.827	0.803
		AWBM	0.845	0.763	0.838
2	Kabalega	HMSV	0.768	0.696	0.751
		AWBM	0.708	0.623	0.688
3	Mpanga	HMSV	0.411	0.689	0.652
		AWBM	0.525	0.674	0.676
4	Blue Nile	HMSV	0.806	0.806	0.807
		AWBM	0.807	0.821	0.812
5	Ribb	HMSV	0.634	0.485	0.583

		AWBM	0.603	0.468	0.557
6	El-Diem	HMSV	0.837	0.735	0.795
		AWBM	0.753	0.731	0.745

The details of the model parameters of the catchment are attached in Appendix Table A.4 with model NSE.

4.3 Characterization of hydro-climatic conditions

Figure 4.10 shows the mean value and annual maxima for flow, rainfall, and PET for Malaba, Kabalega, Blue Nile, Mpanga, El-Diem, and Ribb catchments from the 1998 to 2018 period. The flow for the Kabalega and Mpanga were low between 2m^3/s to 180m^3/s compared to the flow of El-Diem, and Blue Nile between 700m^3/s to 12000m^3/s at both mean Value and annual maxima (Fig. 10a, b).

The rainfall at mean value ranges between 2m^3/s and 6m^3/s except for Ribb which was between 15m^3/s and 45m^3/s (Fig. 10c) while for annual maxima rainfall ranged between 20m^3/s and 60m^3/s for all the sub-catchments (Fig. 10d).

The PET at mean value and annual maxima are the same for all the sub-catchments and it ranged between 2m^3/s to 12m^3/s (Fig. 10e, f).

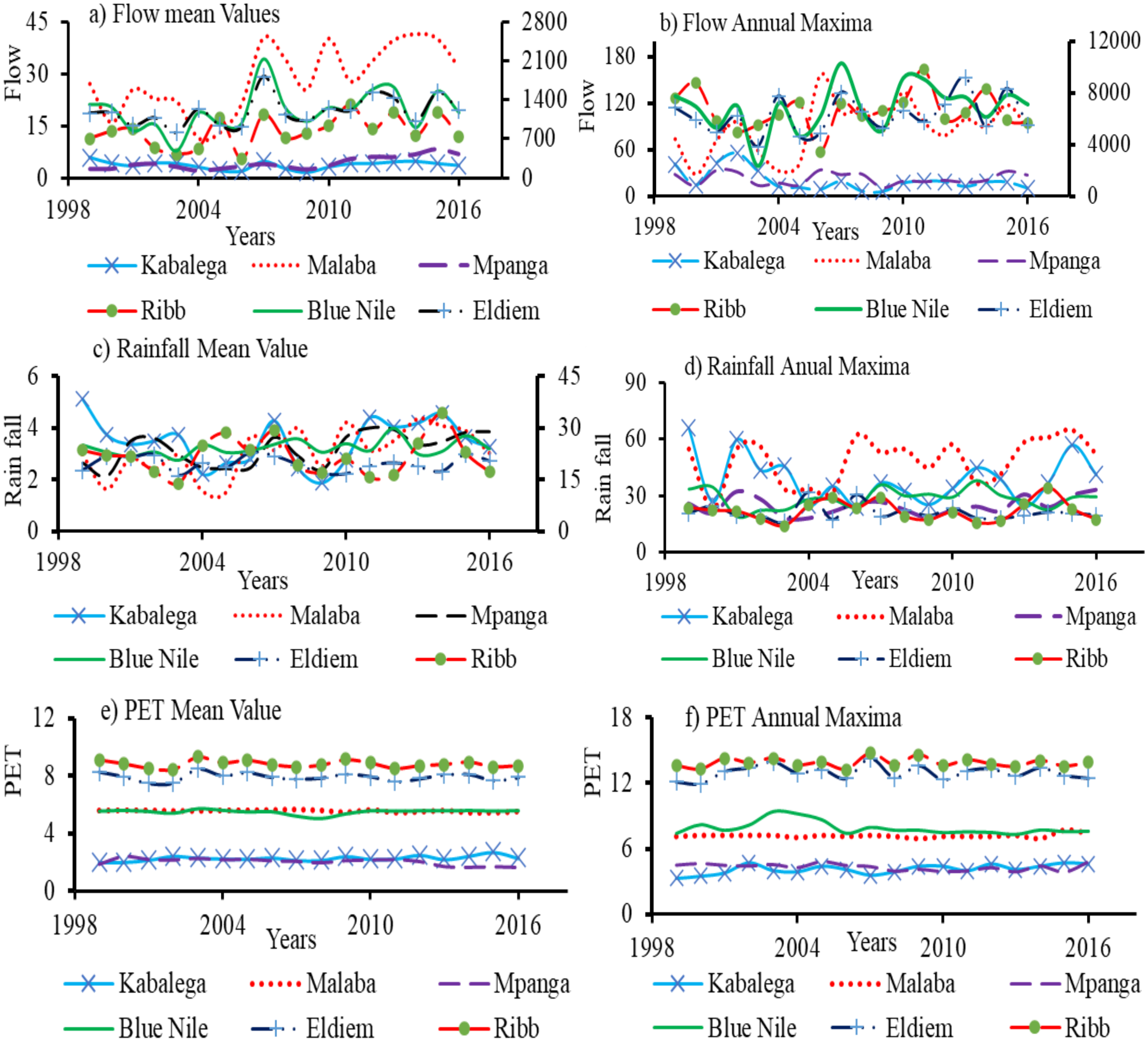


Figure 4.10: Mean Values and Annual maxima for Kabalega, Malaba, Mpanga, Blue Nile, El-Diem, and Ribb Catchments. Secondary Axis: - Flow at Min. value (Blue Nile and El-Diem), Flow at Maxima (Blue Nile and El-Diem); Rainfall at Min. value (Ribb) (Source: Primary data)

4.3.1 Trend analysis

Table 4.4 shows detailed results of sub-catchments, the trend at the mean value for the sub-catchments was as follows: - Flow for Kabalega was negative while the five sub-catchments flow was positive that is Mpanga, Malaba, Blue Nile, El-diem, and Ribb. This means the tropics experience dry conditions in Kabalega and wet conditions for other sub-catchments.

The rainfall trend showed negativity in El-diem and Ribb, while positivity was observed in Kabalega, Malaba, Mpanga, and Blue Nile, respectively. Negative conditions is implying drought conditions in El-diem and Ribb while positive conditions imply possibilities of flooding in Kabalega, Malaba, Mpanga, and Blue Nile.

The trend in PET was positive for Kabalega and Blue Nile then negative for Malaba, Mpanga, El-diem, and Ribb. This implies that there was evaporation in the Kabalega and Blue Nile and no evaporation in the Malaba, Mpanga El-diem, and Ribb.

The trend at Annual maxima for the sub-catchment was as follows: - Kabalega and Mpanga registered a Negative trend in flow, Malaba El-diem, Blue Nile, and Ribb registered positive flow. This is an indicator of reduced flow for Kabalega and Mpanga, an increase in trends of flow was registered in Malaba, El-diem, Blue Nile, and Ribb

Rainfall trends differed across regions. Kabalega and El-diem experienced negative rainfall patterns, indicating either a lack of rainfall or a reduction in precipitation. Conversely, Malaba, Mpanga, Blue Nile, and Ribb exhibited positive rainfall trends, suggesting consistent or increasing rainfall in these areas. These distinctions emphasize the absence of a decreasing rainfall trend in Kabalega and El-diem while highlighting the presence of rainfall in Malaba, Mpanga, Blue Nile, and Ribb

PET in the sub-catchment Mpanga and Blue Nile registered a negative trend in the PET compared to Kabalega, Malaba, El-diem, and Ribb with a positive trend in PET.

Table 4.5: Trend analysis

RESULTS OF TREND									
	Flow			Rainfall			PET		
Catchment Area	SLOPE	TREND	*P*-value	SLOPE	TREND	*P*-value	SLOPE	TREND	*P*-value
MEAN VALUES									
Kabalega	-0.310	-0.015	0.988	0.157	0.006	0.995	17.947	0.140	0.889
Malaba	0.370	0.164	0.869	3.654	0.148	0.882	-50.510	-0.141	0.888
Mpanga	2.294	0.196	0.845	5.132	0.144	0.885	-16.455	-0.166	0.868
Blue Nile	0.005	0.070	0.944	6.473	0.082	0.935	0.730	0.005	0.996
El-diem	0.008	0.086	0.932	-1.971	-0.023	0.982	-2.446	-0.026	0.979
Ribb	0.506	0.089	0.929	-2.397	-0.026	0.979	-4.076	-0.040	0.968
ANNUAL MAXIMA									
Kabalega	-0.204	-0.128	0.898	-0.077	-0.044	0.965	8.100	0.155	0.877
Malaba	0.071	0.108	0.914	0.163	0.093	0.926	6.725	0.055	0.956
Mpanga	-0.011	-0.004	0.997	0.311	0.067	0.947	-7.400	-0.103	0.918
Blue Nile	0.001	0.065	0.948	0.126	0.027	0.978	-3.916	-0.099	0.921
El-diem	0.001	0.064	0.949	-0.221	-0.037	0.970	0.405	0.010	0.992
Ribb	0.008	0.008	0.994	0.051	0.011	0.991	0.463	0.008	0.994

4.3.2 Temporal variability

The annual rainfall temporal variability is depicted in Fig. 4.11. Rainfall annual maximums were obtained from six sub-catchments. The values of Z over sub-periods alternated between positive and negative values. This shows how rainfall exhibits oscillating behavior over a multi-decadal time scale. The graphs represent oscillations that are high or low, or above or below the reference line (Z=zero line). This contains information on the dry and wet conditions of the catchment.

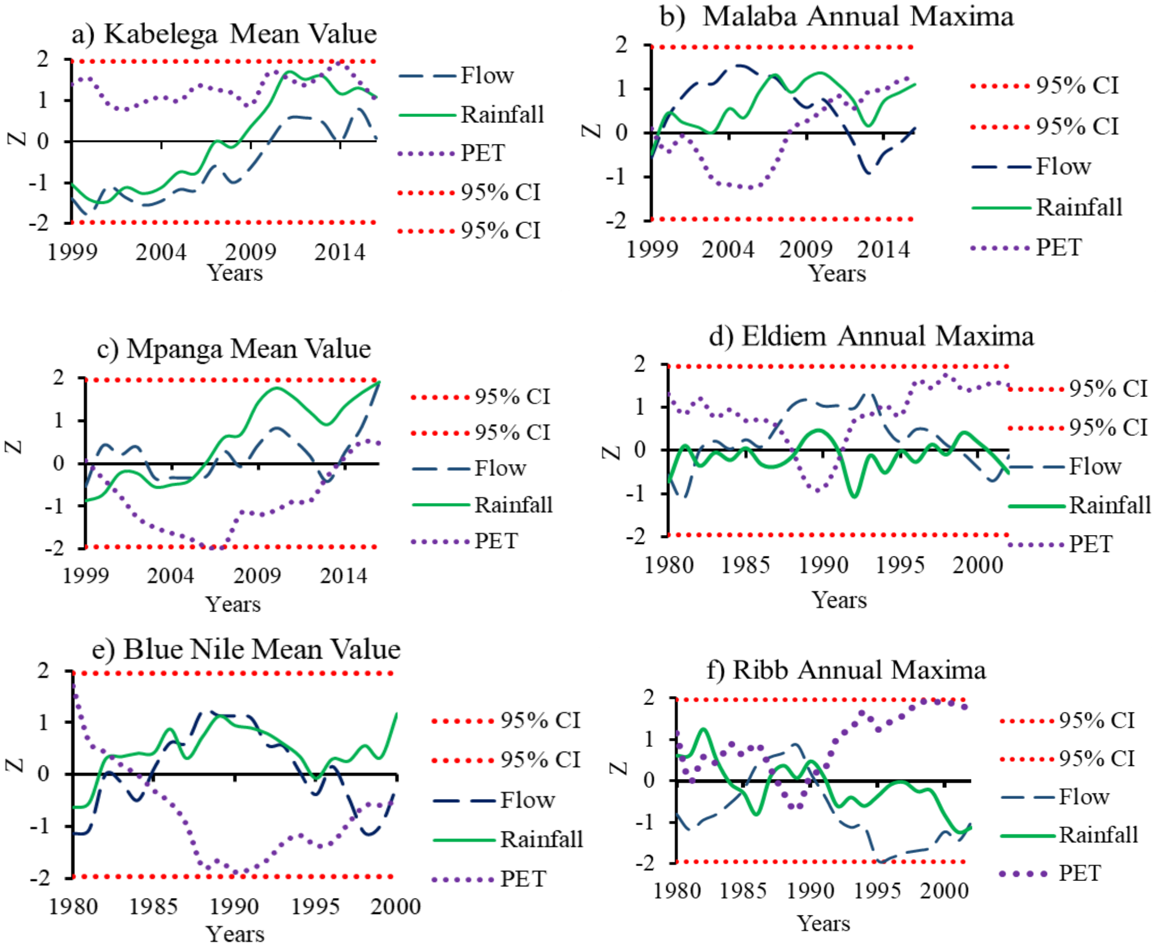


Figure 4.11: Variability in hydro-climate of: - Kabalega, Malaba, Mpanga, El-Diem, Blue Nile, and Ribb Annual Maxima (Source: Primary data)

The annual rainfall and the series of mean maximum values for each year showed both negative and positive trends from 1999 to 2016, these change variations imply the impacts of climate variability.

This result agrees with a previous study by Chelangat and Abebe, (2021) shows a decrease in the river flow of the same sub-catchment. This effect of the decrease in flow negatively affected the amount of power generated (Chelangat and Abebe, 2021).

A negative trend was obtained in the rainfall over the Kabalega catchment. This was the case for the annual maxima series. In contrast, the mean value exhibited a positive trend.

An appositive trend was obtained in the rainfall of the Kabalega catchment at annual maxima, which is the opposite of rainfall at mean maxima for the study period of 1999-2016. This implies the possibility of flooding, and excess rainfall, which can cause runoff (landslides) catchment. This is consistent with research on trends in water availability across water management zones (Onyutha et al., 2021). This knowledge is essential for planning for water, and smallholder farmers might use drought-resistant crops (Onyutha, 2021).

PET when there is more water in the air due to increased evaporation, storms can create more powerful rainfall events in regions that are prone to regular rainfall, landslides, floods, extended dry spells, and drought.

The Malaba catchment has time series and yearly maxima covered a vertical pattern in stream throughout 17 years, from 1999 to 2016. This proposes an expansion in the waterway stream, which is reliable with concentrates on led on a similar catchment in 2022 and 2013 (Bernard et al., 2013). These investigations showed that the catchment experienced seasonal flooding occasions, with various financial effects on the close by networks, including the deficiency of lives.

Throughout the research period from 1999–2016, the Malaba catchment has mean and annual maxima showed an upward trend in rainfall results. This suggests that the catchment experienced rain throughout the year. Similar to this, Mubialiwo et al. (2020) showed that positive sub-trends in rainfall occurred in the 1950s and from the mid-2000s to 2016 whereas negative sub-trends persisted from 1960 until around 2005.

PET trend for the Malaba catchment at mean values is negative which is contrary to PET for the same catchment at annual maxima for the period of 1999-2016.The Negative trend implies possibilities of drought conditions in the catchment. Positive trends implies that there was an increase in the possibility of the formation of rainfall in the future period (Mubialiwo et al., 2020).

Mpanga catchment exhibited a positive trend in flow at mean value and a negative trend for annual maxima for the study period of 1999-2016. This implies an increase in the flows of a study done on the same catchment (Onyutha et al., 2021) characterized by expanding patterns in yearly rainfall and river flows.

Both annual rainfall and the series containing the maxima values in each year exhibited a positive trend for the Mpanga catchment from 1999-2016. This implies increasing surface runoff. This means a river catchment implies the possibility of flooding down streams. Crop misfortune, soil disintegration, and an expansion in the gamble of floods are possible consequences of weighty rainfall. These impacts can bring about wounds, drownings, and other flooding-related health problems.

The catchment PET showed negative trend values in both mean value and annual maxima indicating reduced vapor in the air over the study period 1999-2016. This implies the possibility of drought in the catchment.

The trend of flow for the Blue Nile for mean value and annual maxima exhibited positive for the study period 1980-2000. This implies an increase in flow and the possibility of flooding downstream. These results are similar to that of 1964 -2003 (Tesemma et al., 2010). It showed no discernible pattern in the seasonal and annual average rainfall over the basin, which is the source of irrigation to turn the surrounding dry terrain into fertile agricultural land.

Over the research period of 1999–2000, the trend for rainfall in Blue Nile a mean value and annual maximum was all positive. This suggests that rainfall in this watershed has increased. Similarly, the sub-basin receives 1346mm of rainfall annually on average, most of the Nile Basin Initiatives sub-basins as of 2016. According to the Nile Basin Initiative (2016), variations in runoff and shifting stream demand would be the main ways that temperature and rainfall changes will impact flow of the Blue Nile.

The PET trend at the mean value was positive and negative for annual maxima. This implies that at mean value evaporation at the possibility of meteorological drought.

The flow trend for El-Diem for the series containing mean values and annual values of each year exhibits a positive trend over the period 1980-2002 for 17 years. This implies an increase in flow by the contributing factors. This outcome is in strong agreement with past research in the region, including (Conway and Hulme, 1993, Elshamy et al., 2009, Tesemma et al., 2010). According to those research, seasonal fluctuations may have happened but there has not been a noticeable change in rainfall over the Upper Blue Nile in recent years.

The rainfall trend for El-Diem for mean value and annual maxima were negative for the study period 1980-2002. This is an indicator of reduced rainfall along the catchment period for seasonal and annual. This statement agrees with previous studies on upper Niles that showed that between 1953 and 2014 on-trend and variability of rainfall over the Upper Blue Nile, the basin has been experiencing variable rainfall occasions causing extreme dry spells and floods over various years (Samy et al., 2019).

Unlike the PET trend at yearly maxima, which is positive for the study period, the PET for El-Diem the mean value showed a negative trend. Evapotranspiration is one of the major contributors to the water balance over the Nile basin, accounting for about 87% of the basin rainfall (Allam et al., 2016, Nile Basin Initiative, 2016). However, evapotranspiration shifts starting with one sub-basin and then onto the next given land use/cover and the close environment.

The Ribb catchment generally indicated a positive flow trend at the annual maxima series for the study period of 1980-1990 and from 1990-2000 trend in flow was decreasing on the same catchment. Positive flow implies an increased in flow on the catchment. This is predictable with a study that showed that river flow greatly increased when modeled using groundwater, evaporation, and runoff characteristics from the Gumara area (Worqlul et al., 2015).

The Ribb catchment rainfall trend at the mean value was negative and a positive trend at annual maxima for the study period of 22 years from 1980-2002. This implies the trend of rainfall was increasing in heavy rainfall in the study period. Worqlul et al. (2015) studied the Ribb sub-catchment with Gumara and the results showed that flow significantly increased and the Ribb sub-catchment and its normal stream would increase by 4.3%. The PET for the Ribb catchment indicated a negative trend at mean value and a positive annual maxima trend for 22 years from 1980-2002. This is an indicator of prolonged drought in the mean value and heavy rainfall in the annual maxima.

The H_o (natural randomness) was not rejected for flow, rainfall, and PET. According to the findings in Table 4.3, all trends in flows were not significant since the P-values were all above 0.05.

4.4 Effects of changes in rainfall and evaporation

Research findings are organized under various sub-sections for findings of specific objectives two, three, and four. The catchments under the study area in the tropics included Malaba, Kabalega, Mpanga, El-Diem, Ribb, and Blue Nile during simulations using HMSV and AWBM models.

4.4.1 Effects of changes in rainfall and with PET kept constant

Figure 4.12 shows the effects of changes in rainfall intensities on river flow when the PET rate was kept constant during simulation by selected models HMSV and AWBM. The flow in the selected catchments increased about the percentage increase of rainfall intensities. The relationship of the slope between the increments of flow and rainfall varied across sub-catchments. Noticeable changes of increase and decrease were exhibited in Blue Nile with a gradient of 2.699m^3/s (AWBM), El-Diem with a gradient of 2.480m^3/s (AWBM), Kabalega with 1.087m^3/s (HMSV), and Malaba 0.968m^3/s (HMSV). The details of the flow gradient for sub-catchments were 2.561m^3/s and 1.742m^3/s in the Blue Nile using AWBM and HMSV respectively. The gradient of flow was an average of 2.328m^3/s and 1.618m^3/s using AWBM and HMSV respectively for the El-Diem. The gradient of flow was at an average of 0.961m^3/s and 1.024m^3/s using AWBM and HMSV respectively for Kabalega. The gradient of flow was at an average of 0.806m^3/s and 1.559m^3/s using AWBM and HMSV respectively for Malaba. Mpanga catchment the average flow gradient is 1.559m^3/s and 1.144m^3/s for AWBM and HMSV respectively. The average flow gradient for Ribb was 1.298m^3/s and 1.319m^3/s respectively. The slopes and intercepts are given in Table 4.5 and 4.6 respectively detailing the effect of changes in flow at given rainfall intensities. The increase in flow is an indicator of flood in the area, the floods of 2020 could be attributed to an increase in inflow results of rainfall this is similar to studies done in the region (Elshamy et al., 2009, Onyutha, 2021). The increase in flow is contributed by many factors example land use/land cover, geological characteristics, catchment slope, and soil types. Some of the factors such as land use can be considered in planning the catchment management. For example, control of the rate of runoff afforestation can be undertaken (Gabiri et al., 2020, Kilama Luwa et al., 2021, Sugianto et al., 2022). Planning for future changes in climate variability would help to prevent and adequately reduce/control the effects of rains, which increase river flow hence floods that affect lives people and property (Nsubuga et al., 2014). Some of the measures include improving research, the use of new technology, which preserves the environment, and others.

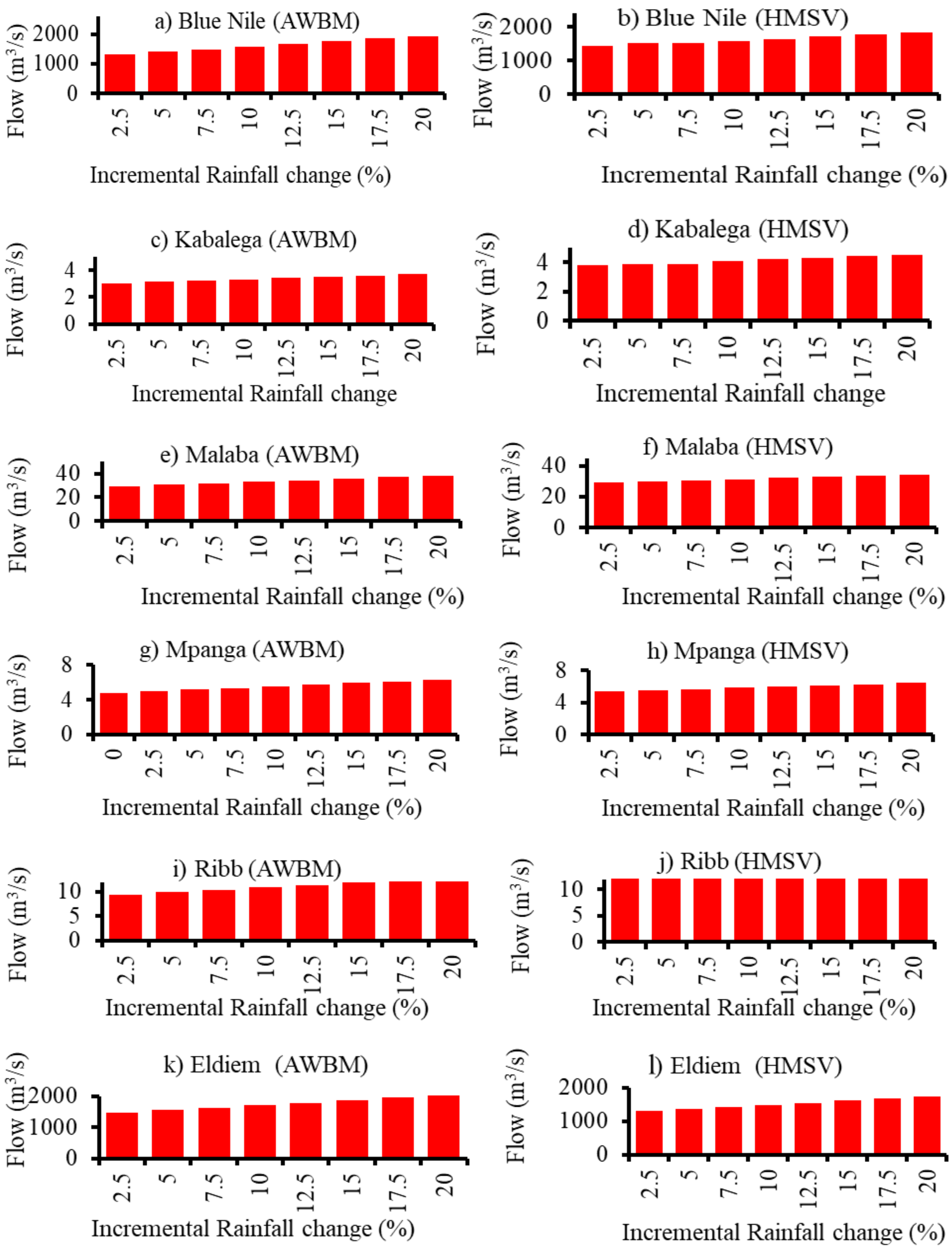


Figure 4.12: Changing rainfall and with PET kept constant (Source: Primary data)

4.4.2 Effects of changing PET with rainfall kept constant

Figure 4.13 shows the impact of changing PET on river flow when rainfall is kept constant during simulations using HMSV and AWBM models. Flow in the selected catchments decreased about the percentage increase in PET intensities. Noticeable high decreases in flow were exhibited in the Blue Nile with -1.288m^3/s (AWBM), -1.233m^3/s (HMSV), and El-Diem of -1.023m^3/s (AWBM), -1.185m^3/s (HMSV). Details of other reductions in flow for the other sub-catchment are Kabalega with -0.360m^3/s (AWBM) and -0.425m^3/s (HMSV), Malaba with -0.562m^3/s (AWBM) and -0.713m^3/s (HMSV), Mpanga with -0.472m^3/s (AWBM) and -0.364m^3/s (HMSV), and Ribb catchment with -0.555m^3/s (AWBM) and -1.154m^3/s (HMSV) for the models. The relationship between slope and intercepts of decrease in flow and PET are found in Tables 4.5 and Table 4.6 respectively.

A decrease in flow is an indicator of drought in sub-catchments. The size of the reduction in stream flow changes from one catchment to another relying upon the various variables that decrease sediment stream in the catchment. Factors that affect flow in the catchment area include the intensity of rainfall, duration of rainfall, direction of storm movements, PET, and area distribution. The effect of PET causes water loss, which affects the composition of groundwater flow as well, as how groundwater interacts with surface vapor (Winter, 2007). Several factors affect the movements of air from water, surface area, wind speed, humidity, and heat. Variation in changes is contributed by many factors mainly human activities on changing land use overgrazing, urbanization, deforestation, etc. The stakeholders should have a compressive plan for future climate variability, which is expected to be a major challenge given the effects of serious weather and how extensively these patterns and changeability have been reported over the past 20–30 years, with the majority of studies showing a decrease in rainfall (Nsubuga and Rautenbach, 2018).

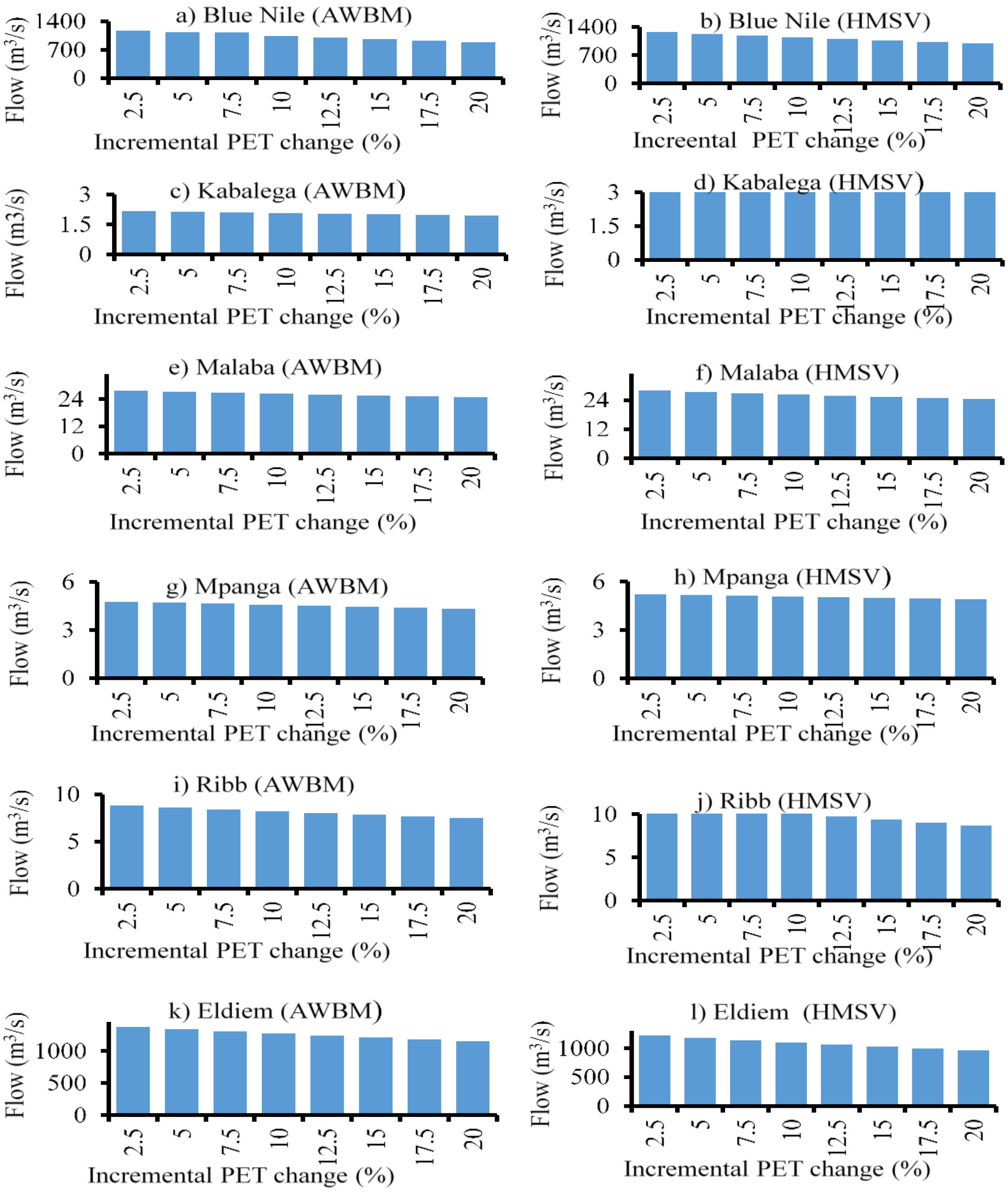


Figure 4.13: Changing PET while rainfall kept constant (Source: Primary data)

4.4.3 Effects of increasing both PET and rainfall simultaneously

Figure 4.14 shows the effects of increasing PET totals and rainfall totals in the simulation using HMSV and AWBM. The increase in flow linearly depended mainly on rainfall intensities and partly on PET in the catchment. The magnitude effect of rainfall on flow is higher than PET across selected catchments. Visible increases in flow were exhibited in Blue Nile with 1.222m^3/s (AWBM), El-Diem with 1.146m^3/s (AWBM), Malaba with 1.112m^3/s (AWBM,) and Malaba with 0.767m^3/s. The gradient of flow in the selected catchments exhibited a positive flow average of 0.889m^3/s and 1.188m^3/s using AWBM and HMSV for the selected catchments. The slope magnitude and intercepts characterizing the increase in flow at a given percentage change in PET and rainfall area in Table 4.5 and 4.6 respectively for the selected sub-catchments. The effect of increased rainfall and evaporation is that an increase in evaporation reduces the flow, and again when vapor escapes into the atmosphere causing condensation of clouds after saturation causing rainfall.

Characteristics of the temperature of the region are influenced by mainly natural factors, which include latitude, ocean current, and elevation whereas the factors that influence rainfall include wind speed and topography of the area (Hendriks, 2010, Kew et al., 2021). This result implies that there is a need for proper management of flow to prevent flooding downstream, which can cause the destruction of property and claim lives people. Thus, planning for future changes will help to predict changes in climate variability.

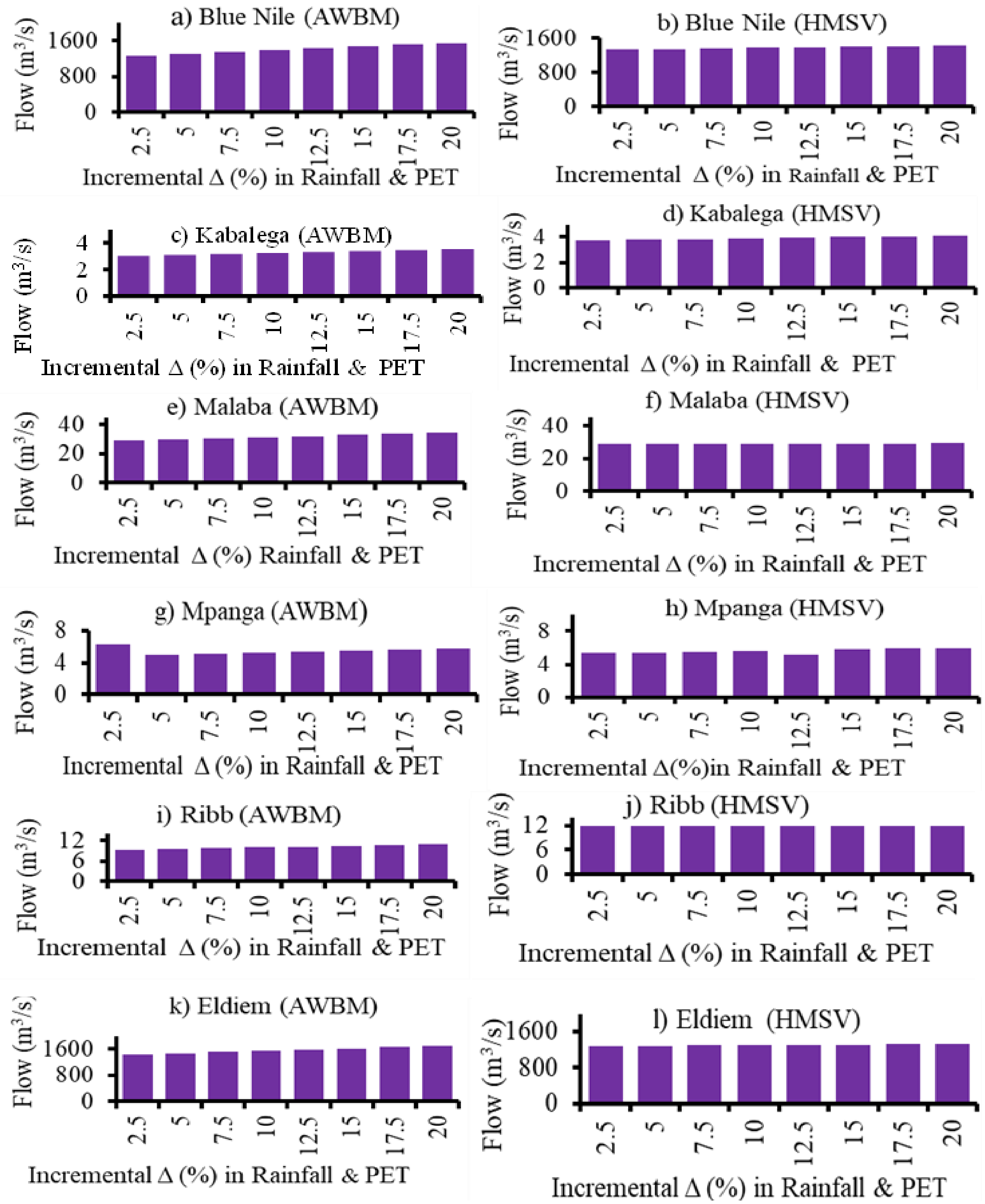


Figure 4.14: Effects of simultaneously changing both rainfall and PET by the same amount (%) (source: Primary data)

4.4.4 Effects of changing rainfall at different PET rates

Figures 4.15, 4.16, and 4.17 show the effects of changes in rainfall with PET kept constant at a different rate during hydrological simulation. The increase in flow magnitude of the selected catchment depends on the percentage increase of the rainfall. Noticeable increase in the sub-catchment is exhibited in the Blue Nile and El-Diem from rate 2.5%-20% with flow above 2m^3/s, Blue Nile at 10% rate being the highest flow of 2.602m^3/s (AWBM), and El-Diem at 2.5% rate with 2.466m^3/s (AWBM). Tables 4.5 and 4.6 give the details of the slope and intercepts indicating the effects of change in rainfall to flow. When both evaporation and transpiration occur, they cause the formation of clouds and after condensation, they form rainfall or ice. After rainfall, water either invades into the ground or becomes runoff to lakes and rivers depending on the period. Included among the variables that determine infiltration rate are soil properties, land cover, rainfall frequency, slope, moisture content, and soil organic matter. Depending on these factors, rainfall can cause overland flow, interflow, and base flow. Depending on the different factors and changes in land use, runoff can cause flooding downstream and can cause a chain of damages to the environment including pollution of the environment, the deposition of silts and sediments, and destruction of property (Sugianto et al., 2022). The recurrence event of rainfall and stream is essential because of contributing elements to changes in land use and land cover change (Kitheka et al., 2019, Onyutha et al., 2021). This implies that there is a need for strategic planning for prevention and relief measures to control and diminish the impacts of flooding, for example, the construction of physical structures like additional channels and retention ponds limiting urbanization

, conservation of the environment, etc. Changes in hydrology are presumed to be more often, and several hence increasing flow changes downstream

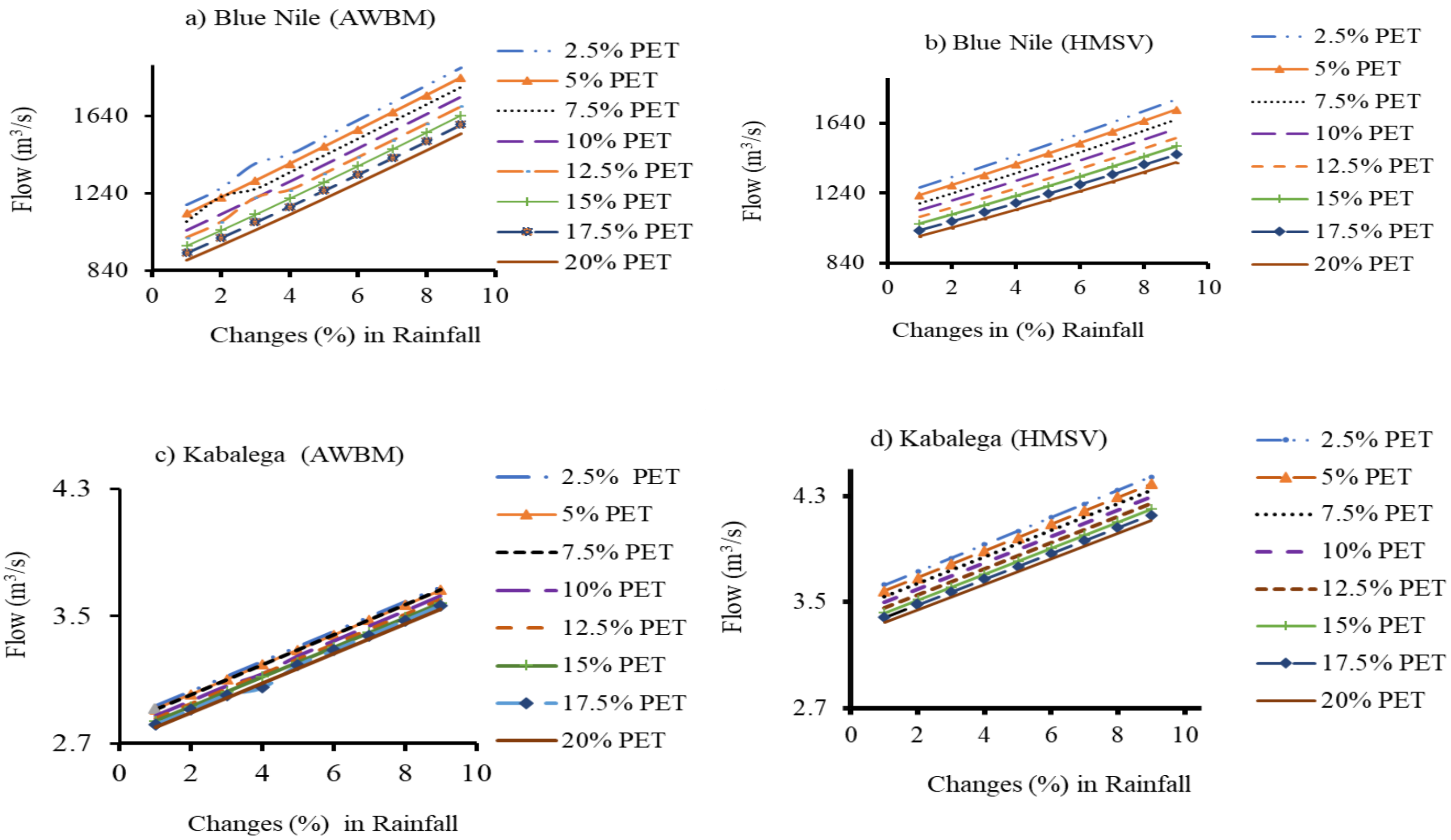


Figure 4. 15 Effects of changing in rainfall at different PET intervals (Source: Primary data)

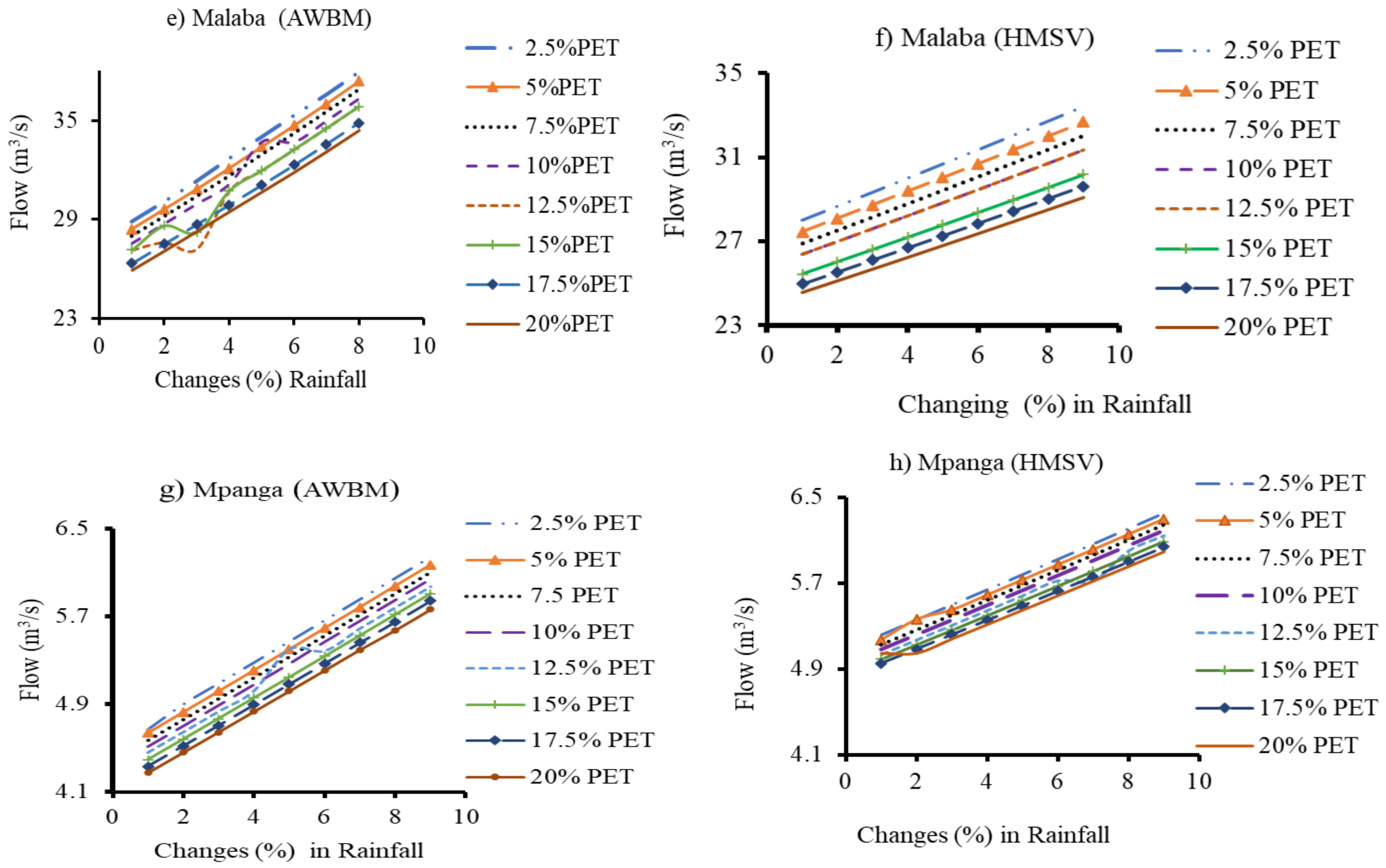


Figure 4.16 : Effects of changes in rainfall at different PET intervals (Source: Primary data)

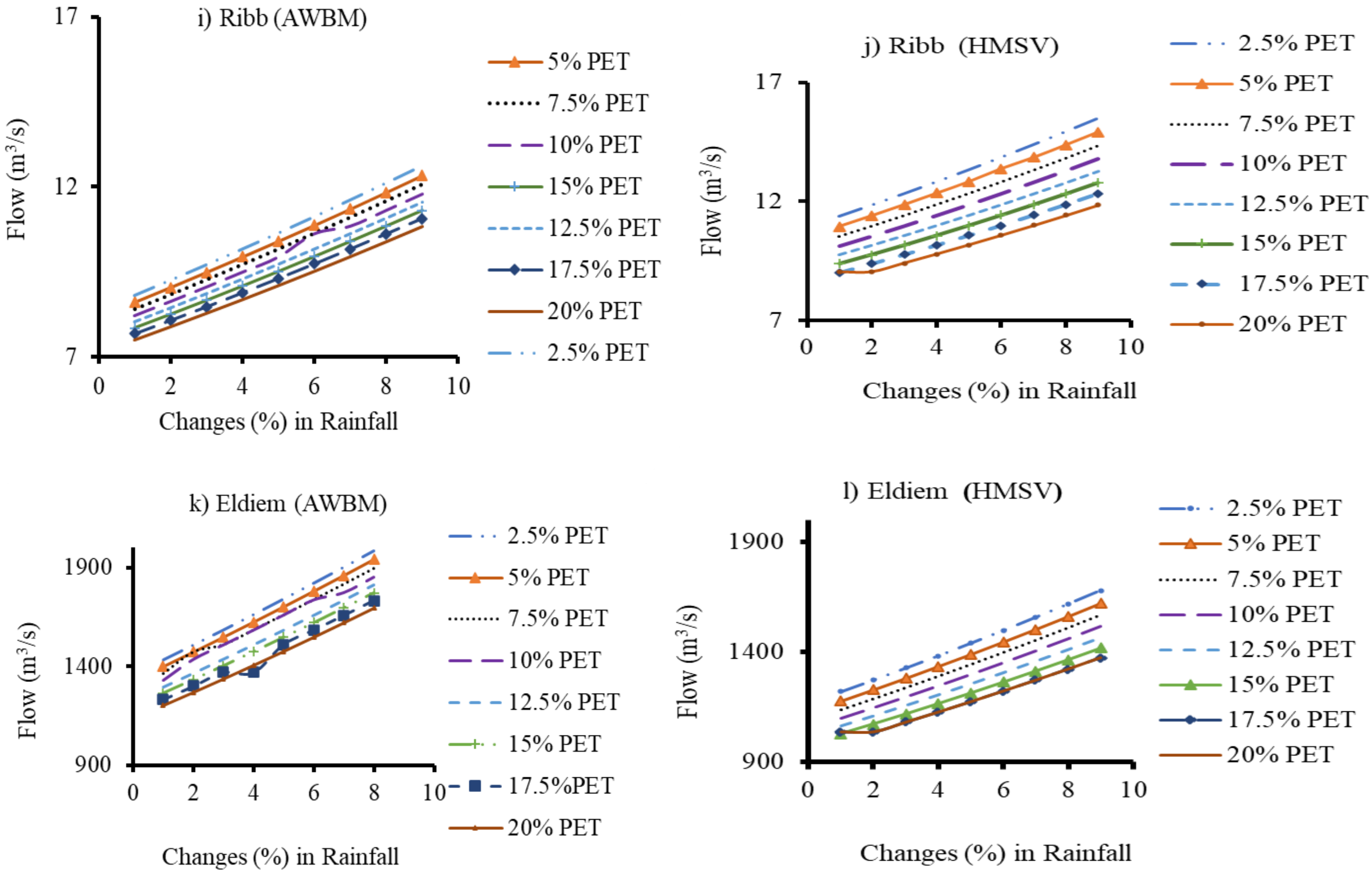
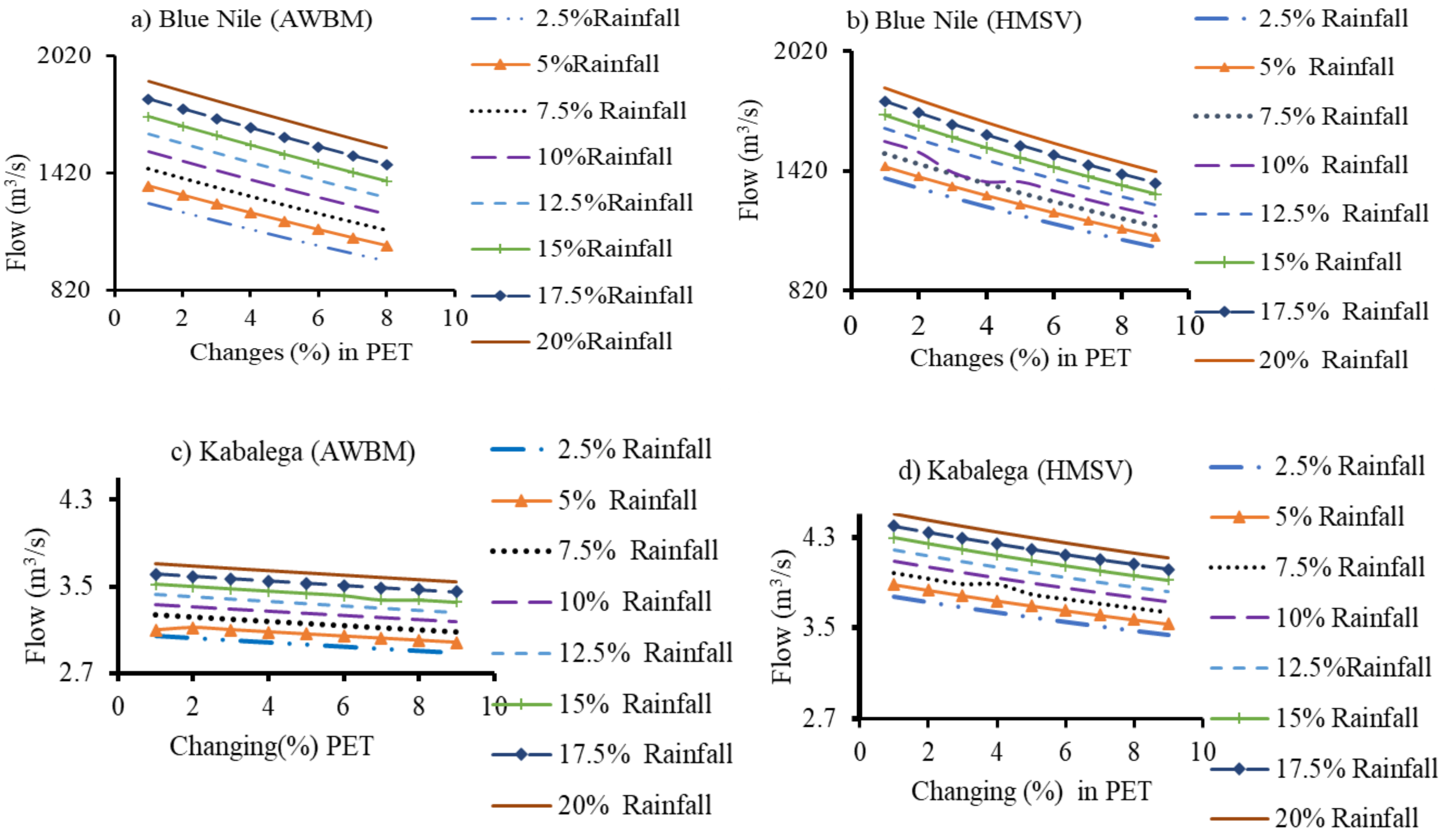


Figure 4.17: Effects of changes in rainfall at different PET intervals (Source: Primary data)

4.4.5 Effects of changing PET with rainfall kept constant at different intensities

Figures 4.18, 4.19, and 4.20 show the effect of changing PET at different rainfall intensities during simulation using HMSV and AWBM models. As the percentage of PET increased flow reduced in magnitude. These were noticed in the results from both models when applied to selected sub-catchments. Sub-catchments with the noticeable flow were in Blue Nile the highest with -1.589m^3/s (HMSV), El-Diem with -1.615m^3/s (HMSV), Kabalega with -0.501m3/s (HMSV), Malaba -0.884m^3/s (HMSV), Mpanga with -0.431m^3/s (HMSV) and Ribb with -1.557m^3/s (HMSV). The slopes and intercepts of the lines characterizing the effects of changes in PET given rainfall on flow can be summarized in Table 4.5 and 4.6, respectively. Water can be lost in various ways, that is, evaporation and transpiration. If the evaporation rate is high, the evaporation demand of the atmosphere can be met while other processes are affected as well.

The key processes that reduce as evaporation increases include infiltration and peroration. Low rates of infiltration and percolation lead to a reduced amount of interflow and base flow components of flow. Overland flow to due changes in land use and land cover, evaporation rate can also change for example evaporation rate in peak areas and vegetated land are not something very similar. While some land, use types affect runoff generation including overgrazing deforestation bush burning, and urbanization. These results indicate the importance of proper water shade management. For instance, some activities such as afforestation can be adopted (Onyutha and Willems, 2018). The droughts are becoming longer and more intense with unpredictable rainfall thus indicating a need for a proper strategy to overcome this shortly (Link et al., 2012).


a) Blue Nile (AWBM)

b) Blue Nile (HMSV)

c) Kabalega (AWBM)

d) Kabalega (HMSV)

Figure 4. 18 : Changes in PET at different rainfall intensities (Source: Primary data)

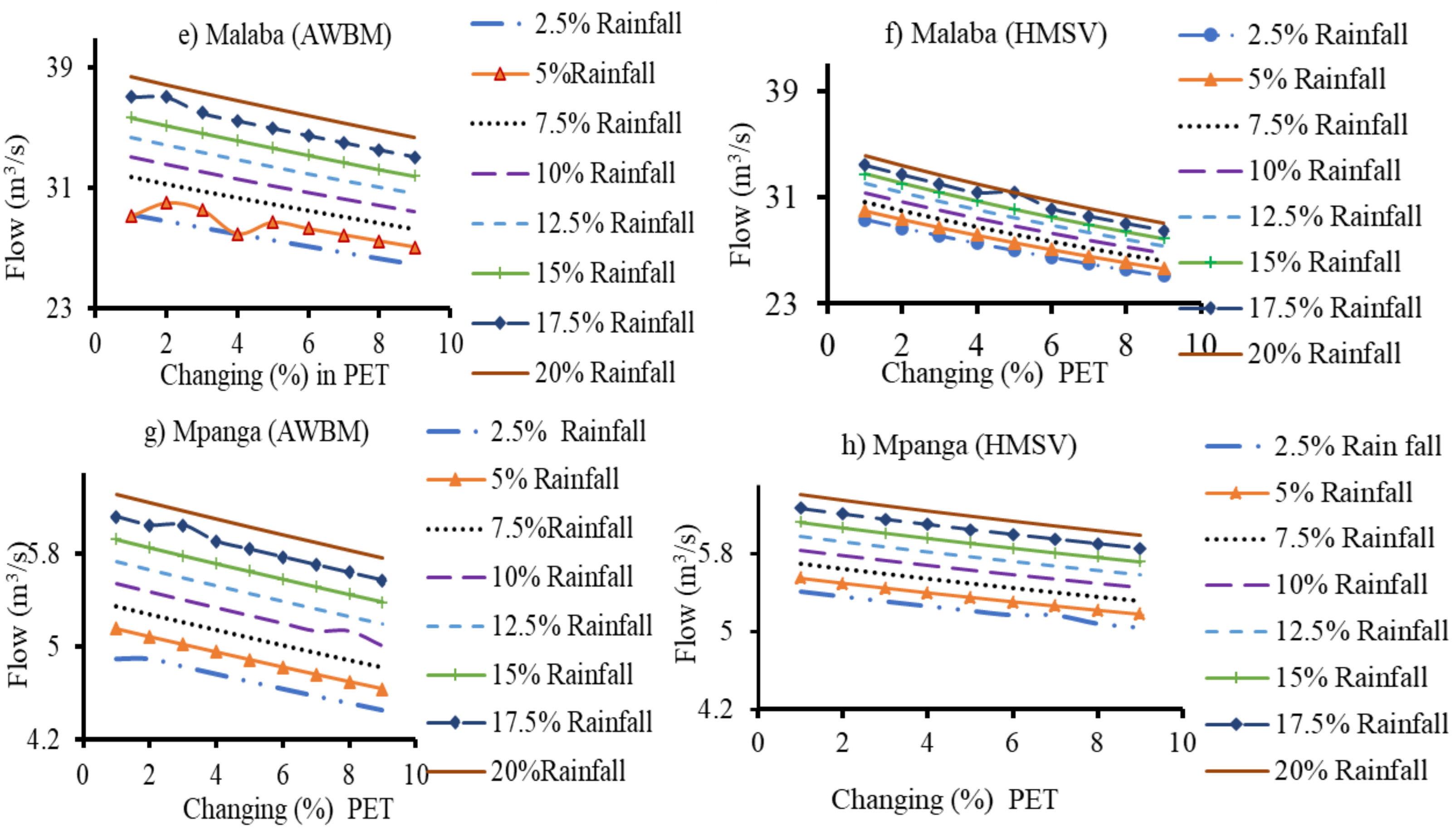


Figure 4.19: Changes in PET at different rainfall intensities (Source: Primary data)

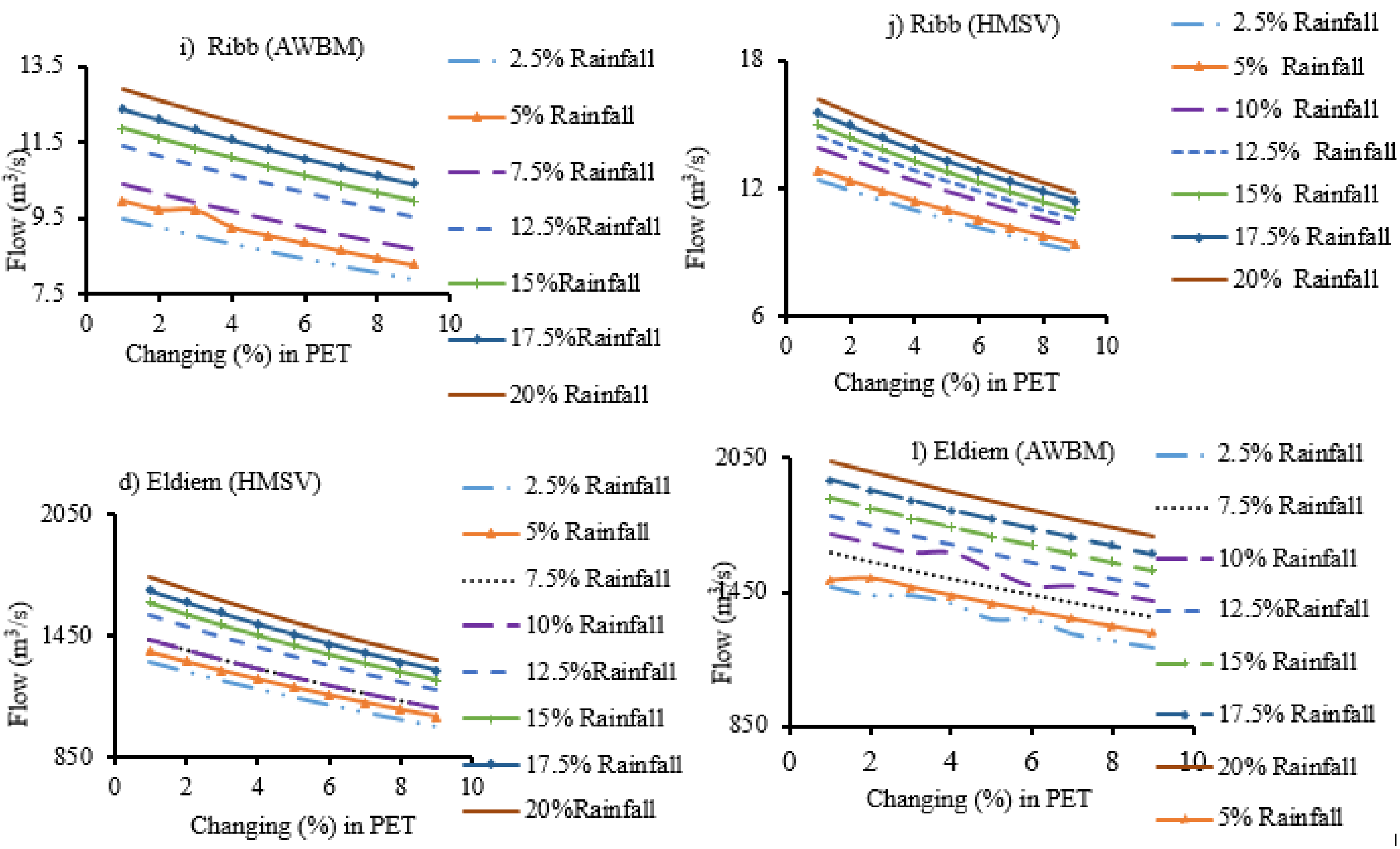


Figure 4.20 : Changes in PET at different rainfall intensities (Source: Primary data)

Table 4.6: Gradients for catchments in different intensities during simulation using HMSV and AWBM models

CATCHMENTS		Blue Nile		EL-DIEM		KABALEGA		MALABA		MPANGA		RIBB	
		Gradient		Gradient		Gradient		Gradient		Gradient		Gradient	
MODELS USED		AWBM	HMSV	AWBM	HMSV	AWBM	HMSV	AWBM	HMSV	AWBM	HMSV	AWBM	HMSV
Change PET Constant rainfall	Gradient	-1.2884	-1.2337	-1.0236	-1.1855	-0.3603	-0.425	-0.5621	-0.7131	-0.4717	-0.3637	-0.5551	-1.1564
Changes in rainfall constant PET	Gradient	2.6985	1.757	2.4796	1.8735	0.9755	1.087	1.831	0.9683	1.5781	1.1753	1.406	1.5323
Simultaneous change in both PET & rainfall	Gradient	1.2218	0.3606	1.1463	0.2548	0.7668	0.567	1.1121	0.00821	0.4323	0.673	0.658	-0.0023
Changes in rainfall at different PET rates	2.5%	2.6332	1.9013	2.4657	1.813	0.9748	1.0583	1.8048	0.9405	1.5943	1.1658	1.3828	1.5005
	5.0%	2.652	1.8535	2.4268	1.7544	0.9731	1.0479	1.78	0.9168	1.5675	1.3343	1.3568	1.4954
	7.5%	2.5608	1.8073	2.3499	1.698	0.9718	1.0378	1.7607	0.8941	1.5624	1.1477	1.3313	1.3908
	10.0%	2.6018	1.7625	2.3566	1.6435	0.9737	1.0281	1.7723	0.8722	1.5736	1.1393	1.318	1.3394
	12.5%	2.5287	1.7192	2.3126	1.5909	0.9693	1.0188	1.9995	0.8512	1.5531	1.0931	1.2832	1.2907
	15.0%	2.5397	1.6769	2.2753	1.5401	0.968	1.0099	1.9995	0.8312	1.5495	1.1231	1.2601	1.2443
	17.5%	2.5062	1.6213	2.238	1.4004	0.8884	1.0012	1.6864	0.8122	1.5432	1.1154	1.2374	1.1996
	20.0%	2.4727	1.5948	2.2009	1.5099	0.9654	0.9928	1.6671	0.794	1.5259	1.0348	1.2149	1.0876
Changing in PET at different rainfall intensities	2.5%	-1.2903	-1.2786	-1.1074	-1.2384	-0.2531	-0.4347	-0.5874	-0.7343	-0.8595	-0.3605	-0.5794	-1.2039
	5.0%	-1.3583	-1.3233	-0.3757	-1.2917	-0.0717	-0.4444	-0.1412	-0.7557	-0.532	-0.3808	-0.6257	-1.2523
	7.5%	-1.3866	-1.3942	-1.1446	-1.3452	-0.2416	-0.462	-0.612	-0.7772	-0.5376	-0.3893	-0.6276	-1.2523
	10.0%	-1.4123	-1.338	-1.2224	1.6435	-0.2039	-0.4635	-0.6345	-0.7988	-0.5169	-0.3976	-0.3035	-1.3509
	12.5%	-1.4123	-1.456	-1.2208	-1.4526	-0.2052	-0.4731	-0.6586	-0.8203	-0.5484	-0.406	-0.676	-1.4018
	15.0%	-1.4358	-1.5004	-1.2581	-1.5066	-0.3997	-0.4825	-0.6787	-0.8416	-0.5533	-0.4145	-0.7004	-1.4533
	17.5%	-1.4566	-1.5447	-1.295	-1.5609	-0.2076	-0.4919	-0.7335	-0.8628	-0.577	-0.4229	-0.7249	-1.5052
	20.0%	-1.4759	-1.5888	-1.3313	-1.6151	-0.2087	-0.5013	-0.7157	-0.8839	-0.562		-0.7492	-1.5573

Table 4.7: The intercepts for different changes in catchments using AWBM and HMSV Models in a Tropical catchment

CATCHMENTS		BLUE NILE		EL-DIEM		KABALEGA		MALABA		MPANGA		RIBB	
		INTERCEPT		INTERCEPT		INTERCEPT		INTERCEPT		INTERCEPT		INTERCEPT	
MODELS USED		AWBM	HMSV	AWBM	HMSV	AWBM	HMSV	AWBM	HMSV	AWBM	HMSV	AWBM	HMSV
Change PET constant rainfall	Gradient	-7.58	-0.96	10.94	-0.81	-19.12	-4.85	-1.99	-0.23	-1.59	7.90	-34.41	-14.13
Changes in rainfall constant PET	Gradient	-7.76	3.38	10.32	-0.54	-23.43	-5.15	-2.39	0.04	-2.18	7.97	-34.42	-14.13
Simultaneous change in both PET and rainfall	Gradient	-8.00	-0.30	10.75	-0.05	-23.41	-4.66	-2.07	-1.98	6.87	7.57	-34.14	-13.47
Changing in rainfall at different PET rates	2.5%	-10.43	-4.24	7.05	-4.07	-23.94	-5.89	-3.63	-1.98	-3.84	6.96	-36.03	-17.34
	5.0%	-14.56	-7.65	4.24	-7.41	-24.44	-7.06	-5.16	-3.98	-4.88	6.31	-37.56	-20.55
	7.5%	-16.82	-10.92	2.24	-10.58	-24.94	-8.18	-6.61	-5.89	-6.21	5.03	-39.02	-23.64
	10.0%	-21.09	-14.06	0.52	-13.60	-25.53	-9.26	-7.83	-7.70	-7.58	4.11	-40.36	-26.57
	12.5%	-23.41	-17.07	-3.60	-16.47	-25.94	-10.30	-11.51	-9.43	-8.21	3.28	-41.79	-29.37
	15.0%	-27.22	-19.96	-6.04	-19.21	-26.43	-11.30	-10.03	-11.08	-9.90	2.35	-43.09	-32.04
	17.5%	-30.16	-22.65	-9.00	-20.53	-27.13	-12.26	-12.12	-12.66	-11.16	1.52	-44.35	-34.61
	20.0%	-33.02	-25.39	-10.65	-22.08	-27.40	-13.20	-13.40	-14.17	-12.34	1.70	-45.55	-36.08
Changing in PET at different rainfall intensities	2.5%	-1.33	3.65	17.21	3.51	-26.58	-2.20	2.39	2.13	1.17	10.78	-31.11	-10.61
	5.0%	5.33	8.34	20.51	7.93	-18.98	0.46	4.11	4.50	5.62	13.71	-27.35	-6.99
	7.5%	12.04	13.25	28.03	12.44	-19.23	3.34	11.06	6.88	9.55	16.63	-24.33	-6.99
	10.0%	18.79	16.37	34.67	-13.60	-13.70	5.79	15.59	9.28	13.38	19.56	-26.45	0.55
	12.5%	25.58	22.82	40.56	21.77	-11.26	8.46	20.22	11.69	17.45	22.50	-17.30	4.48
	15.0%	32.41	27.79	46.96	26.58	-8.80	11.14	24.87	14.11	21.41	25.45	-13.69	8.50
	17.5%	39.26	32.82	53.44	31.49	-6.37	13.81	30.19	16.79	25.73	28.41	-10.02	12.61
	20.0%	46.16	37.92	60.01	36.47	-3.92	16.49	34.46	18.98	29.35	31.38	-6.30	16.81

4.5 Chapter Summary

This chapter has presented the results, their interpretation, and a discussion of the results. The results in this chapter were organized in line with the four specific objectives of this study. The next/last chapter of this study presents study conclusions and recommendations.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The significance of changes in climatic conditions in the tropics holds profound implications for various hydrological processes. Findings from recent studies underscore the importance of understanding these shifts. Analyzing trends in flows, rainfall, and PET reveals crucial insights. In this study, it was observed that the trends in these variables were not statistically significant, as indicated by p-values above 0.05. Consequently, the null hypothesis of no trend was upheld.

Examining catchment responses under different scenarios elucidates potential outcomes. When rainfall varies while PET remains constant, an increase in rainfall correlates with heightened flow in the catchment, suggesting a heightened risk of flooding. Conversely, when PET fluctuates while rainfall remains constant, flow diminishes, potentially leading to drought conditions. Reduced infiltration and percolation rates contribute to groundwater depletion in this scenario.

Understanding the combined impact of changing rainfall and PET on catchments is crucial. It is noted that while fluctuations in both variables may have a discernible effect on flow, the magnitude of this impact is comparatively minimal. Sub-catchments exhibit positive flows, albeit not as pronounced as under solely rainfall-induced variations. This underscores the complex interplay of climatic factors on hydrological systems in Tropical regions.

While the study provides valuable insights into the significance of climatic changes in the tropics, several limitations must be acknowledged. Firstly, the lack of significant trends in flows, rainfall, and PET suggests that other factors beyond those considered in this study may influence hydrological processes. Additionally, the reliance on p-values above 0.05 to determine significance may overlook subtle trends or relationships within the data.

Regarding catchment responses, the analysis primarily focuses on the direct impact of changing rainfall and PET on flow dynamics. However, it overlooks potential interactions with other factors such as land use changes, soil properties, and vegetation cover, which could significantly modulate catchment responses. Furthermore, the study assumes constant PET or rainfall, neglecting potential variations over time that could alter the observed outcomes.

When considering changes in both rainfall and PET, the minimal effect on flow in selected catchments raises questions about the comprehensiveness of the analysis. The study focus on specific catchments may limit the generalizability of its findings to broader Tropical regions. Moreover, the observed positive flows in sub-catchments under changing conditions may mask underlying complexities that warrant further investigation.

In conclusion, while the study sheds light on the implications of climatic changes for Tropical hydrology, its findings should be interpreted within the context of these limitations. Future research should aim to address these constraints to provide a more nuanced understanding of the multifaceted interactions between climatic variables and catchment responses in Tropical regions.

5.2 Recommendations

Key stakeholders ought to check the magnitude of the effects to strategically plan for preventive measures and relief measures to diminish/control the impacts of floods in the region.

Key stakeholders and decision-makers ought to strongly consider activities that preserve the environment including afforestation, reduction of urbanization and land use, and stopping activities like deforestation, burning bushes, and overgrazing.

Policymakers, decision-makers, and scientists ought to ensure that there is regional balance in preserving vegetation cover to reduce the effects of negative flows in the tropics.

5.3 Future research

More studies ought to be carried out on how much green cover is required to counteract the rate of climate variability that is already increasing. Research could find out other factors that could cause sensitivity of the catchment apart from rainfall and PET.

5.4 Policy implication

The decision-makers with the help of good policies on the environment be able to mitigate or control the effects of climatic variability. Some of the effects include flooding, drought, and how these effects affect catchment in Tropics

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APPENDICES

Table A.8: Model calibration values for HMSV and AWBM

HMSV				
BLUE NILE			MALABA	
Parameter	Range/value	Optimal value	Range/value	Optimal value
SMI	[85, 92]	88.000	[10, 12]	92.000
SMAX	[78, 87]	82.500	[175, 180]	178.800
a1	[1, 15]	1.500	[14.9, 16]	15.900
tb1	[1,15]	1.500	[190,205]	200.000
a2	[1,10]	0.380	[5,5.7]	6.380
tb2	[0.1,10]	0.195	[26,30]	28.000
a3	[0.1,10]	2.913	[5.5,6.5]	6.133
c3	[1,20]	2.150	[3.5,4]	3.8.000
tb3	[2,50]	3.500	[2.5,4]	3.000
tb4	[15,40]	30.500	[21,23]	22.99
KABALEGA			MPANGA	
SMI	[197,201]	198.000	[20,23]	2000.000
SMAX	[109,117]	115.700	[18,25]	22.800
a1	[15.4,25]	21.301	[14,18]	15.510
tb1	[2,4]	2.800	[10,15]	12.550
a2	[188,192]	190.040	[6.5,9]	8.800
tb2	[190,210]	200.000	[6,9]	8.200
a3	[6,8]	7.460	[18,22]	20.130
c3	[2.5,2.999]	2.802	[3.7,3.9]	3.780
tb3	[40,55]	50.000	[20,26]	25.000
tb4	[3,4]	3.000	[30,35]	34.990
RIBBEN			ELDIEM	
SMI	[450,550]	500.000	[2,550]	2.000
SMAX	[109,250]	120.000	[100,250]	207.500
a1	[0.1,2]	0.930	[0,1.5]	0.0125
tb1	[0,0.5]	0.010	[0.51.5,5]	0.255
a2	[1,5]	2.540	[0.2,0.5]	0.240
tb2	[0.1,1.5]	0.200	[0.1,5]	0.199
a3	[0,0.5]	0.030	[0,5]	0.310
c3	[0.5,2]	1.000	[0,2.5]	0.0125
tb3	[2.5,5]	3.250	[2,8]	3.340
tb4	[9,11]	10.500	[2,5.5]	4.000

AWBM				
BLUE NILE			**MALABA**	
Parameter	Range/value	Optimal value	Range/value	Optimal value
A1	[0, 1]	0.300	[0, 1]	0.072
A2	[0, 1]	0.383	[0, 1]	0.323
BFI	[0,1]	0.614	[0,1]	0.599
C1	[0,50]	0.000	[0,50]	0.000
C2	[0,200]	160.900	[0,200]	0.000
C3	[0,500]	113.600	[0,500]	384.900
KBASE	[0,1]	1.000	[0,1]	0.997
KSURF	[0,1]	0.965	[0,1]	0.946
KABALEGA			**MPANGA**	
A1	[0, 1]	0.0248	[0, 1]	0.730
A2	[0, 1]	0.45052	[0, 1]	0.160
BFI	[0,1]	0.117	[0,1]	0.960
C1	[0,50]	32.308	[0,50]	0.000
C2	[0,200]	0.000	[0,500]	370.390
C3	[0,500]	0.000	[0,900]	896.260
KBASE	[0,1]	0.8320	[0,1]	1.000
KSURF	[0,1]	1.000	[0,1]	0.940
RIBBEN			**ELDIEM**	
A1	[0, 1]	0	[0, 1]	0.134
A2	[0, 1]	0.233	[0, 1]	0.433
BFI	[0,1]	0.368	[0,1]	0.459
C1	[0,50]	0.000	[0,50]	23.5
C2	[0,200]	0.000	[0,200]	0.200
C3	[0,500]	0.000	[0,500]	1.800
KBASE	[0,1]	0.960	[0,1]	0.975
KSURF	[0,1}	0.963	[0,1]	0.990