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ASSESSING THE EFFECT OF RAINFALL VARIABILITY ON STREAMFLOW IN RIVER MPOLOGOMA CATCHMENT

BY

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Declaration

I, Maria Sarah Nadunga, declare that this is my original work and has not been submitted for any other degree award to any other University before.

Signature……………………………………Date……………………………..

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Dedication

I dedicate this work to my Dear Family.

Acknowledgement

My sincere gratitude goes to the Almighty God for the gift of life, good health He gave me throughout the course!

Special thanks goes to the MSc. 2016 cohort for the family spirit and to my friends Ronald, Kevin, Rhoda and Priscilla, for the support and guidance throughout the Course of study. It was such a hard time but leaning on God and support from colleagues made me hang on.

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List of Acronyms

ADF	NedborAfstromnings
ANN	Artificial Neural Networks
CLM	Classical Linear Model
CMIP	Coupled Model Intercomparison Project Phase 5
CORDEX	Coordinated Regional Downscaling Experiment
CV	Coefficient of Variation
DSSAT	Decision Support System for Agro technology Transfer
DWD	Directorate of Water Department
DWRM	Directorate of Water Resource Management
ENSO	El Niño-Southern Oscillation,
FDL	Finite Distributed Lag
GCM	Global Circulation Model
GHG	Green House Gas
GLM	Generalised Linear Models
GMAO	Global Modelling and Assimilation Office
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter-tropical Convergence Zone
IOD	Indian Ocean Dipole
MAM	March, April, May (MAM)
MERRA	Modern Era Retrospective-Analysis for Research & Applications
MWE	Ministry of Water and Environment
NAM	NedborAfstromnings
NASA	National Aeronautics and Space Administration
OLS	Ordinary Least Squares
POWER	Prediction of Worldwide Energy Resources
Q_{10}	Peak flow exceedance (10^{th}) percentile
Q_{7max}	7-day maximum flow duration
Q_{7mean}	7-day mean flow duration
Q_{7min}	7-day minimum flow duration
Q_{90}	Low flow exceedance (90^{th}) percentile
QBO	Quasi-Biennial Oscillation
RCM	Regional Climate Model

RCP	Representative Concentration Pathways
RDF	Recursive Digital Filters
SON	September, October, November (SON)
SSTs	Sea-Surface Temperatures
SWAT	Soil and Water Assessment Tool
UNMA	Uganda National Meteorological Authority
VHM	Veralgemeend Conceptueel Hydrologisch
WMO	World Meteorological Organization
WWAP	World Water Assessment Program

Abstract

River Mpologoma catchment is one of Uganda's water resources that is vastly relied on for supporting agricultural livelihoods among other activities. Stream flow is an important feature used to determine availability of water in surface water resources and is partly formed from rainfall. This study sought to assess the effect of rainfall variability on streamflow behaviour in Mpologoma catchment and to project future streamflow behaviours. Daily rainfall and discharge data for four stations located in the catchment were obtained for the period 1981 – 2015. Totals (for rainfall) and averages (for discharge) were generated for the annual period as well as for the major wet seasons March-May and September-November after which low flow, average flow and peak flow statistics were computed. The Mann-Kendall test was used to assess trends in streamflow while the Pearson correlation and time-series regression analysis were used to investigate the relationship between rainfall and streamflow. Future rainfall data (2021 – 2040) were down scaled using the CORDEX program for 2 climate scenarios (RCP 4.5 and RCP 8.5) after which streamflow were forecasted from the fitted regression equations by extrapolation. The Mann-Whitney U-test was used to examine if future changes in streamflow were significant. Results reveal that over time, low and peak flow within Mpologoma catchment are highly variable (CV > 60%) especially during the wet seasons. Significant negative and positive trends were observed in the MAM low flows and SON peak flows respectively. The results further show that low flow, peak flow and average flow are positively correlated ($p < 0.05$) with MAM, SON and annual rainfall respectively. Time series regression shows that rainfall has a significant influence on streamflow where a 1 mm increase in rainfall at a given time resulted in a 0.2%-0.7% instant rise in streamflow. Future projections suggest that low flow during the MAM season is expected to decline by 66%-77% whilst annual average flow is expected to fall by 58%-64%. On the contrary, peak flow for the SON season is not expected to change in the near future. The study concludes that annual and seasonal rainfall variability threatens water availability in the Mpologoma river catchment. The projected decline in streamflow is expected to bring about water scarcity in the area which would threaten agricultural production and livelihood in general. The study recommends that adaptation measures be devloped to mitigate the anticipated impacts of water shortages.

CHAPTER ONE
INTRODUCTION

1.1. Background

Globally, fresh water resources are regarded as a key strategic resource, vital for sustaining life, promoting development and maintaining the environment. Water availability is one of the essential conditions that influences the wellbeing of human society and is considered a key factor for sustainable development (Nsubuga *et al*. 2014). It is vital for domestic water supply, livestock, industrial operations, hydropower generation, agriculture, marine transport, fisheries, waste discharge, tourism, and environmental conservation. The general appearance of abundant water resources is quite misleading for it does not highlight the supply, demand and quantity in relation to climate change, which presents a threat to the available water resources (Lagerblad, 2010; Quilbé *et al.* 2008).

Torabi Haghighi et al., (2021) and Chen et al., (2023) reveal that streamflow of many rivers worldwide have been changing because of effects of climate change. The hydrological variables especially rainfall and runoff are greatly impacted by climate change which raises concerns about their future behavior (Sangüesa et al., 2023). The variations in rainfall affects evaporation either positively or negatively with the corresponding effect on streamflow (Akpoti et al., 2016; Coleman & Jain, 2023). Sangüesa et al., (2023) stress that negative trends in streamflow have been realized in central Chile. Higgins et al., (2022) also reveal that the increasing frequency and intensity of rainfall strongly influence streamflow variability in the northern region of Australia. These extreme and unexpected changes in streamflow impact human use and ecosystem health and sustainability (Coleman & Jain, 2023). In West Africa, increase in precipitation has been reported to increase the water yield to streamflow (Akpoti et al., 2016) while 10% relative decrease in precipitation resulted in a 16% decrease in runoff between 1936 and 1998 (Conway et al., 2009; Oti et al., 2020). On a global scale the variability of rainfall in the tropics is influenced by the Sea Surface Temperature (SST) across the equator and this in the end has an impact on streamflow.

Uganda's rivers and lakes, including wetlands, cover about 18% of the total surface area of the country, with rainfall being the greatest contributor to the surface and ground water resources (Nsubuga *et al*. 2014). Mpologoma river catchment is one of Uganda's renown water resources found within Lake Kyoga basin and has an estimated water demand of 250 million m^3 per year of which 77% is used for irrigation (Ministry of Water and Environment - MWE, 2016). The catchment covers a total of 10 districts with an estimated population of about 4.9 million people. The catchment is a major source of livelihood where it is greatly relied on for supporting socio-economic activities. Rain fed agriculture and livestock grazing are the most widespread activities in the catchment. More than half of the total land area is used for cultivation (Verdonck & Michel, 2016).

Stream flow in Mpologoma catchment as a resource has been categorized in different uses: Industry (the fisheries docked use it for processing), Livestock grazing and drinking, water supply development of pipelines and sanitation facilities and Irrigation by the two major rice schemes in the catchment: Doho and Kibimba are key in irrigation. Its demand has ensued stress on the water resources especially during the Period from May to November (DWRM, 2019).

Streamflow also known as river discharge is defined as water flow within a river channel usually expressed in m^3/s. It has two components, namely; base flow that originates from ground water storage and quick flow that is mainly formed by precipitation. Streamflow is directly associated with base flow and other delayed sources like wetlands, lakes and melting snow (Beck et al., 2013). Streamflow features are used by hydrologists, planners and water managers as benchmarks to determine the availability of water for industrial supply, establish waste disposal thresholds, assess aquatic habitat needs and design capacity of reservoirs or bridges, among other purposes (Arora et al., 2014; Bhatt & Mall, 2015; Gotvald, 2017). Water availability from surface water sources depends on the seasonality and inter-annual variability of streamflow. Streamflow evaluation is therefore important for water resource planning, management, and sustainable ecosystem maintenance.

Streamflow regimes continue to play a major role in understanding the river flow variations, conservation planning for ecosystems and providing an inventory for hydrological water resource management (Berhanu *et al.* 2015). However, streamflow regimes have been found to be greatly influenced by climate patterns (Hameed *et al.* 2017). A recent study by the Intergovernmental Panel on Climate Change (IPCC, 2014) relays that climate has changed and will continue to change in response to anthropogenic increases in greenhouse gas emissions. In many regions, changing precipitation or melting snow and ice are altering hydrological systems, affecting water resources in terms of quantity and quality. It has been estimated that global-mean temperature may increase by 1.5^0C to 4.5^0C during the first half of the 21^{st} century.

Along with changes in temperature, changes in precipitation are bound to occur. Thus a growing concern about the potential effect of such changes on water resource features such as natural streams which are an important determinant of fresh water diversity and ecological processes (Dhungel, 2014).

Climate change in Uganda continues to manifest itself in form of increased extremes as well as changes in the rainfall patterns and seasonality, a case in point being the recurrent floods and landslides in Eastern and Western Uganda (Red Cross, 2010). Such variations in climatic patterns have caused alterations in the hydrological cycle of water catchment areas across the country majorly through increased evaporation and intense rainfall that affect the availability, quantity and quality of water resources. Mpologoma is one such catchment that heavily relies on rainfall for its streamflow and is thus prone to floods and prolonged dry-spells as indicated by the recent drying up of some of its streams (Directorate of Water Department - DWD, 2017).

Managing water has always meant dealing with natural variability but climate change threatens to increase this variability by shifting and intensifying extremes. Although increases in temperature may be the clearest indicator of the ongoing climate change, changes in the amount and variability of rainfall and evapotranspiration will have the largest impact on hydrological systems most especially freshwater ecosystems (Bates *et al.*, 2008). Since most of Uganda's population still depends directly on rain-fed agriculture, it is important that the relationship between climate and water resources management is given special consideration. This study therefore undertook a quantitative assessment of the effect of rainfall variability on streamflow with specific reference to Mpologoma river catchment. The goal of the study was to predict streamflow trends for the catchment under future climatic conditions.

1.2. Statement of the problem

Studies conducted in Lake Kyoga basin and Eastern Uganda at large (Kansiime et al., 2013; Ogwang et al., 2012) suggest that there has been an increase in rainfall variability and the frequency and severity of extreme weather events such as droughts and floods in the recent past. In particular, flood and landslide disasters triggered by prolonged rainfall, have been known to frequently occur in Teso region, Butaleja, Sironko, Tororo, Mbale, Bududa and Manafwa districts (UNEMA, 2010). Such variations in rainfall have been majorly attributed to climate change that is associated with the observed increase in anthropogenic greenhouse gas emissions (IPCC, 2014). A study by Oratungye et al. (2017) further shows that the Mar-May season in the region has experienced significant decline in rainfall volume whereas a reverse pattern has been observed for the Sep-Nov season. According to IPCC (2014), these variations in rainfall are expected to continue even in the future.

Rainfall variability has been studied near and over the study area. For instance (Ngoma et al., 2021; Onyutha, Asiimwe, et al., 2021) studied rainfall variability over Uganda. Onyutha et al., (2020) analysed precipitation changes over Lake Kyoga basin where Mpologoma catchment lies while rainfall variability has been studied in Sipi sub-catchment which forms part of Mpologoma catchment (Luwa et al., 2021). Other studies have been specifically localized to Mpologoma catchment (Mubialiwo et al., 2020, 2023). Even with the wide study of rainfall variability, results from different spatio-temporal scales are inconclusive and give mixed results (Luwa et al., 2021)(Nsubuga et al., 2014). Additionally, few studies have related rainfall variability to streamflow changes (Kangume & Mulungu, 2018; Luwa et al., 2021). It is important to conduct trend analyses for both rainfall and streamflow at localised Mpologoma catchment scale (Mubialiwo et al., 2023). Rainfall and streamflow data are vital in understanding stream flow dynamics in any given watershed *(Ashraf et al., 2020).*

Studies on the impact of rainfall variability on the streamflow within River Mpologoma catchment have often used models like SWAT, HEC-HMS to determine stream flow (*Ogwang et al., 2012; Kansiime et al. 2013)* These models have been with limitations in determining streamflow characteristics because they do not consider some stream flows parameters e.g. quartiles and percentiles that are key to study climatic related effects .There are limited studies that have deployed some models like the CORDEX and parameters such as 7Q10 7Qmin, 7Qmax to provide information on how stream flow responds to rainfall and or climate change in the present and near future.

It remains unknown to what extent rainfall will affect streamflow in river catchments such as Mpologoma. Previous studies on prediction of streamflow behaviour from climate patterns have reported mixed conclusions with some projecting declines in streamflow in the future (IPCC, 2008; Kigobe and Griensven, 2010) while others have predicted significant rise in streamflow under future climate scenarios (Bates et al., 2008; Taye et al., 2011; Adem et al. 2016). Such contrasting findings cannot be generalized to the study area. Therefore, the study sought to provide information on how streamflow in Mpologoma river catchment will respond to rainfall variations in the near future.

1.3. Objectives of the study

1.3.1 General Objective

To contribute to the understanding of streamflow behavior within the Mpologoma catchment under future climate conditions

1.3.2 Specific Objectives

1. Determine the trend in streamflow for R. Mpologoma catchment from 1981 to 2015
2. Establish the relationship between rainfall and streamflow in R. Mpologoma catchment
3. Predict streamflow for Mpologoma River catchment in the near future (2021 – 2040)

1.4. Hypotheses

1. Stream flow of river Mpologoma significantly increases in the MAM compared to the SON
2. Rainfall has a significant relationship with stream flow of river Mpologoma irrespective of the season
3. Streamflow for River Mpologoma will decline significantly due to climate change in the near future (2021 – 2040)

1.5. Significance of the study

The findings of this study will enable the stakeholders in the River Mpologoma catchment to Plan ahead in terms of water availability for the different water users in the near future. This is very important since many people living around the catchment depend on it for livelihood support especially farmers NDP 111. The results from the study will enable the Ministry of Water and Environment in Uganda to design policies that strengthen the water management processes and help conserve similar water resources. Such policies will ensure that the communities in the sub-catchment attain maximum benefits from utilizing the available natural resources in a more sustainable manner accruing to Sustainable Development Goal 6(SDG). At the end of this research, the findings will be published in a research journal which will benefit researchers and academicians as the study will be used as reference and as a benchmark for further studies to be carried out on similar catchments.

1.6. Scope of the study

This study concentrated on how Mpologoma River catchment has responded and will respond to variability in rainfall in regard to magnitude and duration of its flow regimes. Two climate scenarios were considered while modeling future streamflow namely RCP 4.5 and RCP 8.5. (2021-2040) the study did not take into account other climatic factors besides rainfall such as temperature and evapotranspiration. Neither did it investigate the impact of non-climatic factors on streamflow which include socio-economic (human) activities usually manifested in form of changes in land use/cover, conservation, among others. The study only looked at the effect of rainfall on water quantity in the catchment and not water quality; and dealt only with streamflow and no other surface flows such as runoff. In terms of geographical scope, the study covered Mpologoma, a sub-catchment found within the Lake Kyoga basin.

CHAPTER TWO
LITERATURE REVIEW

2.1. Introduction

This chapter provides insight of the status-quo of water resources in Uganda with focus on Mpologoma catchment. It also reviews past studies on spatial-temporal variations in climatic parameters especially rainfall and how such variations affect streamflow patterns.

2.2. General overview of water resources in Uganda

Uganda covers a total area of 241,038 square km, of which 18% is open water and wetlands. The area is spread across the equator between latitude 10^0 30' South and 10^0 40' North, and longitude 29^0 30' West and 29^0 35' East. Most areas in the country lie at an average altitude of 1,200 m above sea level with the Albert Nile area having an altitude of 620 m at least and an altitude of 5,110 m above sea level at most at the Mt. Rwenzori peak. Uganda possesses plentiful water resources and one of them is the second largest freshwater lake in the world (Lake Victoria) among others. Major rivers include the Nile which is the longest river in the world, Rwizi, Katonga, Kafu, Mpologoma, Malaba and Aswa (MWE, 2013). Most parts of Uganda lie within the upper river basin of the White Nile except a small part located in the northeast which drains into Kenya's Lake Turkana basin. The country is partitioned into eight major sub-basins that drain into the Nile and these are: L. Victoria, L. Kyoga, R. Kafu, L. George and Edward, L. Albert, R. Aswa, Albert Nile and Kidepo Valley.

According to Taylor et al. (2014) current water supply in Uganda is on average sufficient to meet total demand in most months of the year although there were some periods when unmet demand may be as high as 5% of total demand. These suggestions were made after estimating water demand by sector (households, industry, livestock and agriculture) in eight watersheds in Uganda from 1981-2010. In the future, however, projections indicate a much greater level of demand and some potential reductions in supply. Total demand is expected to increase from 408 million cubic meters a year in 2010 to 3,963 million cubic meters in 2050. Total unmet demand will then rise from 3.7 million cubic meters to 1,651 million cubic meters in this period. In most months water shortages are predicted to be enormous.

Mpologoma is a sub-catchment of the Kyoga basin that is located in the Upper Nile and is mainly characterized by inter-annual and inter decadal variation in precipitation. The most significant tributary flow to the basin is mainly from the Mt. Elgon ranges (in the Eastern parts on the borders of Uganda and Kenya). The Kyoga basin faces high evapotranspiration from the swamp vegetation. Water availability in the basin is mainly important for agriculture, fishing, municipal purposes and many other uses. Water availability is highly influenced by climate variability and climate change presents many challenges for the basin. Human activities in the catchment have increased over the past century and are expected to grow even more rapidly in the future, hence, water management will become even more important with a changing climate (Kigobe & Griensven, 2010).

Climate change and variability are already affecting the availability of water in Uganda and this is expected to increase over time. In recent years the country has been subjected to the La Niña drought event of 1998-2000 and the El Niño wet phase and floods event of 1997-1998, both of which caused considerable loss and disruption. The sources of the effects include changes in precipitation patterns, increased frequency of floods and droughts, and changes in evaporation due to higher temperatures. All of these affect the amount of water available, both directly and through its impacts on infrastructure related to water. At the same time the country is facing major socioeconomic change, especially population growth and increasing incomes, that is resulting in an increased demand for water in the country. Since water is a key base for almost all human activity the consequences of these changes are very significant throughout the economy and society (Taylor et al., 2014).

2.3. Climate trends and rainfall patterns in Uganda

Uganda's rainfall exhibits a high degree of spatial and temporal variability. This variation is mainly controlled by the El Niño-Southern Oscillation (ENSO), the movement of the Inter-tropical Convergence Zone (ITCZ), Quasi-Biennial Oscillation (QBO) and the Indian Ocean Dipole (IOD). The average annual rainfall distribution in Uganda varies from 900mm in the north-eastern semi-arid areas of Kotido to 2000 mm on Ssese Islands in Lake Victoria. The two main rainfall regimes experienced in Uganda are unimodal and bimodal. The bimodal regime is observed over majority of the country with the first wet season occurring between March, April and May (MAM), while the second occurs between September, October and November (SON). The dry seasons generally occur from June, July to August (JJA) and December to February (DJF). The unimodal` pattern on the other hand is predominant in areas far north of Uganda where the two wet seasons merge forming one long wet season from April-September (Phillips & McIntyre, 2000). The spatial variation is also credited to the complex topography, vegetation and existence of large inland water bodies such as Lake Victoria, Lake Kyoga, among others which modulate the local climate. Generally, rainfall tends to decrease with the distance from the lake. The effect of the local topography is such that the highest rainfall is received in mountainous areas. The highest annual maximum rainfall is experienced around the lakeshore and on the slopes of Mt. Elgon (WWAP & DWD, 2006).

Uganda experiences pleasantly cool temperature with a long-term mean of 21^0 C. Over a year, mean temperatures range from a minimum of 15^0 C in July to a maximum of 30^0 C in February. However, following the warming of the African continent by 0.5^0 C in the past century (since 1988), some adverse impacts of temperature rise such as melting of ice and glaciers on mountain-tops has been observed in Uganda. The Rwenzori highlands are one of a few of permanently ice-capped mountains in Africa. Recent studies have shown that the glaciers and ice fields on this mountain have decreased markedly both in number and size and that the rate of shrinkage has been greatest after 1990 (WWAP & DWD, 2006).

Uganda's climate is naturally variable and susceptible to flood and drought events which have had negative socio-economic impacts in the past. Human induced climate change is likely to increase average temperatures in Uganda by up to 1.5 ºC in the next 20 years and by up to 4.3 ºC by the 2080s (NEMA, 2010). Such rates of increase are unprecedented. Changes in rainfall patterns and total annual rainfall amounts are also expected but these are less certain than changes in temperature. The climate of Uganda may become wetter on average and the increase in rainfall may be unevenly distributed and occur as more extreme or more frequent periods of intense rainfall. Regardless of changes in rainfall, changes in temperature are likely to have significant implications for water resources, food security, natural resource management, human health, settlements and infrastructure. In Uganda, as for the rest of the world, there are likely to be changes in the frequency or severity of extreme climate events, such as heat waves, droughts, floods and storms (Environmental Alert, 2010).

Current scientific evidence suggests that climate change is occurring and will continue into the unforeseeable future. Impacts can already be observed in terms of changes in the quality and quantity of drinking water (MWE, 2016). Climate change models predict an overall warming of the earth, increased evaporation, shifts in precipitation patterns, rising sea levels, and increasing extreme events such as floods, droughts, and heat waves (Arnell & Gosling, 2013). Over the past century, the global average surface temperature has risen by 0.7 °C, with warmest year being 2008. Projections suggest that over the next 100 years, temperature in the drier subtropical regions of Africa will increase by a greater amount than in the moister tropics. Northern and southern Africa will become warmer by as much as 4 °C or more and precipitation will fall by 15% or more, while rainfall is likely to increase in eastern Africa and parts of central Africa.

According to Serdeczny et al. (2017), the repercussions of climate change will be felt in various ways throughout both natural and human systems in Sub-Saharan Africa. Climate change projections for this region point towards a warming trend, particularly in the inland subtropics. The anticipated impacts include frequent occurrence of extreme heat events, increasing aridity, and changes in rainfall with a particularly pronounced decline in southern Africa and an increase in East Africa with a higher risk of flooding. The region could also experience as much as one meter of sea-level rise by the end of this century under a 4 ^{0}C warming scenario. Particularly vulnerable to these changes are the rain fed agricultural systems on which the livelihoods of a large proportion of the region's population depend.

Down-scaled Global Circulation Models (GCMs) suggest that mean temperatures will rise by 0.3 to 0.5°C per decade in Uganda whereas annual rainfall is projected to increase by 10-20% during the 21st century. The seasonality of rainfall is also likely to change in the future. The highest percentage increase in rainfall is projected for December, January and February, which is historically the driest season for many parts of Uganda. This indicates that the current wet season from March April to May (known as the "long rains" in Southern and Central Uganda) may shift forwards in time or the September to November rains, known as the "short rains" may extend longer. It must be emphasized that there is already considerable variability in seasonal rainfall totals, much of which is linked to ENSO (Crop et al., 2012).

Uganda has experienced frequent flooding and droughts, which have demonstrated the country's vulnerability to climate variability. Prolonged and severe droughts (as in 1999, 2000 and 2004-05) led to water shortages, the loss of livestock, food insecurity and increased food prices. Water levels in the lakes fell and the Nile flow declined, reducing the generation of hydropower that resulted into power shortages. Recent observations suggest that increased variability in rainfall patterns has brought shorter wet periods and heavier, more violent rains with extreme events like landslides becoming more frequent (Bhatt & Mall, 2015). The impacts of climate changes will affect all human activities, affecting the conditions in which people live and those livelihoods that depend directly on water, notably agriculture but also fisheries and industry. While it is projected that average rainfall may increase, the main concern is the impact of extreme events such as floods and droughts which are expected to increase in frequency and severity (MWE, 2013).

In a study carried out to determine the extent of rainfall trends and variability in Eastern Uganda, Kansiime, Wambugu, & Shisanya (2013) applied trend analysis in form of linear regression on observed rainfall data for the period 1971-2010. The Coefficient of Variation and ANOVA techniques were used to study variability. Their findings showed that for areas around L. Victoria and L. Kyoga basins, significant negative trends were eminent in the MAM rainfall while the SON rainfall showed rising trends. However, areas surrounding Mt. Elgon were found to have experienced positive significant trends in volume of rainfall received during both MAM and SON seasons. They also found significant within and between season variations for L. Victoria and less significant variations for Mt. Elgon and L. Kyoga agro-ecologies although Mt. Elgon exhibited high rainfall variability for SON.

2.4. Relationship between stream flow and rainfall

Observational records and climate projections provide abundant evidence that freshwater resources are vulnerable and have the potential to be strongly impacted by climate change with wide-ranging consequences for human societies and ecosystems. Observed warming over several decades has been linked to changes in the large-scale hydrological cycle such as: increasing atmospheric water vapor content; changing precipitation patterns, intensity and extremes; reduced snow cover and widespread melting of ice; and changes in soil moisture and runoff. Precipitation changes show substantial spatial and inter-decadal variability. Over the 20th century, precipitation has mostly increased over land in high northern latitudes, while decreases have dominated from 10° S to 30 °N since the 1970s. The frequency of heavy precipitation events has increased over most areas. Globally, the area of land classified as very dry has more than doubled since the 1970s (Bates *et al.*, 2008).

Warmer temperatures are predicted to reduce stream and river flows, change timing of runoff and increase the likelihood of salt water intrusion along coasts (Water Research Foundation, 2016, Emami & Koch, 2015). For instance, observed warming has exhibited and linked itself to large scale hydrological cycle changes in terms of increasing atmospheric water vapor content, precipitation pattern changes, intensity and extremes, soil moisture changes among others. Further still, there will be changes in both the quantity and quality of water due to climate change. This will increase the level of vulnerability of the poor rural farmers, food insecurity, increased runoff in some areas will be counterbalanced with variability in precipitation and seasonal runoff in all aspects water benefits (IPCC, 2008).

By the middle of the 21st century, annual average river runoff and water availability are projected to increase as a result of climate change at high latitudes and in some wet tropical areas, and decrease over some dry regions at mid-latitudes and in the dry tropics. Higher water temperatures and changes in extremes, including floods and droughts, are projected to affect water quality and exacerbate many forms of water pollution. Globally, the negative impacts of future climate change on freshwater systems are expected to outweigh the benefits. Changes in river flows, as well as lake and wetland levels, due to climate change depend primarily on changes in the volume and timing of precipitation and, crucially, whether precipitation falls as snow or rain. Changes in evaporation also affect river flows (Bates *et al.*, 2008).

A recent study by Tumusiime & Ageet (2018) assessed the impacts of climate change on hydro-meteorological ecosystem services and water stress in Lake Kyoga Catchment. They analysed trends in meteorological and hydrological observations for the baseline period 1959-2016 and thereafter used the Climate Predictability Tool to project water levels under two climate future scenarios. They also applied the correlation percentage change to estimate the rate of change of flow and water levels under a changing climate. Their findings showed that climate change has already affected water resources in L. Kyoga catchment with continuous reduction in water levels by 6%. Their results also revealed that climate change is likely to increase precipitation received during the wet seasons by 10-20% resulting in higher stream flow and a reduction of 20-40% for precipitation during the dry seasons.

Arora et al. (2014) carried out a study on correlations of streamflow and climatic variables for a large glacierized Himalayan basin. They used data for eight continuous glacier seasons (2000-2011) to investigate correlations, lag cross correlations and multiple regression analysis between daily mean discharge, daily mean temperature and daily mean rainfall. Their results indicate that discharge and temperature are highly auto-correlated and that daily discharge was dependent on present temperature, present rainfall and the previous day's discharge. They concluded that regression equation can be used for forecasting discharge once the input variables namely rainfall and temperature are available.

Liu et al. (2013) analyzed changes in the relationship between precipitation and streamflow in the Yiluo River in China. They used annual precipitation and annual streamflow for the period 1960 to 2006 and Mann–Kendall and Pettitt methods to analyze trends and detect change points in the hydro-climatic variables respectively. Their findings revealed that both annual precipitation and streamflow decreased significantly over the study period and that a change point was detected in annual streamflow series in 1986 after which streamflow decreased more dramatically than precipitation. They attributed the non-stationary relationship between annual precipitation and streamflow after 1986 to human activities, such as water diversion and land use/cover change which accounted for the substantial decrease in streamflow.

In a study to assess the impact of climate change on surface water resources of Wular lake in India, Hameed et al. (2017) applied trend analysis accompanied by 5-year moving averages and Mann-Kendall's test on annual discharge, temperature and precipitation over 21 historical years. They used Kendall correlation test to investigate the strength of pairwise relationships between the variables. They noted an increasing trend for temperature particularly after 1993, while precipitation and dicharge showed negative but insignificant trends. A strong positive correlation was found between annual rainfall and mean annual discharge. Conversely, a negative but weak relationship was noted between annual temperature and annual discharge.

Gül et al. (2010) assessed regional climate change impacts on river flows and environmental flow requirements for a lowland catchment in Denmark. They used a coupling approach where the hydrological model MIKE SHE and hydraulic model MIKE 11 were combined to simulate streamflows and groundwater head levels in a dynamic system. Their results show that whereas scenario estimates mostly show clear deviations from the observed averages, the response of river flows to the changes in climate events varies between the different GCMs. They found that a typical delayed response of flows to any immediate monthly increase or decrease in precipitation was obvious for all the scenario cases.

Kamruzzaman et al. (2014) evaluated the short-term relationship between rainfall and stream-flows in Southern Australia over the period 1990 to 2010. They used data from three rivers, namely Broughton, Torrance and Wakefield. They presented the relationship between rainfall and streamflow using correlations and lagged correlations, and also run deterministic regression based response model to detect linear, quadratic and polynomial trends, while controlling for seasonality effects. Their study showed that lagged rainfall was the best predictor of streamflow with a surge in rainfall significantly leading to increased streamflow. In addition, they also found out that predicted streamflow was more influenced by the previous few days' streamflows as compared to the entire previous period of stream flow.

A study by Karlsson et al. (2014) investigated historical trends in precipitation and stream discharge at the Skjern River catchment in western Denmark using 133 years of data for precipitation, temperature, evapotranspiration and discharge. They examined the degree of change in discharge relative to change in climatic variables using the non-parametric Mann–Kendall test and the hydrological model NedborAfstromnings (NAM). They found that over the study area, a 26% change in precipitation and a 1.4^{0}C temperature change were evident thus demonstrating high non-stationarity of the climatic setting. Their study noted that these changes contributed to a 52% increase in river discharge. They concluded that hydrological models cannot be expected to predict climate change impacts on discharge as accurately in the future, compared to the performance under present conditions.

Ficklin et al. (2016) studied the impacts of recent climate change on trends in baseflow and stormflow in United States watersheds. Using daily streamflow (1980 to 2010), they derived baseflow and stormflow for 674 sites in the United States. They analyzed the associations of these attributes with precipitation, potential evapotranspiration, and maximum/minimum temperature at monthly and seasonal time scales using Mann-Kendall non-parametric trend test. Their findings reveal that spatial variation in trends of natural baseflow and stormflow were largely as a result of recent trends in climate as an increase in precipitation led to an increase in baseflow or stormflow and vice versa. They observed consistent negative and positive trends in baseflow and stormflow respectively for the northeastern and southwestern United States. They further noted that whereas baseflow increased notably during fall and winter in the northeast, stormflow decreased during all seasons in the southwest and that trends elsewhere and at other times of the year were more variable but still associated with changes in climate.

Birsan et al. (2005) analyzed trends in annual and seasonal streamflow records from 48 watersheds in Switzerland. They applied the Mann–Kendall test on three time periods (1931–2000, 1961–2000, 1971–2000). They correlated the identified trends in streamflow with changes in precipitation and air temperature and together with watershed attributes using Spearman's correlation. Their study found rising trends in annual runoff, seasonal runoff, winter maximum streamflow and in spring and autumn moderate and low flows. However, their study revealed that changes in precipitation were not sufficient to explain the observed trends in streamflow. They noted that streamflow trends were rather strongly associated with basin properties such as elevation, glacier and rock coverage and soil depth.

In their study on the impact of climate change on global river flow, Falloon & Betts (2006) used the the Hadley Centre General Circulation Model to predict changes in global river flow under the IPCC SRES A1B and A2 scenarios. Their findings indicate that global total river flow will increase by 4–8% during the 2071–2100 period relative to 1961–1990, but with some notable regional differences, such as, large increases in river flow in boreal regions and western Africa, and large decreases for southern Europe and North Africa. They also note that changes in the seasonality of river flow may occur, such as earlier peaks in spring runoff in boreal rivers due to earlier snow melt. Their simulations generally reveal large increases in monthly maximum flow and decreases in monthly minimum flow, although the increases in the former might be larger. They conclude that climate change is likely to increase the occurrence of both high and low flows, although the increased peak flows could be dominant.

Zhao et al. (2014) conducted a study to quantify the impact of climate variability and human activities on streamflow in the middle reaches of the Yellow River basin in China. They applied Mann–Kendall test and Pettitt's test to characterize the trends and abrupt changes of hydro-climatic variables as well as streamflow data taken over the period from the 1950s to 2010. They observed significant decreases in annual streamflow and precipitation whereas temperature showed positive trends. Furthermore, they used Budyko's curve (a simple water balance model) and linear regression to evaluate the potential impacts of climate variability and human activities on mean annual streamflow. Their findings show that climate variability had a greater effect on the streamflow reduction in the major rivers whereas human activities such as soil and water conservation projects, operation of dams and reservoirs, and water consumption, accounted for more of the streamflow declines in other tributaries.

The relationship of Streamflow-Precipitation-Temperature in the Yellow River Basin of China was studied by Yang, Yan, & Liu (2012). They used Mann-Kendall method to analyze trends in natural runoff and observed streamflow, as well as monthly precipitation and air temperature of the basin for the period 1961-2000. They applied the Geostatistical Analyst module of ArcGIS 9.3 to plot the quantitative Streamflow-precipitation-temperature relations. Besides detecting a change in natural streamflow in 1991, their findings revealed notable declines in precipitation and increments in temperature for majority of stations in the basin. Their findings further suggested that streamflow responded differently to various extents of precipitation and air temperature and that generally, the index of precipitation elasticity to streamflow was estimated to be 1.95 over the period. They concluded that both precipitation decrease and temperature increase were responsible for the streamflow decline of the Yellow River.

Li et al., (2007) conducted a study to assess the impact of climate variability and human activities on streamflow from the Wuding River basin in China. They employed the non-parametric Mann–Kendall–Sneyers rank test to detect trends/changes in annual streamflow for the period of 1961 to 1997 after which they measured the sensitivity of annual streamflow to precipitation and potential evaporation and constructed relationships between annual streamflow and precipitation. Their findings revealed a significant downward trend in annual streamflow with an abrupt change detected in 1972. Annual streamflow reduced by 42% between 1972 and 1997 while flood-season streamflow declined by 49%. Their results also showed that streamflow regime of the catchment reduced by 31% for most percentile flows except for low flows which recorded a 57% reduction. Overall, changes in precipitation and potential evaporation accounted for 13% reduction in total mean annual streamflow whereas soil conservation measures accounted for the remaining 87%.

The impacts of climate change on hydrological regime and water resources management of the Koshi River Basin in Nepal were investigated by Devkota & Gyawali (2015). They used two Regional Climate Models (RCMs) and the calibrated SWAT model to simulate future climatological (A1B Scenario) and hydrological impacts respectively. Their results on future projections showed a decrease in the long term monthly flow by more than 30% in the drier months and an increase by more than 25% in the peak flow months when compared to the baseline values. These results suggest a shift of the peak monthly flow under projected future conditions. In general, their findings relayed that climate change was less likely to pose a major threat to average water availability although temporal flow variations were expected to increase in the future. They noted that the magnitude of projected flow for given return periods, however, strongly depends on the climate model considered. They concluded by stating that flow decreases during the wet season and increases during the peak flow season.

Kibria *et al*. (2016) analyzed streamflow trends and responses to climate variability and land cover change in South Dakota in the United States. They evaluated trends in high, moderate, and low streamflow as well as observed rainfall data for selected watersheds for the period 1951–2013 using a modified Mann-Kendall test. In addition, they applied the elasticity coefficient to examine the sensitivity of streamflow to variation in rainfall and land cover. Their results show significant increasing trends in annual streamflow for most of the gauging stations. They found that about half of the streams exhibited significant positive trends in low flow (1-day minimum and 7-day minimum flow) and moderate flow (median daily and daily average flow) conditions compared to peak flow (1-day maximum flow and 7-day maximum flow) conditions. They also observed that half of the rainfall stations showed slight increasing trends in annual rainfall. Their findings from elasticity analysis revealed that streamflow was highly influenced by rainfall with a 10% increase in annual rainfall resulting in 11%–30% rise in annual streamflow for most streams.

Aich *et a*l. (2014) studied the impacts of climate change on streamflow in four large African river basins Niger, Upper Blue Nile, Oubangui and Limpopo. They compared trends in mean discharges, seasonality and hydrological extremes for the 21st century. They employed the Eco-hydrological model SWIM (Soil and Water Integrated Model) for streamflow measurements, and an ensemble of Coupled Model Intercomparison Project Phase 5 (CMIP5) models for climate impact assessment in Africa using Representative Concentration Pathways (RCPs) scenarios of 2.6 and 8.5. They found evidence of climate change impact for mean discharges and also for extremes in high and low flows. With regard to future changes in quantity and seasonality of streamflow, they reported that the most extreme changes in discharge were likely to happen in the Upper Blue Nile catchment. However, they noted an unclear direction and magnitude of trend for the Niger and Limpopo basins as well as insignificant impacts on the Oubangui River. Overall, they concluded that there was a tendency for increased streamflows in all river basins with the exception of Oubangui.

Taye, Ntegeka, Ogiramoi, & Willems (2011) investigated the potential impact of climate change on hydrological extremes in two source regions of the Nile River Basin, namely Nyando River and Lake Tana catchments. They used 17 GCMs to simulate rainfall and potential evapotranspiration under two future climate change (emission) scenarios A1B and B1 after which two conceptual hydrological models VHM (Veralgemeend Conceptueel Hydrologisch) and NAM were calibrated and used for the impact assessment. Their results revealed increasing mean runoff and extreme peak flows for Nyando catchment for the 2050s while unclear trend was observed for Lake Tana catchment for mean volumes and high/low flows. They however , noted that the hydrological models for Lake Tana catchment performed better in simulating the hydrological regimes than for Nyando therefore inducing a difference in the reliability of the extreme future projections for both catchments.

Adem *et al*. (2016) examined basin-level impact of climate change on streamflow in the upper Gilgel Abay catchment of the Blue Nile basin in Ethiopia. By taking 1961 to 1990 as a baseline period, they applied a statistically down scaled global climate model HadCM3 to study future impacts of climate change for the periods of 2020s, 2050s and 2080s based on A2 (medium–high) and B2 (medium–low) emission scenarios. They also performed an impact assessment on streamflow using the soil and water assessment tool (SWAT) hydrological model. Their results predicted a systematic increase in precipitation and temperature for all future time periods for both A2 and B2 scenarios. These increases in climate variables was expected to increase mean annual streamflow by 7.1, 9.7, and 10.1 percent for A2 scenario and by 6.8, 7.9, and 6.4 percent for B2 scenario for 2020s, 2050s, and 2080s, respectively.

Ma et al. (2010) conducted a study on the impact of climate variability and human activity on streamflow decrease in the Miyun Reservoir catchment in China using historical records of 1953-2005. Climate variability was expressed in terms of changes in precipitation and temperature whereas human activity was estimated as direct withdrawal (abstraction) of water from the river and indirect impact due to man-made changes in land use and vegetation in the upstream of the reservoir. They used a geomorphology-based hydrological model and a climate elasticity model to conduct a quantitative assessment of the impact of the two factors on the inflow into the reservoir. It was found that annual streamflow in the reservoir had decreased significantly over time. Their results showed that climate impact was accountable for slightly more than half of the decrease in reservoir inflow. Their findings also revealed that direct and indirect impact of human activity accounted for 23% and 18% of the decrease in reservoir inflow respectively.

In a study on the implication of climate change and variability on the river flow within the traditional irrigation farming system in Iringa region in Tanzania, (Kassian et al., 2017) employed a mixed study approach. They collected primary data from 189 farmers through questionnaires and also obtained secondary data on monthly rainfall and river flow for the period 1997-2014. They applied Mann–Kendall’s test and linear regression to analyze long-term annual trends of rainfall and river flow. They found a significant decreasing pattern in historical rainfall and a slight decline in river flow during the past 17 years. Their study relayed that a decline in river flow, combined with rainfall fluctuations, forced farmers to employ various adaptation strategies such as increasing the depth of water wells in the fields and diverting the river through water channels to the fields.

Kigobe & Griensven (2010), investigated the hydrological response of Mpologoma basin within the upper Nile to changes in climate. They used statistical downscaling techniques for climate projections with particular emphasis on rainfall simulation for the Lake Kyoga basin while employing Generalised Linear Models (GLMs). They also used the SWAT semi-distributed hydrological model to examine sensitivity of streamflow to changes in climate. They observed that having corrected for bias, simulations from the model indicate major shifts in hydrological regimes, with a tendency of significantly higher monthly average flows and higher evapotranspiration rates which may subsequently lead to variation in the timing of floods and droughts. Their findings generally suggest that a warmer climate would lead to a basin-wide increase in rainfall and subsequent increase in streamflows for the Mpologoma basin in the near future (2050s) and far future (2080s). They also did not consider stream flow percentiles and quartiles in their study.

2.5. Summary of literature

Various studies have been reviewed empirically of which most assessed trends in river flow and climatic factors such as precipitation and temperature. They further examined the impact of climatic factors on river discharge both at catchment and basin scales. Majority of these studies employed hydrological and/or statistical modelling techniques. Examples of statistical methods used were: trend analysis using Mann–Kendall and Pettitt tests; correlations, lagged cross correlations, regression analysis, generalised linear models and elasticity coefficient to investigate the relationship between streamflow and rainfall. Hydrological models used included SWAT, SWIM, NAM, MIKE, among others which were all driven by scenarios based on climate model simulations. Generally, these studies focused vastly on large scale basins and catchments where they reported mixed conclusions. Some reported statistically significant links between stream flow and climatic variables (Tumusiime and Ageet, 2018; Arora et al., 2014; Hameed et al., 2017; Karlsson et al., 2014; Kibria et al., 2016; Ma et al., 2010). Other studies however, found no association between river discharge and climatic predictors (Birsan et al., 2005; Devkota and Gyawali, 2015). Further still, some studies projected declines in stream flow in the future (IPCC, 2008; Kigobe and Griensven, 2010) whereas others predicted significant rise in streamflow under future climate scenarios (Bates et al., 2008; Taye et al., 2011; Adem et al., 2016).

CHAPTER THREE
METHODOLOGY

3.1. Study area

Mpologoma River catchment (Figure 3.1) is part of Lake Kyoga Water Management Zone (basin) which is one of the eight major surface water basin delineations for Uganda. The catchment is of intermediate type and covers an area of about 8,996 square kilometeres both land and water. The catchment is characterized by the presence of Mount Elgon (4,321 masl) at the extreme northeast corner of the catchment, where the steepest slopes are found and a few extinct volcanoes and ridges along its southern and eastern rim at lower elevations along the border with Kenya. The altitude of the remainder of the catchment is betw een 1,033 m and 1,150 m above sea level, with the latter being the mean altitude of Lake Kyoga. Most wetlands in the catchment are located in this relatively flat area. The main rivers in the Mpologoma catchment are: Rivers Manafwa and Namatala flowing from the North-Eastern side of the catchment; River Malaba flowing from the Southern slopes of Mount Elgon; and Rivers Kimbimba and Naeombwa flowing from the south to the lower part of the catchment (Mugume et al, 2017).

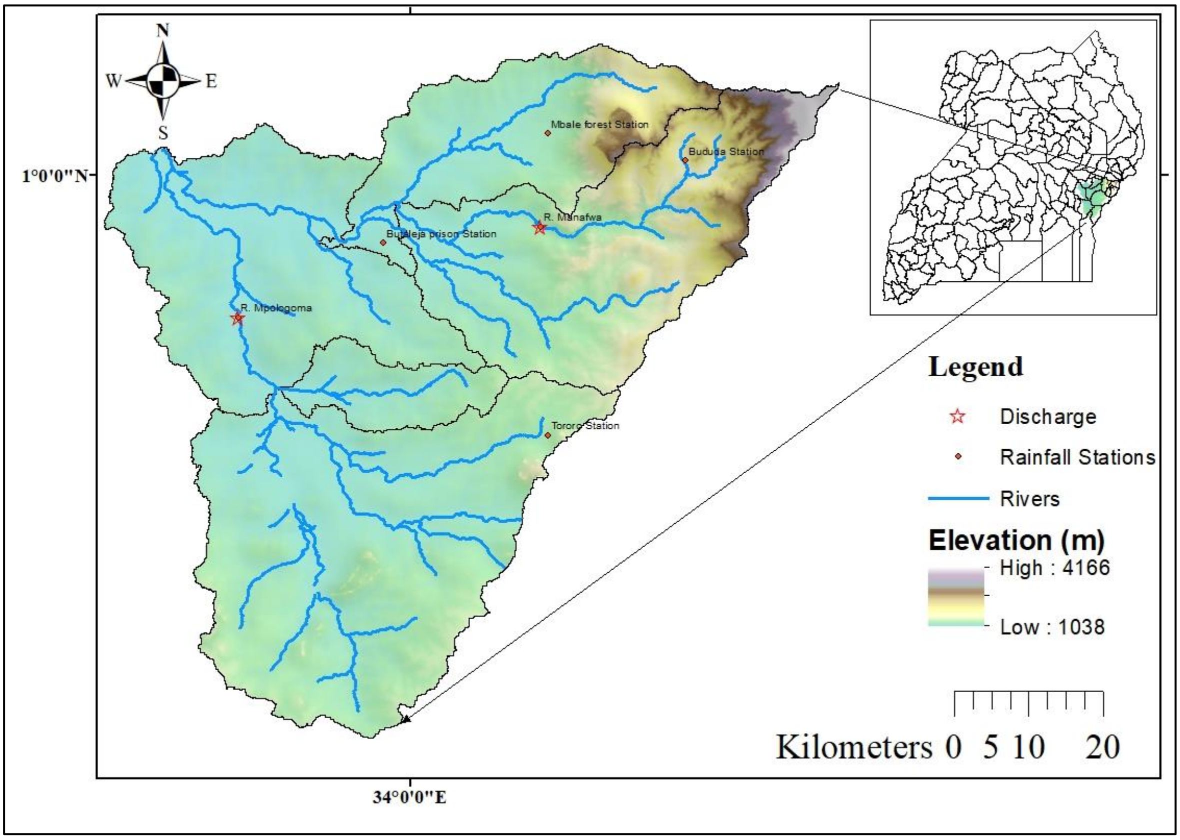

Figure 3.1: Location map of Mpologoma River catchment

The catchment is located in Eastern Uganda, between 0.53 and 1.17 degrees North and between 33.59 and 33.75 degrees East and drains over 10 districts. Most of the catchment is classified as “dry sub-humid” and is characterized by moderate water surplus during the rainy seasons, while water deficits occur during the dry season (MWE, 2013). Rainfall distribution in the region is bimodal, allowing two cropping seasons annually. There is a first rainy season from March, April to May (MAM) and a second one from September, October to November (SON). On average, the catchment receives about 1,472 mm of rainfall annually, with a runoff and evapotranspiration of 64 m^3/s and 1,354 mm respectively. Rainfed agriculture and livestock grazing are the most wide spread activities in the catchment, covering half of the total land area. Most cultivation is done by smallholders of whom a large majority are rural and directly dependent on agriculture. Rice is the most important crop in the wetlands although maize is also coming up as a key crop especially in Butaleja, Namutumba and Iganga districts. Only two formal irrigation schemes, namely Kimbimba and Doho, are currently operating in the catchment albeit informal small-scale irrigation is also rising (Verdonck & Michel, 2016).

3.2. Source of data

Daily rainfall satellite observations for Butaleja, Bududa, Tororo and Mbale meteorological stations (Table 3.1) spanning the period 1981 to 2015 were obtained from open data portal of National Aeronautics and Space Administration (NASA) under the Prediction Of Worldwide Energy Resources (POWER) project (https://power.larc.nasa.gov/data-access-viewer/). The data were downloaded at a spatial resolution of 0.5° latitude x 0.5° longitude. The rainfall observations are mean daily values of the long-term climatologically averaged estimates derived from the Global Modelling and Assimilation Office (GMAO) Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) assimilation model products (Rienecker et al., 2011). These satellite and model-based products have been shown to be accurate enough to provide reliable meteorological resource data over regions where surface measurements are sparse or non-existent (Ashouri et al., 2016).

Table 3.1: Hydrological and meteorological stations used in the study

Station type	Name (ID) of station	Longitude (^{0})	Latitude (^{0})	Elevation (m)
Hydrological	R. Mpologoma at Budumba (82217)	33.790278	0.826944	1062
	R. Manafwa at Mbale - Tororo Rd (82212)	34.157778	0.936944	1122
Meteorological	Tororo met. station (89340190)	34.166667	0.683333	1176
	Mbale forest station (88340530)	34.166667	1.050000	1121
	Butaleja prison (89330280)	33.966667	0.917000	1087
	Bududa agricultural station (88340560)	34.333333	1.017000	1297

Daily average flow data for the same time period for R. Mpologoma and R. Manafwa gauging stations (Table 3.1) were acquired from the Ministry of Water and Environment (MWE) database through the Directorate of Water Resources Management (DWRM). The stations above were selected to represent the catchment as they had less than 10% missing data, a criteria recommended by World Meteorological Authority (WMO) for hydro-meteorological studies.

3.3. Definition of variables

Stream flow, also known as discharge is defined as water flow within a river channel. In this study, three characteristics of stream flow were investigated namely: low flow, average flow and peak flow. Low flow is the water in a stream during prolonged dry weather, or the smallest sustained average daily flow rate or volume with time (Aseffa &Moges 2018) (WMO, 2010) whereas peak flow is maximum discharge during the period of runoff caused by heavy rainfall or flood event (Bamutaze et al., 2014). Average flow is the mean flow of an individual period of a stream or river. Stream flow is known to vary at monthly, seasonal and annual scales (Ashraf et al., 2020). Stream flow in this study was defined in mainly in two ways, namely: 1) Exceedance percentiles that measure the magnitude of flow; 2) Flow duration statistics which estimate the duration of continuous low flow or peak flow events (Smakhtin, 2001; Stogner, 2000).

The notation for the former is Q_p which is interpreted as the flow discharge that is possibly exceeded p-percent of the time and is calculated as the $(100-p)^{th}$ percentile of daily-mean stream flow. The latter measure is denoted by $Q_{\text{n-stat}}$, which is interpreted as *n*-day stream flow and is computed by averaging daily-mean discharge for *n*- consecutive days (where *n* can be 7 or 14 or 30). Peak flows and low flows are used in assessing the risk of floods and droughts respectively (Aich et al., 2014). The most widely used low flow metrics **are** $Q_{7\text{min}}$, Q_{90} and Q_{95}. Peak flow on the other hand is usually expressed as $Q_{7\text{max}}$, Q_{10} and Q_5. The exceedance percentiles Q_{90} and Q_{10} are robust indicators for low flow and peak flow respectively. The values are interpreted as flow discharge which is exceeded 90% and 10% of the time respectively. Average flow is computed as Q_{50} which indicates the flow that is exceeded 50% of the time (Pyrce, 2004). The variables used in this study are listed in table 3.2 below.

Table 3.2: Variables used in the study

Regime	**Variable**	**Definition**	**Unit of measurement**
Low flow	$Q_{7\text{min}}$	7-day minimum flow duration	m^3s^{-1}
	Q_{90}	Low flow exceedance (90th) percentile	m^3s^{-1}
Peak flow	$Q_{7\text{max}}$	7-day maximum flow duration	m^3s^{-1}
	Q_{10}	Peak flow exceedance (10th) percentile	m^3s^{-1}
Average flow	$Q_{7\text{mean}}$	7-day mean flow duration	m^3s^{-1}
	Q_{50}	Median flow exceedance (50th) percentile	m^3s^{-1}
Rainfall	R	Total volume (amount) recorded	Mm

Definitions cited from Smakhtin (2001); Stogner (2000) , Pyrce (2004)

3.4. Data preparation and processing

3.4.1 Missing data estimation and homogeneity test

Missing data presents a major challenge in hydro-meteorological studies. Filling missing gaps in data is needed to generate continuous time series that can be used in analyses. Some of the methods suggested in recent studies to overcome this challenge include the: Artificial Neural Networks (ANN) based on temporal and spatial auto-correlation (Wambua et al., 2016); interpolation, extrapolation and Inverse Distance Weighting (IDW) conventional techniques (Egeru et al., 2019; Jiang, Bamutaze, & Pilesjö, 2017); and a combination of regression and auto regressive modeling techniques that take advantage of neighboring stations (Tencaliec et al., 2015).

In the current study, there were no gaps in rainfall time series. However, some gaps (<10%) were present in stream flow data. This study employed regression analysis technique in filling gaps in discharge data as suggested by Tencaliec et al., (2015). Pairwise correlations of daily streamflow observations were computed between the target station (R. Mpologoma gauge) and the neighbouring station (R. Manafwa gauge) using periods where data were available for both stations. The two gauging stations are in close proximity and have similar topography, climate, soil type, geology, vegetation cover and land use (MWE, 2013). Having established evidence of a significant relationship, a least-squares linear regression model was fitted between the two stations' streamflow observations. The fitted regression equation was then used to estimate missing discharge data for the target station by extrapolation method.

Rainfall and discharge series were thereafter tested for homogeneity. Hydro-meteorological data often tend to exhibit trends or sudden jumps in the mean or variance over time as a result of changes in observing site, observing equipment and observing procedures hence the need to test for homogeneity (von Storch & Zwiers, 2003). Any conclusions drawn from analyzing such data may thus be biased. The study used Petit test (Pettit, 1979) to detect departures from homogeneity in the rainfall and discharge series. The test works by locating the time where a break or change point occurs in the series**.**

3.4.2 Calculating average catchment rainfall

In order to obtain rainfall that is representative of catchment-wide variations, it is necessary to compute the average catchment rainfall from the available stations. There are three conventional methods that are suggested for estimating catchment rainfall, namely**:** mean arithmetic, Thiessen polygon and isohyetal method. Studies have shown that these methods do not show much variation in estimating catchment rainfall and therefore non of the methods is superior over the others (Balany, 2011; Bhavani, 2013). This study applied the arithmetic mean method to compute average rainfall for R. Mpologoma catchment. Monthly rainfall totals of four stations were used, namely: Tororo, Mbale, Butaleja and Bududa. This method yields good results only when rainfall stations in the catchment area are uniformly distributed and the individual station rainfall values do not vary widely. It is given by the equation below

$$R_m = \{(R_1 + R_2 + \cdots + R_n)/n\} \qquad \text{.Eqn. (3.1)}$$

where R_m is the value of mean rainfall over the catchment area; R_1, R_2,….., R_n are the rainfall values at respective stations in a given period; n is number of stations within the catchment area. The computed average monthly rainfall was then used to obtain the seasonal and annual rainfall for the catchment across the study period.

3.5. Data analysis

3.5.1 Determining the trend in streamflow for Mpologoma river catchment

Streamflow characteristics namely low flow, average flow and peak flow were summarized using descriptive statistics, namely mean, median, standard deviation, coefficient of variation and skewness. Time series plots superimposed with trend lines were used to detect potential trends in the streamflow statistics (exceedance percentiles and flow duration). Trends in annual as well as seasonal streamflow statistics were evaluated for the period 1981–2015 using a non-parametric test known as Mann-Kendall test. The test investigates the null hypothesis that the data come from a population with independent realizations and are identically distributed (no trend); against the alternative hypothesis that the data follow a monotonic trend. The Mann-Kendall test statistic is given by:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k) \qquad (3.2)$$

Where *n* is the number of observations; x_i and x_k are sequential data values for the i^{th} and k^{th} observations respectively; sgn (ɵ) is the sign function which can be defined as follows:

$$sgn(\theta) = \begin{cases} 1 \ if \ \theta > 0 \\ 0 \ if \ \theta = 0 \\ -1 \ if \ \theta < 0 \end{cases} \qquad (3.3)$$

The Mann-Kendall test has two parameters that are important for trend detection. These are Kendall's correlation coefficient **(τ)** and significance **(p).** The former shows the direction, strength/ magnitude of the trend where positive and negative values of τ indicate increasing and decreasing trend respectively; and the latter checks whether the trend is statistically significant (at α significance level) by comparing the *p*-value of the test statistic with α.

3.5.2 Investigating the relationship between rainfall and streamflow in R. Mpologoma catchment

Pairwise correlation was used to determine the strength of linear relationship between streamflow and rainfall by employing Pearson product-moment correlation as shown below:

$$r = \frac{\sum_{t=1}^{T}(Q_t - \overline{Q})(R_t - \overline{R})}{\sqrt{\sum_{t=1}^{T}(Q_t - \overline{Q})^2 \sum_{t=1}^{T}(R_t - \overline{R})^2}} \qquad (3.4)$$

where *r* = sample correlation coefficient that measures the strength of relationship between streamflow and rainfall; Q_t is discharge at time *t* with arithmetic mean $\overline{Q}$ and R_t is rainfall at time *t* with mean $\overline{R}$; *T* is the length of time period under study. By letting the population correlation to be denoted by ρ, the hypothesis that the correlation is significantly different from zero (H_0: $\rho = 0$) was tested at α level of significance. The null hypothesis H_0 was rejected on condition that the associated probability value is less than α.

Streamflow statistics that correlated strongly with rainfall at bivariate level of analysis were transformed by taking their natural logarithms. Logarithmic transformation is known to remove trends and can be used to make highly skewed distributions less skewed. In other words, it helps in realizing normality and stationarity of variables and also generates the desired linearity in parameters. The practical advantage of the natural logarithm is that the interpretation of the regression coefficients is straightforward (Wooldridge, 2009).

The study adopted regression analysis of time series data using Ordinary Least Squares (OLS) method of estimation. There are majorly two time series regression models commonly used in empirical time series analysis namely, static model and finite distributed lag (FDL) model. The static model measures contemporaneous relationship between two time series variables, i.e. the immediate effect on a given variable as a result of a change in the other at time t. In a FDL model, one or more predictor variables are allowed to affect the dependent with a lag. Both models are easily estimated by ordinary least squares (Wooldridge, 2009).

In order to measure the static effect of rainfall on streamflow, the static regression model was applied on the transformed streamflow series. The static model was preferred over the FDL model since the latter is more applicable when modeling the relationship between daily rainfall and daily streamflow (Kamruzzaman et al., 2014). The resulting log-linear regression model is given by Equation 3.6 below. The individual coefficients measure the percentage change in streamflow per unit change in rainfall at a particular time.

The static model relating original streamflow (Q) to rainfall (R) is

$$Q_t = \beta_0 + \beta_1 R_t + u_t \qquad t = 1,2,\ldots,n \tag{3.5}$$

The static model relating log-transformed streamflow to rainfall is

$$ln(Q_t) = \beta_0 + \beta_1 R_t + \varepsilon_t \qquad t = 1,2,\ldots,n \tag{3.6}$$

Where Q_t = Low flow or average flow or peak flow in m^3/s at time t; R_t = Rainfall volume in mm at time t; β_0 = intercept/constant; β_1 = regression coefficient to be estimated; it measures the immediate percentage change in streamflow given a one-mm increase in rainfall at a given time t; ε_t = random error term. The model assumes that: ε_t is normally distributed with zero mean and constant variance; ε_t is uncorrelated with the explanatory variables; and that errors in two different time periods are uncorrelated. These Classical Linear Model (CLM) assumptions were checked by running diagnostic tests on the estimated model residuals.

3.5.3 Projection of streamflow for R. Mpologoma catchment in the near future

Global Climate Models (GCMs), representing numerous atmospheric processes of the global climate system, are the main tools to estimate future climate patterns, and study likely changes in precipitation and temperature patterns. The spatial resolutions of GCMs range from 100–500 km in grid size with a temporal resolution of daily, monthly or a longer time step. Hence, they are not able to represent local scale features such as, local topography, land use and clouds as their outputs are at a relatively coarse spatial resolution (Kaini et al., 2019). Hydrological assessment of climate change impacts requires climate data at finer spatial scales, which limits direct use of GCM outputs at catchment level. However, GCM outputs can be used to generate climate data at a finer scale to represent local climatic conditions through a process known **as** downscaling.

The process used to reduce the scale of any information finer than 100 × 100 km^2 scales (spatially) and shorter than monthly values is called downscaling, and it assumes that the local climate is a combination of local conditions and large-scale atmospheric features. Downscaling future climate data can be done statistically or dynamically (Attique, 2018). Dynamic techniques are based on the links between the climates of small and large scales whereas statistical downscaling methods use relationships between locally observed weather variables and atmospheric variables at large scale. The latter is usually preferred because it derives local scale data from larger scale using random and or deterministic functions (Salathe et al., 2008).

There are many approaches that have been put forward by previous scholars for making climate projections with high resolution downscaled data. (Skamarock & Klemp, 2008) and (Done et al., 2004) advocate for the Weather Research and Forecasting (WRF) model in predicting numerical weather observations for short-term, mid-century and end-century time periods. The model simulates small-scale atmospheric weather at relatively higher resolution and has the ability to capture climate extremes, but its schemes have been found to underestimate seasonal rainfall amount over Uganda (Mugume et al., 2017). One other suggested approach is the Coordinated Regional Downscaling Experiment (CORDEX), a project of the World Climate Research Program aimed at coordinating the science and application of regional climate downscaling models and techniques (Giorgi & Gutowski, 2015)

Future rainfall data for four meteorological stations in R. Mpologoma catchment (Table 3.1) were extracted from the CORDEX program under two climate scenarios Representative Concentration Pathways 4.5 and RCP 8.5. CORDEX has been widely used by other researchers including (Oti et al., 2020; Negewo & Sarma, 2021; Onyutha, 2021) because it is statistically downscaled and bias corrected. CORDEX also provides an opportunity for generating high resolution climate projections which are important for assessment of future impacts of climate change (Kisembe et al., 2019). The output data were accessed via the Earth System Grid Federation (ESGF) web portals as an ensemble mean of simulations from ten Regional Climate Models (RCMs) (Table 3.3). They comprised of daily rainfall (mm/day) for the period 2021-2040 at a spatial resolution of 0.44° x 0.44° that corresponds to a horizontal and vertical distance of about 50 square km.

The RCMs within the CORDEX framework have been shown by Kisembe et al. (2019) to ably reproduce the space-time variability of inter-annual and seasonal rainfall over Uganda while properly capturing the unimodal and bimodal distributions of the annual cycle over the north and south parts of the country respectively. However, it was noted that the models underestimate the mean annual and MAM seasonal rainfall over the country, but overall, the ensemble mean of the CORDEX RCMs reproduces the rainfall climatology over Uganda with reasonable skill.

Table 3.3: The list of RCMs used to simulate future rainfall

Acronym	**Centre of research**	**RCM**
BCCR-WRF331	Uni Research and the Bjerknes Centre for Climate Research	WRF331
CCCma-CanRCM4	Canadian Centre for Climate Modelling and Analysis (Canada)	CanRCM4
CLMcom-CCLM4-8-17	CLM community	CCLM4-8-17
CNRM-ALADIN52	Centre National de Recherches Météorologiques (France)	ALADIN52
DMI-HIRHAM5	Danmarks Meteorologiske Institut (Denmark)	HIRHAM5
KNMI-RACMO22T	Koninklijk Nederlands Meteorologisch Instituut (Netherlands)	RACMO22T
MOHC-HadRM3P	Met Office Hadley Centre (UK)	HadRM3P
MPI-CSC-REMO2009	Max Planck Institute (Germany)	REMO2009
SMHI-RCA4	Sveriges Meteorologiska och Hydrologiska Institut (Sweden)	RCA4
UQAM-CRCM5	Université du Québec à Montréal (Canada)	CRCM5

Source: Kisembe et al. (2019)

The process of producing downscaled rainfall projections using CORDEX involved two steps: The first step involved running GCMs for a base period (1981–2010) using observed/ natural and anthropogenic forcings such as green-house gas (GHG) concentration. This was followed by a transient future climate simulation for the period 2021–2040 using scenarios of time-evolving GHG concentrations known as Representative Concentration Pathways (RCPs). The RCPs predict possible global future climate scenarios based on the level of GHG concentration (CO_2, CH_4, N_2O, etc.) and represent the range of radiative forcing values by the year 2100 (IPCC, 2014). The RCPs used in the study and their corresponding radiative forcing along with a CO_2- equivalent concentration in 2100 are summarized in Table 3.4.

Table 3.4: Description of RCP scenarios used in the study

RCP	**Description**
RCP4.5	Total radiative forcing is stabilized without overshoot to 4.5 W/m^2 (580–720 ppm CO_2-equivalent) before 2100 by employing a range of technologies and strategies for reducing GHG emissions.
RCP8.5	Rising radiative forcing to 8.5 W/m^2 (>1,000 ppm CO_2-equivalent) by 2100. It is characterized by increasing GHG emissions over time leading to high GHG concentration levels.

Source: IPCC (2014) CO_2: Carbon-dioxide W/m^2: Watts/square meter ppm: Parts per million

One lower end stabilization scenario RCP4.5, and one high emission scenario RCP8.5, were selected to be used in this study as they cover the entire range of stabilization and high emission scenarios. For each RCP scenario, the projected daily rainfall for the four stations in the study area was aggregated into annual and seasonal (MAM, SON) totals after which the arithmetic mean method was used to estimate the average catchment rainfall for the period 2021-2040. By inputting the downscaled rainfall data into the estimated regression models, projections were made for low flow, average flow and peak flow for the period 2021-2040 by extrapolation. The effect of the natural logarithm ($\ln(x)$) was removed by computing the exponent (e^x) of the predicted flow values.

The projected streamflow values were summarized using descriptive statistics and line plots were used to explore patterns in the forecasted series under both climate scenarios. In order to determine by how much streamflow will change in the catchment in the near future, the averages of the streamflow characteristics were compared between the study period (1981-2015) and future period (2021-2040) using Mann-Whitney *U-t*est to check for statistical differences. Mann-Whitney *U*-test also called the Wilcoxon rank-sum test (Mann & Whitney, 1947) is used to test the null hypothesis that two independent samples (groups) have the same distribution (also expressed as: the medians of two independent samples are not different). The test is non-parametric and hence does not require large normally distributed samples. All the analyses stipulated above were run using STATA version13.

CHAPTER FOUR
RESULTS

This section presents the results that were obtained using the methods described in the previous chapter. The findings are presented per specific objective of the study.

4.1 Trend in streamflow over Mpologoma River catchment

The results from descriptive analysis (Table 4.1) show that over the study period, River Mpologoma catchment on average recorded 4.0 m^3s^{-1}, 7.3 m^3s^{-1} and 8.7 m^3s^{-1} as the annual, Mar-May (MAM) and Sep-Nov (SON) low flow percentiles respectively. In regard to low flow duration, the catchment recorded 3.3 m^3s^{-1}, 6.2 m^3s^{-1} and 5.7 m^3s^{-1} as the annual, MAM and SON 7-day low flow on average. In regards to variation, majority of the low flow statistics exhibited a high degree of variability (CV > 60%). Generally, the low flow statistics were found to be relatively normally distributed (skewness < 1).

Table 4.1: Summary of streamflow statistics (in m^3/s) at Mpologoma River gauge station over the period 1981-2015

Streamflow (*No. of obs. = 35*)			**Min.**	**Max.**	**Median**	**Mean ± SD**	**CV (%)**	**Skewness**
Low flow	Annual	Q_{7min}	0.11	8.79	2.96	3.3 ± 2.15	64.9	0.465
		Q_{90}	0.10	9.48	3.46	4.0 ± 2.75	68.3	0.410
	MAM	Q_{7min}	0.11	12.83	6.77	6.2 ± 3.73	59.8	0.081
		Q_{90}	0.02	18.06	5.09	7.3 ± 5.53	75.7	0.351
	SON	Q_{7min}	0.12	14.77	5.40	5.7 ± 3.87	67.4	0.553
		Q_{90}	0.58	19.92	8.60	8.7 ± 5.88	67.5	0.199
Average flow	Annual	Q_{7mean}	6.34	43.83	20.94	21.5 ± 10.97	51.0	0.425
		Q_{50}	5.50	39.57	14.75	17.7 ± 09.62	54.3	0.781
	MAM	Q_{7mean}	7.76	67.39	26.51	29.2 ± 17.49	59.8	0.660
		Q_{50}	8.12	47.31	15.83	20.5 ± 11.71	57.0	1.036
	SON	Q_{7mean}	7.31	71.80	23.49	28.8 ± 17.48	60.6	0.808
		Q_{50}	7.85	61.69	22.01	26.6 ± 15.69	59.0	0.674
Peak flow	Annual	Q_{7max}	15.60	145.52	48.09	60.4 ± 30.97	51.2	0.669
		Q_{10}	16.18	110.18	43.29	46.2 ± 23.46	50.7	0.817
	MAM	Q_{7max}	15.59	124.36	39.11	50.3 ± 31.71	63.0	0.893
		Q_{10}	15.54	110.40	37.82	46.7 ± 28.78	61.7	1.118
	SON	Q_{7max}	16.82	145.52	51.06	56.1 ± 30.81	54.9	0.803
		Q_{10}	16.38	110.18	34.73	43.1 ± 25.95	60.3	1.041

CV: Coefficient of Variation *SD: Standard deviation*

The results further show that over the study period, the catchment recorded 17.7 m^3s^{-1}, 20.5 m^3s^{-1} and 26.6 m^3s^{-1} as the annual, MAM and SON median flow respectively. For average flow duration, the catchment recorded 21.5 m^3s^{-1}, 29.2 m^3s^{-1} and 28.8 m^3s^{-1} as the annual, MAM and SON 7-day mean discharge on average. In regard to variability in the average flow statistics, the 7-day mean flow duration for the SON season showed the highest variability (CV=60.6%) whereas the MAM median flow was found to be the most highly skewed (skewness = 1.036). Other average flow statistics exhibited moderate skewness.

Furthermore, the results indicate that over the study period, River Mpologoma catchment on average recorded 46.2 m^3s^{-1}, 46.7 m^3s^{-1} and 43.1 m^3s^{-1} as the annual, MAM and SON peak flow percentiles respectively. In regard to peak flow duration, the catchment recorded 60.4 m^3s^{-1}, 50.3 m^3s^{-1} and 56.1 m^3s^{-1} as the annual, MAM and SON 7-day peak flow on average. It was also observed that the seasonal peak flow statistics were highly variable (CV > 60%) and highly skewed (skewness > 1) compared to the annual peak flow statistics.

A plot of 7-day low flow against time for the MAM season shows a negative trend whereby a steady decline was observed in the low flow duration statistic with near-zero discharge recorded in 1984, 1992 and 1998 (Figure 4.1). The declining trend in low streamflow in the catchment is attributed to change in Climate and land use land cover change over the catchment (Luwa et al. 2021)

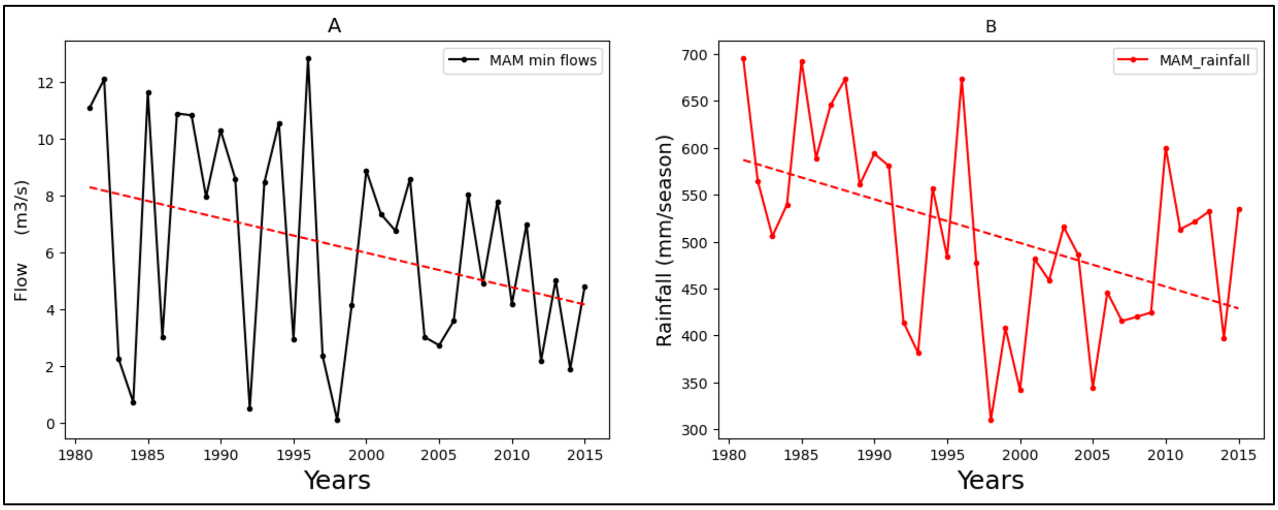

Figure 4.1: Trend in low flow and Rainfall over time during MAM rainfall season

On the contrary, a plot of the annual 7-day mean flow against time showed no trend. In other words, there was no consistent pattern in the average flow duration statistic. However, sharp declines in average flow were observed in 1984 and 2009 (Figure 4.2).

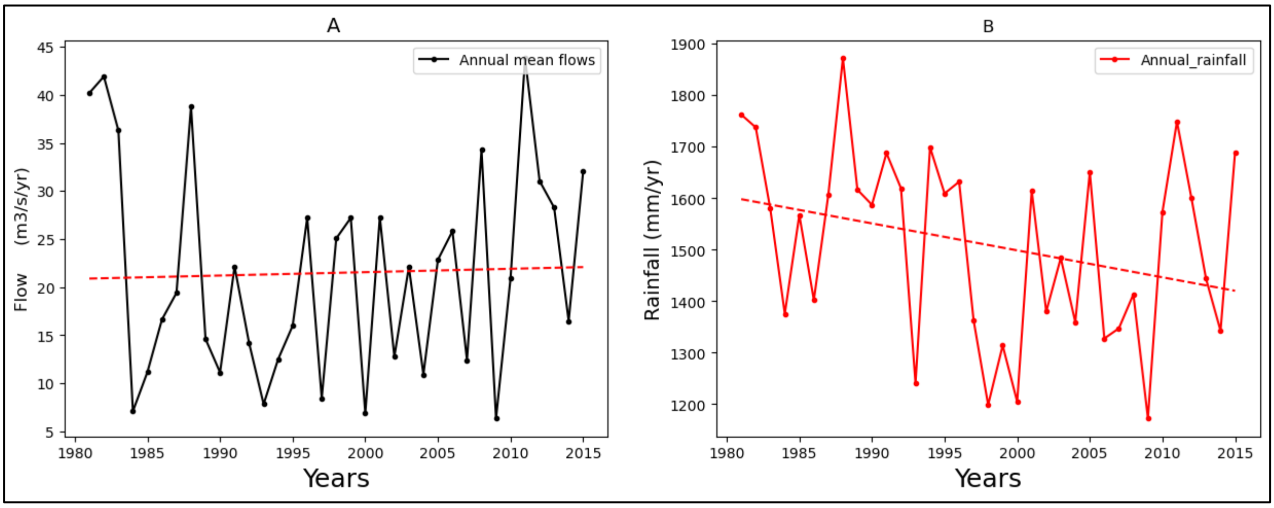

Figure 4.2: Trend in annual average flow and Rainfall over time

A plot of 7-day peak flow against time for the SON season indicates an upward trend whereby a gradual rise was observed in the peak flow duration statistic with extreme values in the years 2005 and 2011 (Figure 4.3).

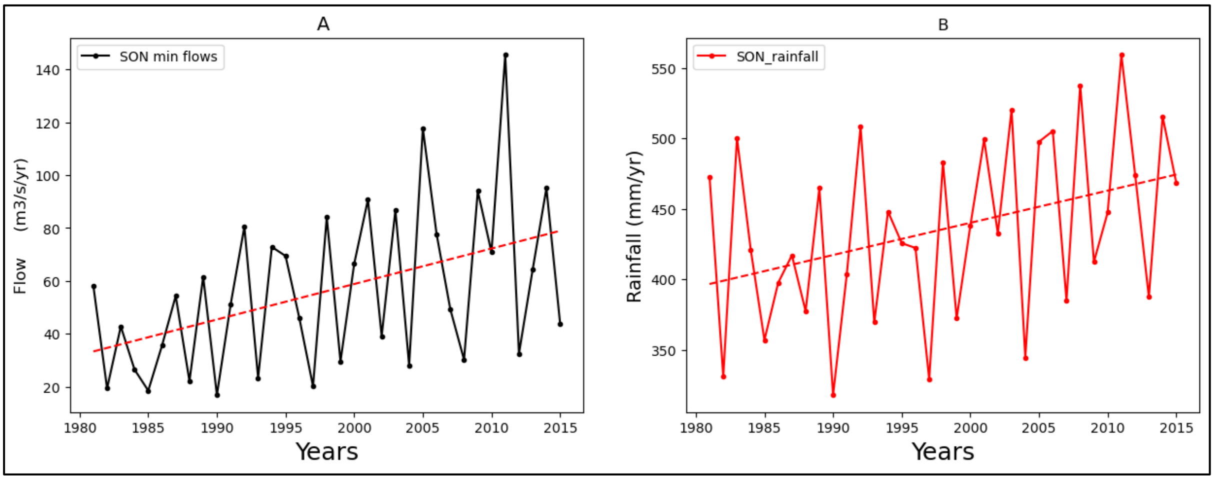

Figure 4.3: Trend in peak flow over time during SON rainfall season

Results from the Mann-Kendall test (Table 4.2) confirm that over the study period, there was a statistically significant negative trend in low flow statistics for the MAM season ($\tau > -0.25$, $p < 0.05$). In particular, the low flow percentile decreased at an average rate of 0.12 m^3s^{-1} per year whereas the 7-day low flow duration declined at a rate of 0.27 m^3s^{-1} per year. The results further confirm that there was no evidence of trend in both the annual and seasonal average flow statistics across the study period ($p > 0.05$). On the other hand, statistically significant upward trends were eminent in the peak flow statistics for the SON season ($\tau > 0.31$, $p < 0.05$). In particular, the peak flow percentile increased at an average rate of 1.34 m^3s^{-1} per year whereas the 7-day peak flow duration rose at a rate of 1.51 m^3s^{-1} per year. The findings indicate however that the trends in the seasonal as well as annual low flow and peak flow statistics were weak and non-significant ($p > 0.05$). Overall, there was a tendency of decreasing low flow in the MAM season and increasing peak flow in the SON season across R. Mpologoma catchment. This could be attributed to increase in surface flow in the rainy season which is related to reduced infiltration after the conversion of other land uses (Ashraf et al., 2020; Asare et al., 2021; Mewded et al., 2021) .

Table 4.2: **Mann-Kendall trend test on streamflow data at R. Mpologoma gauge station for the period 1981-2015**

Streamflow (No. of obs. $n = 35$)			**Kendall tau (τ)**	**Significance (p)**	**Trend slope (m^3s^{-1} per year)**
Low flow	Annual	Q_{7min}	-0.052	0.6701	-0.027
		Q_{90}	-0.072	0.5501	-0.027
	Mar-May	Q_{7min}	**-0.254**	**0.0332**	**-0.121**
		Q_{90}	**-0.422**	**0.0004**	**-0.271**
	Sep-Nov	Q_{7min}	0.217	0.0691	0.112
		Q_{90}	0.156	0.1914	0.132
Average flow	Annual	Q_{7mean}	0.062	0.6092	0.035
		Q_{50}	0.065	0.5894	0.010
	Mar-May	Q_{7mean}	-0.123	0.3065	-0.398
		Q_{50}	-0.176	0.1397	-0.315
	Sep-Nov	Q_{7mean}	0.187	0.1183	0.385
		Q_{50}	0.113	0.3486	0.146
Peak flow	Annual	Q_{7max}	0.163	0.1728	0.779
		Q_{10}	0.156	0.1914	0.364
	Mar-May	Q_{7max}	-0.200	0.0938	-1.064
		Q_{10}	-0.207	0.0832	-0.511
	Sep-Nov	Q_{7max}	**0.318**	**0.0076**	**1.342**
		Q_{10}	**0.435**	**0.0002**	**1.515**

4.2 Relationship between rainfall and streamflow in R. Mpologoma catchment

Results from pairwise correlation analysis (Table 4.3) confirm that there was a moderately strong positive statistically significant relationship between annual rainfall volume and both annual median flow ($r = 0.65$, $p < 0.05$) and annual 7-day mean flow ($r = 0.57$, $p < 0.05$). The findings mean that an increase in annual rainfall brought about an increase in annual average flow and vice-versa. On the contrary, annual low flow and peak flow statistics showed no correlation with annual rainfall ($p > 0.05$).

Similarly, the study found a strong positive statistically significant relationship between MAM rainfall volume and each of the MAM low flow statistics, that is, low flow percentile ($r = 0.66$, $p < 0.05$) and 7-day low flow duration ($r = 0.56$, $p < 0.05$). These results mean that an increase in MAM rainfall corresponded to an increase in MAM low flow and vice-versa. On the other hand, there was no evidence of association between MAM rainfall and either of MAM average flow and peak flow statistics ($p > 0.05$).

The results further suggest that there was a strong positive statistically significant relationship between SON rainfall volume and the SON peak flow statistics, that is, peak flow percentile ($r = 0.69$, $p < 0.05$) and 7-day peak flow duration ($r = 0.70$, $p < 0.05$). This means that an increase in SON rainfall was associated with an increase in SON peak flow and vice-versa. Conversely, the relationship between rainfall and both low flow and average flow statistics in the SON season was non-significant ($p > 0.05$).

Table 4.3: Pairwise correlation coefficient matrix showing strength of relationship between streamflow statistics and rainfall volume for the period 1981-2015

Streamflow (No. of obs. *n* = 35)			Correlation coefficient (*r*)		
			Annual rainfall	**MAM rainfall**	**SON rainfall**
Annual	Low flow	Q_{7min}	0.175		
		Q_{90}	0.314		
	Average flow	Q_{7mean}	**0.574***		
		Q_{50}	**0.648***		
	Peak flow	Q_{7max}	0.294		
		Q_{10}	0.207		
Mar-May	Low flow	Q_{7min}		**0.565***	
		Q_{90}		**0.662***	
	Average flow	Q_{7mean}		0.230	
		Q_{50}		0.108	
	Peak flow	Q_{7max}		0.281	
		Q_{10}		0.309	
Sep-Nov	Low flow	Q_{7min}			0.237
		Q_{90}			0.213
	Average flow	Q_{7mean}			0.260
		Q_{50}			0.279
	Peak flow	Q_{7max}			**0.705***
		Q_{10}			**0.694***

**Correlation is significant at 5% level.*

From the correlation analysis, the streamflow statistics that showed a significant positive linear relationship with rainfall include: annual average flow, MAM low flow and SON peak flow. Results from the time series regression analysis (Table 4.4) show that the static models relating rainfall to transformed low flow statistics for the MAM season were significant fits ($p^* < 0.05$). MAM rainfall accounted for about 25.7% and 23.1% of the variation in the transformed 7-day low flow duration and low flow percentile respectively. Similarly, the static models linking annual rainfall and transformed average flow statistics were good fits ($p^* < 0.05$). Annual rainfall explained about 34.4% and 43.0% of the variation in the transformed 7-day mean flow duration and median flow respectively. Furthermore, the static models associating rainfall with transformed peak flow statistics for the SON season were significant fits ($p^* < 0.05$). SON rainfall accounted for about 54.0% and 43.9% of the variation in the transformed 7-day peak flow duration and peak flow percentile respectively.

Table 4.4: Time series (static) regression of streamflow on rainfall volume

Dependent variable	**Predictor variable**	**Coefficient (β)**	**SD. error**	**Test statistic (t)**	**Significance (p)**	**95% Conf. Intv.**	
						Lower	**Upper**
ln(MAM low flow duration)	MAM rainfall	0.005	0.001	3.38	0.002	0.002	0.008
	Intercept	-1.028	0.769	-1.34	0.190	-2.592	0.535
	Goodness of fit:	*Obs.*(n)=35, F-statistic=11.4, p^*=0.0019, R-squared=0.257					
ln(MAM low flow percentile)	MAM rainfall	0.007	0.002	3.15	0.003	0.003	0.012
	Intercept	-2.263	1.188	-1.90	0.066	-4.680	0.154
	Goodness of fit:	*Obs.*(n)=35, F-statistic=9.9, p^*=0.0035, R-squared=0.231					
ln(Annual mean flow duration)	Annual rainfall	0.002	0.000	4.16	0.000	0.001	0.003
	Intercept	0.191	0.662	0.29	0.775	-1.157	1.538
	Goodness of fit:	*Obs.*(n)=35, F-statistic=17.3, p^*=0.0002, R-squared=0.344					
ln(Annual median flow percentile)	Annual rainfall	0.002	0.000	4.99	0.000	0.001	0.003
	Intercept	-0.294	0.610	-0.48	0.633	-1.535	0.947
	Goodness of fit:	*Obs.*(n)=35, F-statistic=24.9, p^*=0.0000, R-squared=0.430					
ln(SON peak flow duration)	SON rainfall	0.007	0.001	6.23	0.000	0.004	0.009
	Intercept	0.977	0.470	2.08	0.045	0.021	1.933
	Goodness of fit:	*Obs.*(n)=35, F-statistic=38.8, p^*=0.0000, R-squared=0.540					
ln(SON peak flow percentile)	SON rainfall	0.006	0.001	5.08	0.000	0.003	0.008
	Intercept	1.039	0.509	2.04	0.050	0.002	2.075
	Goodness of fit:	*Obs.*(n)=35, F-statistic=25.8, p^*=0.0000, R-squared=0.439					

Q_{7min} | Q_{90} = *Low flow;* Q_{7mean} | Q_{50}= *Average flow;* Q_{7max} | Q_{10} = *Peak flow*

The estimated regression models relating rainfall to low flow for the MAM season are:

$$\ln\left(\hat{Q}_{7min_t}\right) = 0.005R_{MAM_t} - 1.028 \quad (4.1)$$

$$\ln\left(\hat{Q}_{90_t}\right) = 0.007R_{MAM_t} - 2.263 \quad (4.2)$$

Findings from the time-series regression analysis indicate that for the MAM season, rainfall volume was a significant predictor of low flow statistics ($p < 0.05$). At any given time, a one-mm increase in MAM rainfall resulted in a 0.7% immediate rise in low flow percentile and a 0.5% instant rise in 7-day low flow duration, other factors held constant (Eqn. 4.1 and 4.2).

The estimated regression models linking annual rainfall and annual average flow are:

$$\ln\left(\hat{Q}_{7mean_t}\right) = 0.002R_{Annual_t} + 0.191 \quad (4.3)$$

$$\ln\left(\hat{Q}_{50_t}\right) = 0.002R_{Annual_t} - 0.294 \quad (4.4)$$

Similarly, the results also show that annual average streamflow statistics were significantly influenced by annual rainfall volume ($p < 0.05$). Holding other factors constant, a one-mm increase in annual rainfall at a given time caused a 0.2% instant rise in both the median (50^{th}) percentile flow and the 7-day mean flow duration (Eqn. 4.3 and 4.4).

The estimated regression models associating rainfall with peak flow for the SON season are:

$$\ln\left(\hat{Q}_{7max_t}\right) = 0.007R_{SON_t} + 0.977 \quad (4.5)$$

$$\ln\left(\hat{Q}_{10_t}\right) = 0.006R_{SON_t} + 1.039 \quad (4.6)$$

The results further reveal that for the SON season, peak flow statistics were significantly affected by rainfall volume ($p < 0.05$). At any particular time, a one-mm increase in SON rainfall instantaneously raised peak flow percentile by 0.6% and 7-day peak flow duration by 0.7%, other factors held constant (Eqn. 4.5 and 4.6).

4.3 Projection of streamflow for R. Mpologoma catchment in the near future

A plot of the projected low flow duration against time revealed no trend in the series with a more or less random pattern in the values under both RCP 4.5 and RCP 8.5 climate scenarios (Figure 4.4). However, an extreme discharge of 4 m^3s^{-1} is expected in 2032 under RCP 8.5.

Similarly, the trend plots of projected average flow and peak flow duration statistics showed no consistent patterns in the series under both RCP 4.5 and RCP 8.5 climate scenarios with potential extreme values expected in the year 2034 for the latter scenario (Fig 4.5 and 4.6)

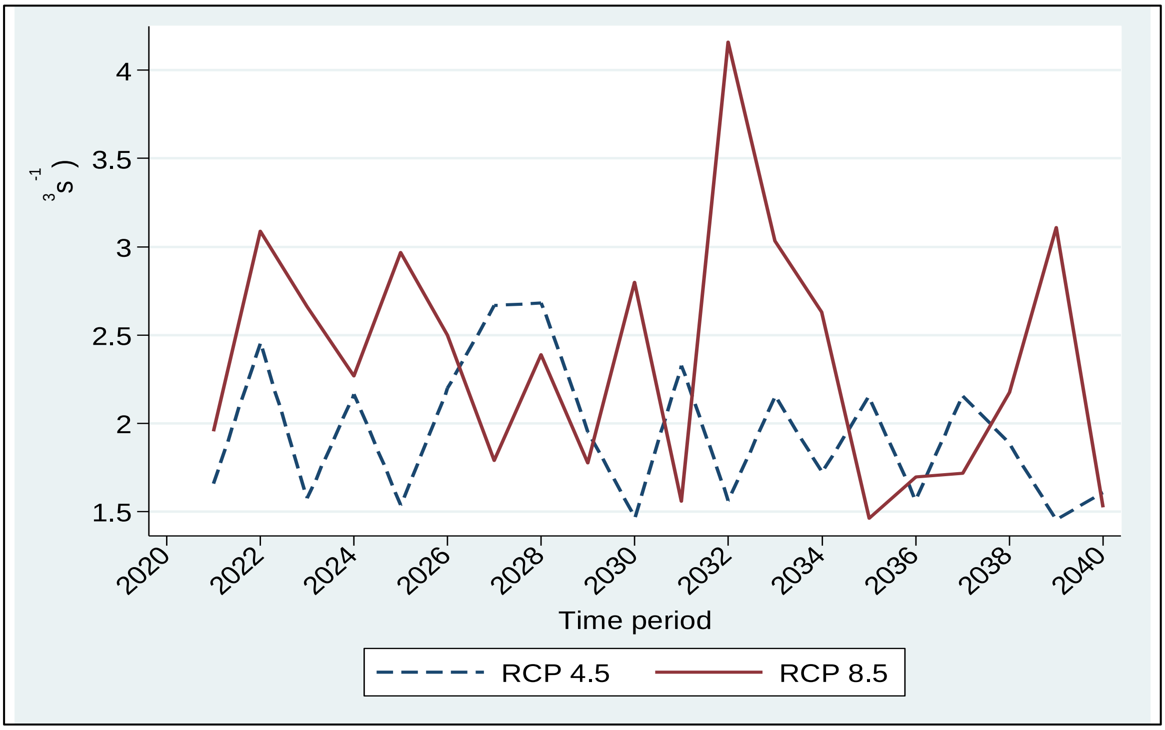

Figure 4.4: Trend in forecasted low flow for the Mar-May rainfall season

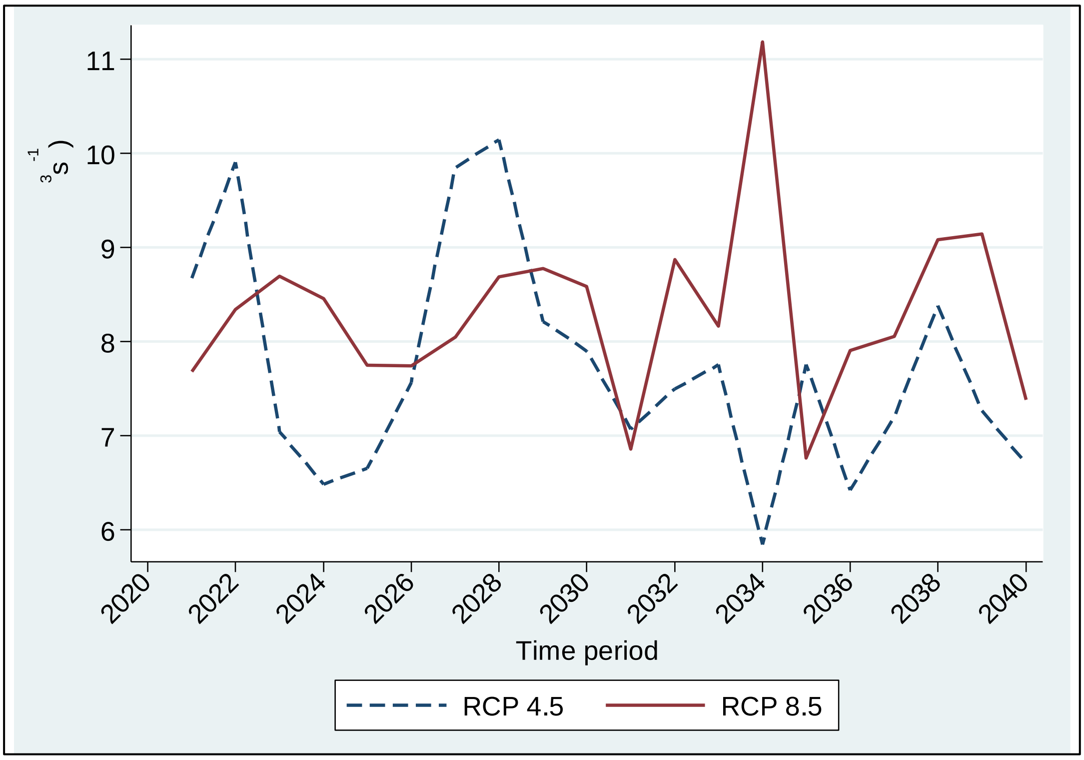

Figure 4.5: Trend in forecasted annual average flow for R. Mpologoma catchment

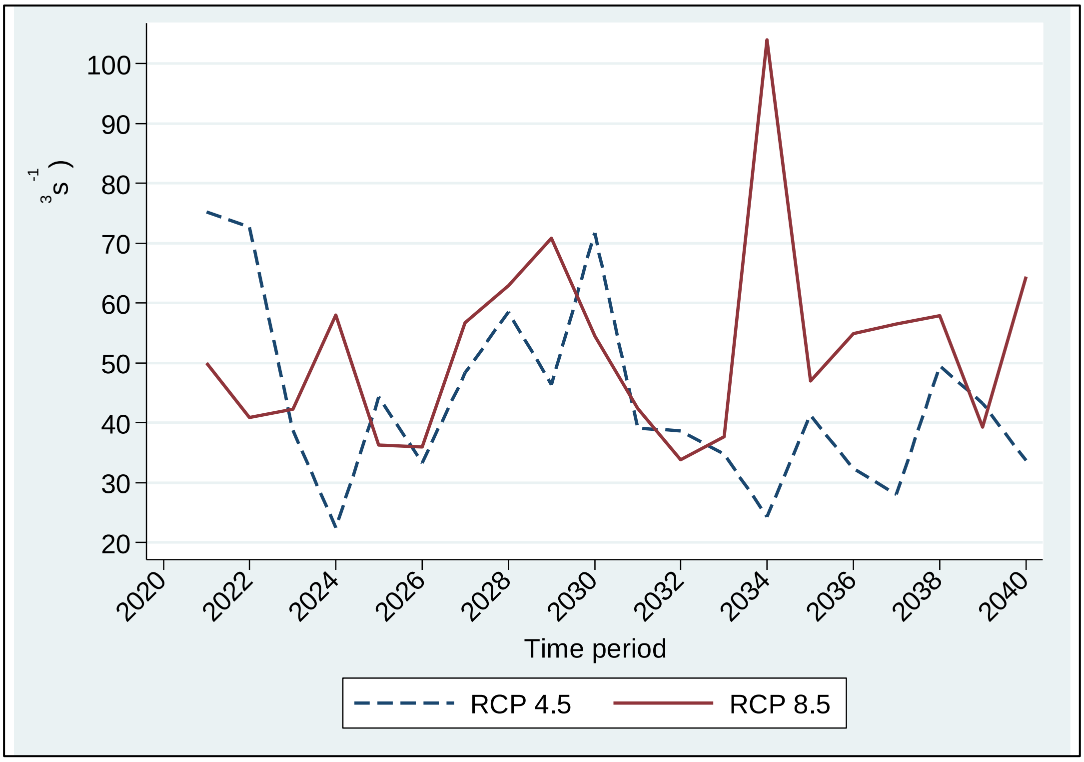

Figure 4.6: Trend in forecasted peak flow for the Sep-Nov rainfall season

Findings from the Mann-Whitney test (Table 4.5) indicate that the average low flow for the MAM season is expected to significantly decrease in the near future under both climate scenarios. Under RCP 4.5, the average of 7-day low flow is expected to decrease by 72% whereas the average of low flow exceedance percentile will decline by 77%. Under RCP 8.5, the average of the 7-day low flow duration is expected to decrease by 66% whereas the average of low flow percentile will decline by 70%. Similarly, the results show that the annual average flow is expected to significantly decrease in the near future under both climate scenarios. Under RCP 4.5, the 7-day average flow is expected to decrease by 64% whereas median flow exceedance percentile will decline by 62%. Under RCP 8.5, 7-day average flow is expected to decrease by 61% whereas median flow exceedance percentile will decline by 58%. On the contrary, averages for the SON peak flow statistics (duration and exceedance percentile) projected for the near future are not expected to differ significantly from those of the study period under both climate scenarios.

Table 4.5: Comparison of average discharge between the past and future time periods

Streamflow		Median discharge (m^3s^{-1})			Difference in medians: *Percentage change*	
		Study	**Future (2021-2040)**			
		1981-2015 (n = 35)	RCP 4.5 (n = 20)	RCP 8.5 (n = 20)	RCP 4.5	RCP 8.5
MAM low flow	Q_{7min}	6.77	1.92	2.33	71.6%*	65.6%*
	Q_{90}	5.09	1.17	1.54	77.0%*	69.7%*
Annual avg. flow	Q_{7mean}	20.95	7.53	8.25	64.1%*	60.6%*
	Q_{50}	14.75	5.63	6.23	61.8%*	57.8%*
SON peak flow	Q_{7max}	51.07	40.19	52.18	21.3%	-2.2%
	Q_{10}	34.73	31.26	39.38	10.0%	-13.4%

**Difference in average discharge between future and study periods is statistically significant at 5% level*

CHAPTER FIVE

DISCUSSIONS

5.1 Trend in streamflow over Mpologoma River catchment

To begin with, the current study shows that majority of the low flow statistics and peak flow statistics were highly variable over time in the Mpologoma River catchment especially during the rainfall seasons. The result implies that streamflow in the catchment is highly unpredictable. Such observations can be partly attributed to variations in climatic patterns that cause alterations in the hydrological cycle of water in catchment areas through increased evaporation and intense rainfall. This builds on the fact that most water catchments in Uganda heavily rely on rainfall for their streamflow (MWE - DWD, 2017).

The significant negative trends in MAM flows and positive trend in SON flows have been reported by other researchers. Kansiime, Wambugu, & Shisanya (2013) noted that for areas around L. Kyoga basin particularly Mt. Elgon region, significant negative trends were eminent in volume of rainfall received during MAM season while the SON rainfall showed rising trends. Similar results were obtained by Kassian et al. (2017) who studied trends in river flow in Iringa region in Tanzania for the period 1997-2014 and found a significant decreasing pattern in river flow. Luwa et al., (2021) who studied trends of rainfall, temperature and river flow in Sipi Sub-Catchment reported high river flows during the SON season compared to MAM. Onyutha, Turyahabwe, et al., (2021) also studied impacts of climate variability and changing land use/land cover on River Mpanga flows in Uganda, East Africa and observed increasing trends in river flows.

The decrease in MAM flows is attributed to the fact that the region had undergone a long dry season DJF where the volume of most rivers is reduced due to high evaporation and low rainfall (Luwa et al., 2021). Luwa et al., (2021) further discusses that the increase in SON flows can be attributed to accumulation of water in the river and ground during the MAM season. Tusingwiire et al., (2023) also discusses that the low streamflows are attributed to the poor land management practices. The increase in streamflow can lead to erosion and sedimentation which can be derimental to the quality of water (Onyutha, Turyahabwe, et al., 2021) from River Mpologoma.

5.2 Relationship between rainfall and streamflow in R. Mpologoma catchment

The current study found strong positive correlations between rainfall volume and streamflow statistics in R. Mpologoma catchment. Rainfall was found to significantly influence streamflow within the catchment. In particular, low flow and peak flow were strongly associated with MAM and SON seasonal rainfall respectively. Overall, an increase in rainfall volume resulted in an instantaneous rise in stream flow duration and exceedance percentiles at any given time. These results confirm findings by Tumusiime & Ageet (2018) whose findings revealed that climate change has already affected water resources in L. Kyoga catchment with continuous reduction in water levels by about 6%.

Overall, an increase in rainfall volume resulted in an instantaneous rise in stream flow duration and exceedance percentiles at any given time. The strong positive correlations between rainfall volume and streamflow statistics in R. Mpologoma catchment have been reported by other researchers. Tumusiime & Ageet (2018) revealed that climate change has already affected water resources in L. Kyoga catchment with continuous reduction in water levels by about 6%. The results further concur with findings by (Kassian et al., 2017) who studied the implication of climate change and variability on the river flow in Iringa region in Tanzania. They observed a gradual decline in river flow and attributed it to significantly declining rainfall in the recent past. Kangume & Mulungu, (2018) also asessed the Impacts of Climate Change on Streamflow in Malaba River Catchment, Uganda and concluded that fluctuations in rainfall have contributed to fluctuations in streamflow.

Variation in rainfall cannot explicitly explain the total streamflow variance. Onyutha, Turyahabwe, et al., (2021) point out that other factors which influence rainfall-streamflow variations are rates of infiltration, evaporation, percolation and river water abstraction. Other factors that contribute to streamflow variance include impacts of human activities such as water abstractios for agricultural, industrial and domestic needs (Tusingwiire et al., 2023).

5.3 Projection of streamflow for R. Mpologoma catchment in the near future

Results on projection of streamflow showed that low flow during the MAM rainfall season and annual average flow are expected to significantly decrease in the near future. Both low flow and average flow statistics (duration and exceedance percentile) are projected to decline under RCP 4.5 and RCP 8.5 climate scenarios. The results point towards increased risk of prolonged dry spells during the MAM season and a general decline in discharge in the near future. This implies that water availability in the catchment is expected to reduce particularly during the first rainfall season which will have negative impacts on agricultural production and farmers livelihoods in general given that MAM is a major cropping season (Verdonck & Michel, 2016).

The results are in line with suggestions by Taylor et al. (2014) who argue that climate change and variability are already affecting the availability of water in Uganda and this is expected to increase over time. They pointed out that in recent years the country has been subjected to changes in precipitation patterns, increased frequency of floods and droughts, and changes in evaporation due to higher temperatures. According to (IPCC, 2008), such changes in climate are expected to affect the quantity and quality of water which will increase the level of vulnerability of poor rural farmers due to food insecurity.

The results support reports by IPCC (2008) who note that climate change in form of variability in precipitation is likely to affect both the quantity and quality of water in streams and rivers and this will increase the level of vulnerability of the poor rural farmers due to increased risk of food insecurity. The results are consistent with findings by Devkota & Gyawali (2015) who assesed the impacts of climate change on hydrological regime of the Koshi River Basin in Nepal from which they projected a future decrease in monthly flow by more than 30% in the drier months and an increase by more than 25% in the peak flow months. However, their findings relayed that climate change was less likely to pose a major threat to average water availability.

The results of the current study however differ from findings by Tumusiime & Ageet (2018) who reported that climate change is likely to increase precipitation received in L. Kyoga catchment during the wet seasons by 10-20% resulting in higher stream flow. Similarly, the results do not agree with findings by Bates et al. (2008) who assert that by the middle of the 21st century, annual average river runoff and water availability are projected to increase as a result of climate change at high latitudes and in some wet tropical areas. The results also differ from suggestions by Kigobe & Griensven (2010) whose simulations of the hydrological response of Mpologoma catchment in L. Kyoga basin to changes in future climate reveal basin-wide increase in rainfall and subsequent increase in streamflows for the Mpologoma basin in the near future (2050s)

The results of this study are in contrast with findings by Taye, Ntegeka, Ogiramoi, & Willems (2011) who examined the potential impact of climate change on hydrological extremes in two catchments of the Nile River Basin under two future climate scenarios and their findings projected increasing peak flows for the catchments during the 2050s. Similarly, the results do not align with observations by Adem et al. (2016) who examined future impact of climate change on streamflow in the upper Gilgel Abay catchment of the Blue Nile basin in Ethiopia using two emission scenarios and predicted a systematic increase in precipitation which was expected to increase mean annual streamflow by 7 percent in the 2020s.

Conversely, the current study showed that peak flow during the SON rainfall season is not expected to change significantly in the near future period under both climate scenarios. The results compare well with suggestions by Aich et al. (2014) who modeled the impacts of climate change on streamflow in four large African river basins under two future climate scenarios and found no significant climate change impact on projected streamflow in most of the basins. In addition, they found no clear trend in projected discharge. The results however,differ from suggestions by (Bates *et al.*, 2008) who argue that by the middle of the 21st century, annual average river runoff and water availability are projected to increase in the tropical regions across the globe as a result of climate change in form of increased precipitation intensity and variability which will increase the risks of flooding in these areas.

CHAPTER SIX
CONCLUSIONS AND RECOMMENDATIONS

6.1.Conclusions

- The trend in stream flow declined in the MAM season but increased in the SON season, thus highlighting a major concern of uncertain water availability for the majority of the population living in the catchment that depends on steam water sources for agricultural production and livelihood support.
- The streamflow and rainfall had a strong positive relationship for the low flow MAM season and high flow for SON season
- There will be a decline in streamflow in the MAM season with low flows under the RCP 4.5 for the near future scenario, an indication of possible water stress for both domestic and economic demands in the year to come.

6.2 Recommendations

- There is need for early maturing and drought tolerant varieties in agricultural related investment that can adapt the low water supply conditions especially for the MAM where there was notable declining streamflow patterns
- The peak flows and low flows characteristics can be used in assessing the risk of floods and droughts in MAM and SON for river-based catchment analyses or studies
- There is need to plan on how to avert the disasters arising from climate change given the future prediction observed under the RCP 4.5 and in similar setting should focus on a comprehensive assessment of streamflow response to other climatic variables besides rainfall such as temperature and evapotranspiration, and considering also the effect of land-use/ land-cover
- There is need to install equipment for early warning system gargets along most streams so as to get proper information for all researchers and managers in the catchment

REFERENCES

Adem, A., Tilahun, S., Ayana, E., Worqlul, A., Assefa, T., Dessu, S., & Melesse, A. (2016). Climate Change Impact on Stream Flow in the Upper Gilgel Abay Catchment, Blue Nile basin, Ethiopia. *Landscape Dynamics, Soils and Hydrological Processes in Varied Climates*, 645–673. https://doi.org/10.1007/978-3-319-18787-7

Aich, V., Liersch, S., Vetter, T., Huang, S., Tecklenburg, J., Hoffmann, P., Koch, H., Fournet, S., Krysanova, V., Müller, E. N., & Hattermann, F. F. (2014). Comparing impacts of climate change on streamflow in four large African river basins. *Hydrology and Earth System Sciences*, *18*(4), 1305–1321. https://doi.org/10.5194/hess-18-1305-2014

Akpoti, K., Antwi, E. O., & Kabo-bah, A. T. (2016). Impacts of rainfall variability, land use and land cover change on stream flow of the Black Volta basin, West Africa. *Hydrology*, *3*(3), 1–24. https://doi.org/10.3390/hydrology3030026

Arnell, N. W., & Gosling, S. N. (2013). The impacts of climate change on river flow regimes at the global scale. *Journal of Hydrology*, *486*, 351–364. https://doi.org/10.1016/j.jhydrol.2013.02.010

Arora, M., Kumar, R., Malhotra, J., & Kumar, N. (2014). Correlations of Stream Flow and Climatic Variables for a Large Glacierized Himalayan Basin. *Journal of Water Resource and Protection*, *06*(14), 1326–1334. https://doi.org/10.4236/jwarp.2014.614122

Asare, A., Thodsen, H., Antwi, M., Opuni-Frimpong, E., & Sanful, P. O. (2021). Land Use and Land Cover changes in Lake Bosumtwi Watershed, Ghana (West Africa). *Remote Sensing Applications: Society and Environment*, *23*, 100536. https://doi.org/10.1016/j.rsase.2021.100536

Ashouri, H., Sorooshian, S., Hsu, K. L., Bosilovich, M. G., Lee, J., Wehner, M. F., & Collow, A. (2016). Evaluation of NASA's MERRA precipitation product in reproducing the observed trend and distribution of extreme precipitation events in the United States. *Journal of Hydrometeorology*, *17*(2), 693–711. https://doi.org/10.1175/JHM-D-15-0097.1

Ashraf, M. S., Ahmad, I., Khan, N. M., Zhang, F., Bilal, A., & Guo, J. (2020). Streamflow Variations in Monthly, Seasonal, Annual and Extreme Values Using Mann-Kendall, Spearmen's Rho and Innovative Trend Analysis. *Water Resources Management*, *35*(1), 243–261. https://doi.org/10.1007/s11269-020-02723-0

Attique, R. (2018). *Comparison between statistical and dynamical downscaling of rainfall under Representative Concentration Pathways scenarios over the Gwadar- Ormara basin, Pakistan*. 58p.

Balany, F. (2011). Different Ways of Calculating Catchment Rainfall: Cases in Indonesia. *Journal of the Civil Engineering Forum*, *20*(1), 1175–1182.

Bamutaze, Y., Thiemann, S., & Förch, G. (2014). *Integrated Watershed Management for Urban Water Security – A Tool for Urban Water Security*.

Bates, B. C., Kundzewicz, Z. W., Wu, S., & Palutikof, J. P. (2008). Climate Change and Water. In *Technical Paper of the Intergovernmental Panel on Climate Change*. https://doi.org/10.1016/j.jmb.2010.08.039

Beck, H. E., Van Dijk, A. I. J. M., Miralles, D. G., De Jeu, R. A. M., Bruijnzeel, L. A., McVicar, T. R., & Schellekens, J. (2013). Global patterns in base flow index and recession based on streamflow observations from 3394 catchments. *Water Resources Research*, *49*(12), 7843–7863. https://doi.org/10.1002/2013WR013918

Berhanu, B., Seleshi, Y., Demisse, S. S., & Melesse, A. M. (2015). Flow Regime Classification and Hydrological Characterization: A Case Study of Ethiopian Rivers. *Water ISSN 2073-4441*, *7*, 3149–3165. https://doi.org/10.3390/w7063149

Bhaskar, A. S., Beesley, L., Burns, M. J., Fletcher, T. D., Hamel, P., Oldham, C. E., & Roy, A. H. (2016). Will it rise or will it fall ? Managing the complex e ff ects of urbanization on base flow. *Freshwater Science, 35*(1), 293–310. https://doi.org/10.1086/685084.

Bhatt, D., & Mall, R. K. (2015). INTERNATIONAL CONFERENCE ON WATER RESOURCES , COASTAL AND OCEAN Surface Water Resources , Climate Change and Simulation Modeling. *Aquatic Procedia*, *4*(Icwrcoe), 730–738. https://doi.org/10.1016/j.aqpro.2015.02.094

Bhavani, R. (2013). Comparision of Mean and Weighted Annual Rainfall in Anantapuram District. *International Journal of Innovative Research in Science, Engineering and Technology*, *2*(7).

Birsan, M. V., Molnar, P., Burlando, P., & Pfaundler, M. (2005). Streamflow trends in Switzerland. *Journal of Hydrology*, *314*(1–4), 312–329. https://doi.org/10.1016/j.jhydrol.2005.06.008

Chen, X., Jiang, L., Luo, Y., & Liu, J. (2023). A global streamflow indices time series dataset for large-sample hydrological analyses on streamflow regime (until 2021). *Earth System Science Data Discussions*, *2023*(March), 1–18. https://essd.copernicus.org/preprints/essd-2023-49/

Coleman, R. L., & Jain, S. (2023). Trends in the seasonal cycle of modelled streamflow across Australia, 1980–2018. *Journal of Water and Climate Change, 14*(3), 843–859. https://doi.org/10.2166/wcc.2023.440

Conway, D., Pereschino, A., Ardoin-Bardin, S., Hamandawana, H., Dieulin, C., & Mahé, G. (2009). Rainfall and water resources variability in sub-Saharan Africa during the twentieth century. *Journal of Hydrometeorology*, *10*(1), 41–59. https://doi.org/10.1175/2008JHM1004.1

Crop, A., Society, S., Nandozi, C. S., Omondi, P., Komutunga, E., Aribo, L., Isubikalu, P., Tenywa, M. M., Box, P. O., Zonal, M., Unit, C. C., & Centre, A. (2012). *Regional climate model performance and prediction of seasonal rainfall and surface temperature of uganda*. *20*, 213–225.

Devkota, L. P., & Gyawali, D. R. (2015). Impacts of climate change on hydrological regime and water resources management of the Koshi River Basin , Nepal. *Journal of Hydrology: Regional Studies*, *4*, 502–515. https://doi.org/10.1016/j.ejrh.2015.06.023

Dhungel, S. (2014). Prediction of Climate Change Effects on Streamflow Regime Important to Stream Ecology. In *All Graduate Theses and Dissertations* (Vol. 3083). Utah State University.

Done, J., Davis, C. A., & Weisman, M. (2004). The next generation of NWP: Explicit forecasts of convection using the weather research and forecasting (WRF) model. *Atmospheric Science Letters*, *5*(6), 110–117. https://doi.org/10.1002/asl.72

MWE. (2017). *Uganda Catchment Management Planning Guidlines* (Issue APRIL 2014).

MWE. (2019). Ministry of Waterand Environment. In KWMZ (Ed.), *Popular Version CMP* (p. 7).

Egeru, A., Barasa, B., Nampijja, J., Siya, A., Makooma, M. T., & Majaliwa, M. G. J. (2019). Past, present and future climate trends under varied representative concentration pathways for a sub-humid region in Uganda. *Climate*, *7*(3). https://doi.org/10.3390/cli7030035

Emami, F., & Koch, M. (2015). *Evaluating the impacts of climate change on streamflow and water resources management : Aharchai River , Iran , case study*.

ENVIRONMENTAL ALERT. (2010). *Climate Change in Uganda Insights for Long term Adaptation and*. *July*.

Falloon, P., & Betts, R. (2006). The impact of climate change on global river flow in HadGEM1 simulations. *Atmospheric Science Letters*, *7*(3), 62–68. https://doi.org/10.1002/asl

Ficklin, D. L., Robeson, S. M., & Knouft, J. H. (2016). Impacts of recent climate change on trends in baseflow and stormflow in United States watersheds. *Geophysical Research Letters*, *43*(10), 5079–5088. https://doi.org/10.1002/2016GL069121

Giorgi, F., & Gutowski, W. J. (2015). Regional Dynamical Downscaling and the CORDEX Initiative. *Annual Review of Environment and Resources*, *40*, 467–490. https://doi.org/10.1146/annurev-environ-102014-021217

Gotvald, A. J. (2017). *Methods for Estimating Selected Low-Flow Frequency Statistics and Mean Annual Flow for Ungaged Locations on Streams in North Georgia*. 36 p.

Gül, G., Rosbjerg, D., Gül, A., Ondracek, M., & Dikgola, K. (2010). Assessing climate change impacts on river flows and environmental flow requirements at catchment scale. *Ecohydrology*, *3*(1), 28–40. https://doi.org/10.1002/eco

Hameed, M., Saqib, N., Ellahi, S., Pandit, B., & Bhat, S. (2017). Assessing the impact of climate change on surface water resources of Wular Lake. *Journal of Pharmacognosy and Phytochemistry*, *6*(5), 1067–1072.

Higgins, P. A., Palmer, J. G., Rao, M. P., Andersen, M. S., Turney, C. S. M., & Johnson, F. (2022). Unprecedented High Northern Australian Streamflow Linked to an Intensification of the Indo-Australian Monsoon. *Water Resources Research*, *58*(3), 1–17. https://doi.org/10.1029/2021WR030881

Intergovernmental Panel on Climate Change. (2014). *Climate Change 2014 Synthesis Report Summary Chapter for Policymakers*.

IPCC. (2008). *Climate change and water* (vi).

IPCC. (2014). *Climate Change 2014 Synthesis Report Summary Chapter for Policymakers*.

Jiang, B., Bamutaze, Y., & Pilesjö, P. (2017). Geo-spatial Information Science Climate change and land degradation in Africa : a case study in the Mount Elgon region , Uganda. *Geo-Spatial Information Science*, *17*(1), 39–53. https://doi.org/10.1080/10095020.2014.889271

Kaini, S., Nepal, S., Pradhananga, S., Gardener, T., & Sharma, A. K. (2019). Representative general circulation models selection and downscaling of climate data for the transboundary Koshi river basin in China and Nepal. *International Journal of Climatology*, 1–19. https://doi.org/10.1002/joc.6447

Kamruzzaman, M., Shahriar, M. S., & Beecham, S. (2014). Assessment of short term rainfall and stream flows in South Australia. *Water (Switzerland)*, *6*(11), 3528–3544. https://doi.org/10.3390/w6113528

Kangume, C., & Mulungu, D. M. M. (2018). Assessing the Impacts of Climate Change on Streamflow in Malaba River Catchment, Uganda. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3210592

Kansiime, M. K., Wambugu, S. K., & Shisanya, C. A. (2013). Perceived and Actual Rainfall

Trends and Variability in Eastern Uganda. *Journal of Natural Sciences Research*, *3*(8), 179–195.

Karlsson, I. B., Sonnenborg, T. O., Jensen, K. H., & Refsgaard, J. C. (2014). Historical trends in precipitation and stream discharge at the Skjern River catchment, Denmark. *Hydrology and Earth System Sciences*, *18*(2), 595–610. https://doi.org/10.5194/hess-18-595-2014

Kassian, L. M., Tenywa, M., Liwenga, E. T., Dyer, K. W., & Bamutaze, Y. (2017). Implication of climate change and variability on stream flow in Iringa region, Tanzania. *Journal of Water and Climate Change*, *8*(2), 336–347. https://doi.org/10.2166/wcc.2016.238

Kibria, K. N., Ahiablame, L., Hay, C., & Djira, G. (2016). Streamflow trends and responses to climate variability and land cover change in South Dakota. *Hydrology*, *3*(1). https://doi.org/10.3390/hydrology3010002

Kigobe, M., & Griensven, A. Van. (2010). *Assessing hydrological response to change in climate : Statistical downscaling and hydrological modelling within the upper Nile*. *Figure 1*.

Kisembe, J., Favre, A., Dosio, A., Lennard, C., Sabiiti, G., & Nimusiima, A. (2019). Evaluation of rainfall simulations over Uganda in CORDEX regional climate models. *Theoretical and Applied Climatology*, *137*(1–2), 1117–1134. https://doi.org/10.1007/s00704-018-2643-x

Komutunga, E., Oratungye, K. J., Ahumuza, E., Akodi, D., & Agaba, C. (2015). New procedure in developing adjustment algorithm for harmonizing historical climate data sets. *Journal of Dynamics in Agricultural Research*, *2*(June), 21–30.

Lagerblad, L. (2010). *Assessment of environmental flow requirements in Buzi River basin,Uppsala University , Mozambique*.

Li, L., Zhang, L., Wang, H., Wang, J., Yang, J., Jiang, D., Li, J., & Qin, D. (2007). Assessing the impact of climate variability and human activities on streamflow from the Wuding River basin in China. *Hydrol. Process.*, *21*, 3485–3491. https://doi.org/10.1002/hyp

Liu, X., Dai, X., Zhong, Y., Li, J., & Wang, P. (2013). Analysis of changes in the relationship between precipitation and streamflow in the Yiluo River, China. *Theoretical and Applied Climatology*, *114*(1–2), 183–191. https://doi.org/10.1007/s00704-013-0833-0

Luwa, J. K., Majaliwa, J.-G. M., Bamutaze, Y., Kabenge, I., Pilesjo, P., Oriangi, G., & Mukengere, E. B. (2021). Trends of Rainfall, Temperature and River Flow in Sipi Sub-Catchment on the Slopes of Mt . Elgon , Uganda. *Water*, *13*(1834).

Ma, H., Yang, D., Tan, S. K., Gao, B., & Hu, Q. (2010). Impact of climate variability and human activity on streamflow decrease in the Miyun Reservoir catchment. *Journal of Hydrology*, *389*(3–4), 317–324. https://doi.org/10.1016/j.jhydrol.2010.06.010

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *Annals of Mathematical Statistics*, *18*, 50–60.

Mewded, M., Abebe, A., Tilahun, S., & Agide, Z. (2021). Impact of land use and land cover change on the magnitude of surface runoff in the endorheic Hayk Lake basin, Ethiopia. *SN Applied Sciences*, *3*(8). https://doi.org/10.1007/s42452-021-04725-y

Ministry of Water and Environment. (2013). *Uganda National Water Resources Assessment*.

Mubialiwo, A., Abebe, A., & Onyutha, C. (2023). Heliyon Changes in extreme precipitation over Mpologoma catchment in Uganda, East Africa. *Heliyon*, *9*(3), e14016. https://doi.org/10.1016/j.heliyon.2023.e14016

Mubialiwo, A., Onyutha, C., & Abebe, A. (2020). *Historical Rainfall and Evapotranspiration Changes over Mpologoma Catchment in Uganda*. *2020*(October 2018).

Mugume, I., Basalirwa, C., Waiswa, D., & Ngailo, T. (2017). Spatial Variation of WRF Model Rainfall Prediction over Uganda. *J Environ Chem Ecol Geol Geophys Eng*, *11*(7), 553–557.

MWE. (2016). *Republic of Uganda Ministry of Water and Environment Mpologoma catchment Management Plan*. *November*, 216.

NEMA. (2010). *State of the Environment Report for Uganda 2010*.

Negewo, T. F., & Sarma, A. K. (2021). Evaluation of Climate Change-Induced Impact on Streamflow and Sediment Yield of Genale Watershed, Ethiopia. In *The Nature, Causes, Effects and Mitigation of Climate Change on the Environment.*

NEMA. (2010). *THE REPUBLIC OF UGANDA STATE OF THE ENVIRONMENT REPORT*.

Ngoma, H., Wen, W., Ojara, M., & Ayugi, B. (2021). Assessing current and future spatiotemporal precipitation variability and trends over Uganda , East Africa , based on CHIRPS and regional climate model datasets. *Meteorology and Atmospheric Physics*, *0123456789*. https://doi.org/10.1007/s00703-021-00784-3

Nsubuga, F. N. W., Namutebi, E. N., & Nsubuga-ssenfuma, M. (2014a). *Water Resources of Uganda : An Assessment and Review*. *October*, 1297–1315.

Nsubuga, F. N. W., Namutebi, E. N., & Nsubuga-ssenfuma, M. (2014b). Water Resources of Uganda : An Assessment and Review. *Journal of Water Resource and Protection*, *2014*(6), 1297–1315. https://doi.org/http://dx.doi.org/10.4236/jwarp.2014.614120

Ogwang, B. A., Guirong, T., & Haishan, C. (2012). Diagnosis of September -November Drought and the Associated Circulation Anomalies Over Uganda. *Pakistan Journal of Meteorology*, *9*(17), 11–24.

Onyutha, C. (2021). Trends and Variability of Temperature and Evaporation Over the African Continent: Relationships with Precipitation. *Atmosfera*, *34*(3), 267–287. https://doi.org/10.20937/ATM.52788

Onyutha, C., Acayo, G., & Nyende, J. (2020). *Analyses of Precipitation and Evapotranspiration Changes across the Lake Kyoga Basin in East Africa*.

Onyutha, C., Asiimwe, A., Muhwezi, L., & Mubialiwo, A. (2021). *Water availability trends across water management zones in Uganda*. *April*, 1–14. https://doi.org/10.1002/asl.1059

Onyutha, C., Turyahabwe, C., & Kaweesa, P. (2021). Impacts of climate variability and changing land use / land cover on River Mpanga flows in Uganda , East Africa. *Environmental Challenges*, *5*(April), 100273. https://doi.org/10.1016/j.envc.2021.100273

Oratungye, K. J., Oludhe, C., Manene, M. M., & Komutunga, E. (2017). A multivariate analysis approach in determining potential hotspots of seasonal rainfall change over Uganda. *International Journal of Statistics and Applied Mathematics*, *2*(1), 31–41.

Oti, J. O., Kabo-bah, A. T., & Ofosu, E. (2020). Hydrologic response to climate change in the Densu River Basin in Ghana. *Heliyon*, *6*(8), e04722. https://doi.org/10.1016/j.heliyon.2020.e04722

Pettitt, A. N. (1979). A Non-Parametric Approach to the Change-Point Problem. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, *28*(2), 126–135.

Phillips, J., & McIntyre, B. (2000). ENSO and interannual rainfall variability in Uganda: Implications for agricultural management. *International Journal of Climatology*, *20*, 171–

182.

Pyrce, R. (2004). Hydrological Low Flow Indices and their Uses. *Watershed Science Centre*, *04*, 37.

Quilbé, R., Rousseau, A. N., Moquet, J., Trinh, N. B., Dibike, Y., Gachon, P., & Chaumont, D. (2008). *Assessing the Effect of Climate Change on River Flow Using General Circulation Models and Hydrological Modelling – Application to the Chaudière River , Québec , Canada*. *33*(December 2007), 73–93.

Red Cross. (2010). *Uganda : Floods & Landslides in Eastern Uganda* (Issue April).

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., & Bacmeister, J. (2011). MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications. *Journal of Climate*, *24*(14), 3624–3648. https://doi.org/https://doi.org/10.1175/JCLI-D-11-00015.1

Salathe, E. P., Mass, C. F., & Steed, R. (2008). *A high-resolution climate model for the United States Pacific Northwest.* https://doi.org/10.5194/gmd-7-1629-2014

Sangüesa, C., Pizarro, R., Ingram, B., Balocchi, F., García-Chevesich, P., Pino, J., Ibáñez, A., Vallejos, C., Mendoza, R., Bernal, A., Valdés-Pineda, R., & Pérez, F. (2023). Streamflow Trends in Central Chile. *Hydrology*, *10*(7), 1–14. https://doi.org/10.3390/hydrology10070144

Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M., & Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. *Regional Environmental Change*, *17*(6), 1585–1600. https://doi.org/10.1007/s10113-015-0910-2

Skamarock, W. C., & Klemp, J. B. (2008). A time-split nonhydrostatic atmospheric model for weather research and forecasting applications. *Journal of Computational Physics*, *227*(7), 3465–3485.

Smakhtin, V. U. (2001). Low flow hydrology: A review. *Journal of Hydrology*, *240*(3–4), 147–186. https://doi.org/10.1016/S0022-1694(00)00340-1

Stogner, B. R. W. (2000). Trends in Precipitation and Streamflow and Changes in Stream Morphology in the Fountain Creek Watershed , Colorado , 1939 – 99. Water-Resources Investigations Report 00-4130. 48.

Taye, M. T., Ntegeka, V., Ogiramoi, N. P., & Willems, P. (2011). Assessment of climate change impact on hydrological extremes in two source regions of the Nile River Basin. *Hydrology and Earth System Sciences*, *15*, 209–222. https://doi.org/10.5194/hess-15-209-2011

Taylor, T., Markandya, A., Droogers, P., & Rugumayo, A. (2014). *Economic Assessment of the Impacts of Climate Change in Uganda: Data Water Sector Report* (Issue November).

Tencaliec, P., Favre, A.-C., Prieur, C., & Mathevet, T. (2015). Reconstruction of missing daily streamflow data using dynamic regression models. *Water Resources Research*, *51*, 9447–9463. https://doi.org/10.1002/2015WR017399

Torabi Haghighi, A., Yaraghi, N., Sönmez, M. E., Darabi, H., Kum, G., Çelebi, A., & Kløve, B. (2021). An index-based approach for assessment of upstream-downstream flow regime alteration. *Journal of Hydrology*, *600*(July). https://doi.org/10.1016/j.jhydrol.2021.126697

Tumusiime, M. D., & Ageet, S. (2018). Assessment of Impacts of Climate Change on Hydro-meteorological Ecosystem Services and Water Stress in Lake Kyoga Catchment. *International Journal of Research and Engineering*, *5*(4), 345–354.

https://doi.org/10.21276/ijre.2018.5.4.2

Tusingwiire, M. A., Tumutungire, M. D., & Sempewo, J. I. (2023). Impacts of climate and land use / cover change on mini-hydropower generation in River Kyambura watershed in South Western part of Uganda. *Water Practice and Technology*, *18*(6), 1576–1597. https://doi.org/10.2166/wpt.2023.079

Verdonck, J., & Michel, J. (2016). *Mpologoma Catchment Management Plan* Issue November issue by GOU.

von Storch, H., & Zwiers, F. W. (2003). Statistical Analysis in Climate Research. In *Journal of the American Statistical Association* (2nd ed.). Cambridge University Press. https://doi.org/10.2307/2669798

Wambua, R. M., Mutua, B. M., & Raude, J. M. (2016). Prediction of Missing Hydro-Meteorological Data Series Using Artificial Neural Networks (ANN) for Upper Tana River Basin , Kenya. *American Journal of Water Resources*, *4*(2), 35–43. https://doi.org/10.12691/ajwr-4-2-2

WRF. (2016). *Climate Change Uncertainties Will Create Unprecedented Challenges*

WMO. (2010). *Manual On Stream Gauging: Vol. II* (Issue 1044).

Wooldridge, J. M. (2009). *Introductory Econometrics, A Modern Approach*.

WWAP, & DWD. (2006). *National Water Development Report: Uganda*. https://doi.org/UN-WATER/WWAP/2006/9

Yang, Z. F., Yan, Y., & Liu, Q. (2012). The relationship of Streamflow-Precipitation-Temperature in the Yellow River Basin of China during 1961-2000. *Procedia Environmental Sciences*, *13*(2011), 2336–2345. https://doi.org/10.1016/j.proenv.2012.01.222

Zhao, G., Tian, P., Mu, X., Jiao, J., Wang, F., & Gao, P. (2014). Quantifying the impact of climate variability and human activities on streamflow in the middle reaches of the Yellow River basin, China. *Journal of Hydrology*, *519*(PA), 387–398. https://doi.org/10.1016/j.jhydrol.2014.07.014

APPENDIX I

Table A: Pettit test for homogeneity on original discharge and original rainfall series

Monthly average discharge (m^3s^{-1})			**Monthly total rainfall (mm)**		
No. of obs. (*n*)	Test statistic (U^*)	Significance (*p*)	No. of obs. (*n*)	Test statistic (U^*)	Significance (*p*)
420	3458	0.760	420	4555	0.374

P-values larger than 0.05 indicate that series are homogenous and hence suitable for analysis

Table B: Dickey-Fuller test for stationarity of log-transformed streamflow statistics

Transformed streamflow		**Obs. (*n*)**	**Test statistic**	**Significance (*p*)[*]**
Annual	Log (Q_{7mean})	34	-6.065	0.0000
	Log (Q_{50})	34	-4.861	0.0000
MAM	Log (Q_{7min})	34	-5.658	0.0000
	Log (Q_{90})	34	-5.896	0.0000
SON	Log (Q_{7max})	34	-6.535	0.0000
	Log (Q_{10})	34	-4.686	0.0001

[*]*P-values lower than 0.05 indicate that the log-transformed series are stationary*

Table C: Diagnostics checks for classical linear assumptions (tests on model residuals)

	Shapiro-Wilk test for normality No. of observations (*n*) = 35		**Portmanteau test for white noise** No. of observations (*n*) = 35	
Fitted model	**Test statistic (*W*)**	**Significance (*p*)[*]**	**Test statistic (*Q*)**	**Significance (*p*)[*]**
Equation 4.1	0.947	0.0896	18.857	0.2203
Equation 4.2	0.944	0.0721	12.761	0.6207
Equation 4.3	0.967	0.3720	15.966	0.3843
Equation 4.4	0.965	0.3213	16.191	0.3694
Equation 4.5	0.976	0.6438	11.109	0.7448
Equation 4.6	0.971	0.4654	11.654	0.7050

[*]*P-values > 0.05 show that the model residuals are independent and normally distributed*

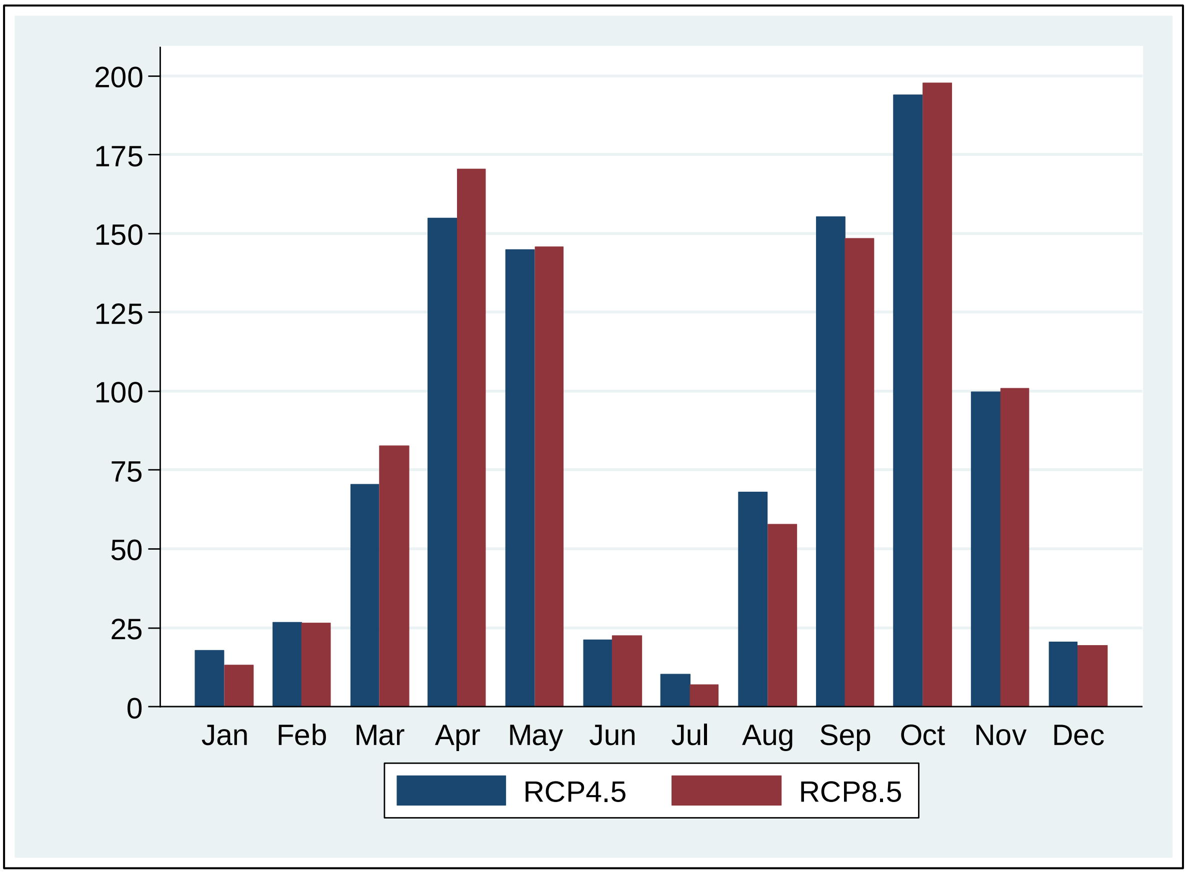

Figure A: Projected monthly rainfall for R. Mpologoma catchment for 2021-2040