ASSESSMENT OF THE IMPACTS OF CLIMATE CHANGE ON SURFACE WATER RESOURCES IN THE RIFT VALLEY REGION: A CASE STUDY OF NAROK COUNTY

BY

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DECLARATION

This dissertation is my original work and has not been presented for a degree in any other university.

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DEDICATION

I dedicate this dissertation to my lovely parents, Mr. Maurice Waswa and Mrs. Susan Waswa, whose love, support, and prayers kept me going. To all my brothers, friends, classmates, and Guardians, this is also dedicated to you.

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I sincerely thank the Almighty God for His mercies, grace, love, and the strength He gave me throughout my entire study at the University of Nairobi.

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ABSTRACT

Over the past century, notable changes in precipitation and temperature have been observed, which has been greatly attributed to a change in climate. These changes have altered the climate system and considerably induce changes in the hydrological cycle, eventually affecting the hydrological system. Narok County is important to the country since it supports several farming activities of both livestock and crop farming, has a stretch of the Mau Forest Complex in the Northern region which is a principal water catchment not only in the County but the Country as well, and earns the country an extra income through tourism by the presence of Maasai Mara game reserve. All these are inter-linked such that, affecting one component eventually affects the other, hence the entire ecosystem.

The main objective of this study was to assess the impacts of climate change on surface water resources with a focus on Narok County. Data employed include; monthly observed rainfall, temperature, and discharge. Rainfall and temperature datasets were obtained from Kenya Meteorological Department (KMD), which were supplemented with gridded datasets (CHIRPS and ERA5 datasets) from IGAD Climate Prediction and Application (ICPAC) and European Centre for Medium-Range Weather Forecasts (ECMWF) respectively. River discharges were from Water Resource Authority (WRA) and the climate projection datasets were obtained from the ESGF website domain. The historical datasets were for the period 1981-2018, while the projection dataset was for the period 2006-2055.

Trend analysis was employed to analyze the past, present, and future patterns climate and hydrology, and tested by Man-Kendall (MK) non-parametric test. PCA was done regionalization and spatial distribution of rainfall evaluated. Spectral estimation was also performed over the study region to identify the cycles of extreme events in the observed rainfall and Probability distribution functions used to assess the change in the Mean, Variance, and skewness in both rainfall and temperature datasets with different time slices with the baseline. The validation was assessed by the use of RMSE, correlation analysis, model BIAS, and standard deviation. To assess the impacts of climate change on surface water availability, the hydrological modeling approach was employed aided by the Water Evaluation and Planning Model (WEAP), with an evaluation of two scenario approach; Synthetic scenarios and General Circulation Model Scenarios.

From the results obtained in this study, six homogeneous rainfall zones were delineated, each with distinct climate characteristics. All zones exhibited high variability of rainfall in space and

time with the dry months (Dec-Feb, Jun-Aug) recording the highest, while the lowest variability recorded during the wet seasons (March-May) and (Sept-Nov). The region also exhibits a bimodal rainfall pattern with much of the rains received in April during the long rain season (MAM) and short-rain season (SON), where rivers in this region follow the patterns of rainfall. Rainfall was also unevenly distributed, with the western region receiving much rain (1400mm) annually compared to the East and Central regions. Spectral estimation over the region identified three dominant spectral peaks; 2-3.2, 4-5.5and 6.5- 10 years cycles which are attributed to Quasi-Biennial Oscillations (QBO), El-Nino, and solar variability respectively.

The future climate projections over the region were provided by two climate change scenarios; RCP4.5 and RCP8.5, with a multimodel Ensemble mean having the best skill in projecting the future climate. It was seen that there was a likelihood of the future climate being warmer and drier as seen in the significant increasing trends in temperatures in both scenarios. A shift in the mean values of both rainfall and temperature indicates a changing climate and this will inimically affect water availability (yields), and this calls for proper adaptation strategies in water management in the County.

There will be a general decrease of water quantity in the region in both scenarios; -30% by 2030 and -23.45% by 2055. In comparison, RCP4.5 and Scenario3 (+2.5°C, +10%P) had higher than RCP8.5 and Scenario2 respectively. There was also a clear indication that the region was highly sensitive to a perturbation in climate from the Synthetic scenarios. A change in either rainfall or temperature (or both) could lead to an impact on the amount of surface water yields.

Findings from this study may be adopted in the water sector for management and both long and short-term development planning, evaluation and monitoring of surface water resources, and assessing the vulnerability of the county to a change in climate that will help the relevant authorities to come up with ideal adaptation and mitigation measures. WEAP hydrological model is recommended for Water Evaluation and Planning and assessment of the impacts of climate change in the county to improve on water-related issues. Policymakers can also adopt results from this study to solve issues related to water resources in the County, and further studies on incorporating other factors such as population, water demands, groundwater, and land use/land cover to assess the impacts of climate change in the region are recommended.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AR5: FIFTH ASSESSMENT REPORT

CO_2: Carbon Dioxide

CHIRPS: Climate Hazard Group Infrared Precipitation with Stations

CMS: Cumecs

CORDEX: Coordinated Regional Downscaling Experiment

CV: Coefficient of Variation

DEM: Digital Elevation Model

DSS: Decision Support System

ECMWF: European Centre for Medium-Range Weather Forecasting

ENSO: El Nino Southern Oscillations

ERA-Interim: ECMWF Re-Analysis Interim

FAO: United Nations Food and Agricultural Organizations

GCM: General Circulation Model

GHGs: Green House Gases

GIS: Geographic Information System

GOK: Government of Kenya

GWP: Global Water Partnership

IPCC: Intergovernmental Panel on Climate Change

ITCZ: Inter-Tropical convergence zone

IWRM: Integrated Water Resource Management

LCP: Low Carbon Pathways

MAM: March-April-May

MCM: Million Cubic Meters

NCIDP: Narok County Integrated Development Plan

NSE: Nash-Sutcliffe Efficiency

OND: October-November-December

PBIAS: Percentage Bias

PCA: Principal Component analysis

QGIS: Quantum GIS

RCM: Regional Circulation Model

RCPs: Representative Concentration Pathways

RGS: River Gauging Station

RMSD: Root Mean Square Difference

RMSE: Root Mean Square Error

SS_E: Sum Square Errors

SD: Standard Deviation

SDGs: Sustainable Development Goals

SEI: Stockholm Environment Institute

SOBJ: Specific Objective

SON: September-October-December

SRTM: Shuttle Radar Topographic Mission

SSP: Shared Socioeconomic Pathways

UNEP: United Nations Environmental Programme

UNFCCC: United Nations Framework Convention on Climate change

WARMA: Water Resource Management Authority

WEAP: WATER EVALUATION AND PLANNING

WMO: World Meteorological Organization

CHAPTER ONE

1.0 INTRODUCTION

The background of the study, statement of the problem, justification, significance of the study, objectives of the study, hypothesis, limitations of study, and also the description of the area of study are presented in this chapter.

1.1 Background of Study

Water is a natural resource and crucial for the support of life on earth. Retrogression of the environment and climate change has posed challenges in the management and allocation of available water resources (Leal Filho, 2015; Okyereh *et al.,* 2019; Wang *et al.,* 2005). However, the world's freshwaters are under stress are under increasing pressure and many still lack access to adequate water to meet their basic needs (Cap-Net, 2006).

Climate has been variable over the past century, attributing to the change in temperature, precipitation, and radiation patterns, and this has led to the alteration in the global hydrology. Surface temperatures have been increasing on a global scale at a rate where the scientists have concluded that there's global climate change. This has been amplified by several factors, among them, anthropogenic factors such as emission of GHG (IPCC, 2007). However, the world's economies, health, and safety of humans in many countries have been greatly affected by climate change making it a threat, since the social, political, and security issues all around the world have been affected (Renton, 2009). In some cases, people have been displaced.

The growth in population increases the economic activities; change in standards of living and eventually results in the depletion of the limited freshwater resources. A report by the World Bank (2005) estimates a larger population of people to be living under stressful conditions of absolute water scarcity and is expected to worsen by the year 2025. Climate and demographic changes are such factors that can effectuate the exhaustion of groundwater and also lead to high demands of energy (Aloysius *et al.,* 2015; Asaf *et al.,* 2007; Kadner *et al.,* 2008; Khadra, 2019). This presents tough decisions especially to policymakers and managers and the only option to curb the shortages is to factor out supply and demands (Conway, 2009).

Globally, less than 1% of freshwater is accessible readily for human use. However, this has resource has greatly been exploited without consideration of the future. According to UNDP (2006), due to poverty and inequality, a bigger population lack access to improved water supply mainly due to governments failing to impose policies to safeguard this water resource. Pollution and extreme exploitation such as selling water is a major alarming crisis in the whole world. A

(2009) report by the World Bank predicts that, by 2030, there would be a global pressure on freshwater supply which would be surpassed by demands.

The African continent has an area of about 30million square kilometers. It has several valuable resources such as natural forests, minerals, wildlife, and diversity in biological existence (Kotchecheeva and Singh, 2000). Climate change impacts can be greatly felt on the communities around the African continent and the ecosystem, depending on the geographical positioning of these countries, population, and their capacity to adapt and mitigate to the changes in climate (Urama and Ozor, 2010). Several countries in Africa are living under the stress of the availability of water. According to Pittock (2005), putting pressure on renewable resources and higher rates of usage of water could lead to total replenishment of these resources. This will significantly increase in the Sub-Saharan regions (dry areas), according to the statement issued from the International Dialogue on Water and Climate (Rosenzweig *et al.*, 2004). Inaccessibility to safe and adequate water for use by a vast population in the Sub-Saharan region has led to the death of more than five million people and animals (UNEP, 2003).

According to Leal Filho (2015), Africa is the most vulnerable continent to climate variability and change. The rate of warming patterns is alarming subjecting the continent to the high variability of rainfall in space and time. Some parts are experiencing extensive drought conditions, with others severely affected by heavy rains and floods resulting in loss of livelihoods to people in these places (Luo *et al.*, 2005; Nelson, 2004; Trenberth *et al.*, 2005; Verdin *et al.*, 2005).

A report by UNFCCC (2018) suggests that Africa faces multiple convergences of stresses, limiting its capability to address climate change. More so, increased variability of rainfall limits the continent's ability to cope with climate change. According to Bates *et al.* (2008), the measure of potential water availability in Africa is below -0.75, compared to the global range of between -0.1 to -0.25 as measured by the Climate Moisture Index (CMI), exposing a vast population in Africa with the stress of water availability currently. By the year 2025, the whole continent with a large population will face the risk of water scarcity following the projected warmer and drier conditions.

Even though a less percentage of the population in Africa resides in the Arid and Semi-arid regions (ASALs), individual access to water when compared to the global average is less than the global average and is on the verge of decline. As the amount of rainfall is declining, groundwater is also falling in some regions. To add on, conflicts within and between countries, political instability, lack of valuation of ecosystems, poor farming, and agricultural practices, and lack of proper governance and water monitoring affects water resources (UNEP, 2003).

The changing patterns of climate which include the variable trends in precipitation and temperatures are inimical on the socio-economic sector of Kenya. Illegal logging, poor farming practices, and encroachment into forest lands have hastened the degradation of these lands and as such the forest cover in Kenya has fallen from 12% as was in the 1960s to 2% as at present state. This has greatly affected the main water towers which are the major catchment in the country and a source of water for consumption in both rural and urban settings (NCCRS, 2010).

The impacts of climate change can be studied by climate modeling using GCMs and RCMs, and its impacts on water resources by hydrological modeling using hydrological models (Khalilian and Shahvari, 2019).

1.2 Statement of the Problem

Kenya has 47 counties as shown in figure 1.1 below. Narok County is among the crucial counties in the country for the achievement of the economic pillar of Kenya's Vision 2030. It supports several activities including both livestock and crop farming, and an ecosystem to the Maasai Mara Game Reserve, which offers important habitats for a great variety of wild animals hence a hub for tourist attraction, earning the County and Country an extra income through revenue collection. The Mau Forest Complex in the north is a source of major rivers including the Mara River and a water Catchment tower that supports other regions as well. Many rivers present in the region supports several activities and also form a livelihood to the people within.

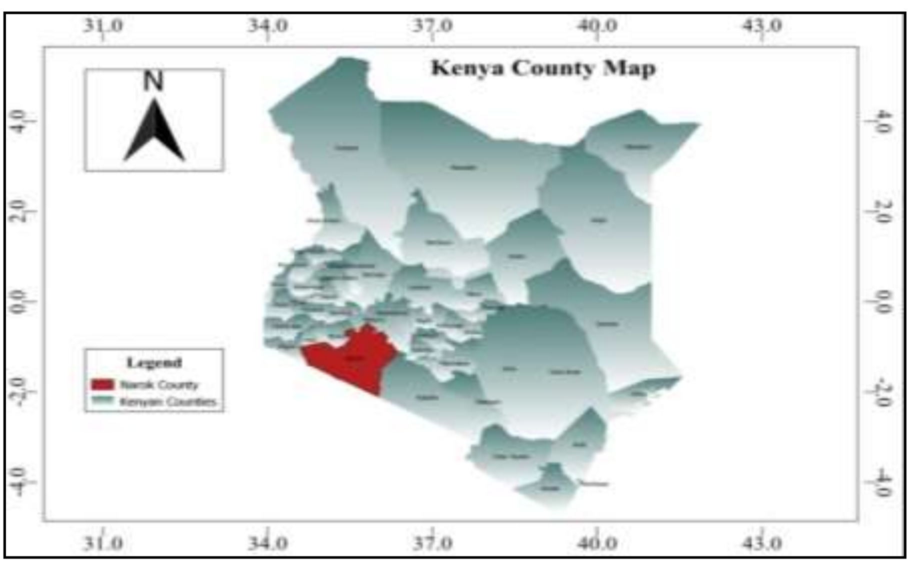

Figure 1.1: Kenya County Map
(Source: Author, 2020; derived from QGIS).

In the recent past, the natural resources and several activities in this region have been hampered. The entire ecosystem has been under threat of drought and famine. Deforestation of the Mau Forest Complex in search of arable farming land and settlement has led to the disruption of the hydrological cycle, which has affected the downstream users. Water levels in the rivers have been decreasing with some drying up completely, and since a larger population depends on these rivers for livelihood, this has posed a greater challenge to the communities living in this region. Farmers in the region have also had challenges in the prediction of the onset and cessation of short and long rains, bringing challenges with regards to the preparation of land, planting, and harvesting, eventually affecting their produce (NCIDP, 2017).

The infestation of human activities such as crop farming, charcoal burning, and human settlement around the Game Reserve has also led to human-wildlife conflicts following the loss of wildlife habitat, and also over water and pasture. Several farmers in this region have switched from pastoral farming to crop farming and other land-use practices, which puts the entire ecosystem under threat following a heavy demand for water for agriculture. The longer drought spells have affected the migration and population of the animals in the Maasai Mara Game reserve, such as the wildebeest migration.

The most severe risk faced by people in this region is the scarcity of water due to extreme climate conditions, and little has been done on the impact of climate change on water resources in this region. This study, therefore, was aimed at assessing the potential impact of climate change on water resources in the Rift Valley region with a focus on Narok County.

1.3 Objectives of the Study

The overall objective of this study was to assess the impacts of climate change on surface water resources in the Rift valley region, with the main focus on Narok County. This was attained with the following specific objectives;

(i) To assess the spatial and temporal distribution of rainfall and discharge in Narok county.
(ii) To assess the future climate change scenarios over Narok county.
(iii) To assess the impacts of climate change on the surface water resources in the county.

1.4 Study hypothesis

If the amount of water in the river channels in the region is mainly determined by runoff from precipitation, and temperature as the main climate variables, then their perturbation will lead to an alteration in the amount of water yields under consideration of different climate change scenarios.

1.5 Justification of the Study

Climate change is likely to increase in frequency and magnitude in the future. Projections made by the General circulation models (GCMs) indicate a warmer and drier environment. These conditions can potentially cause severe changes in the water sector such as decrease volumes in streams and rivers and severe drought conditions. Communities living in the affected areas are more exposed to the impacts of climate change since they lack the ability and capacity to cope with the uncertainty of climate change and variability. And as a consequence, this may also lead to a reduction in farm produce by farmers, animal population, reduced economic income for the country, and communal conflicts over water spots.

Narok County is among the productive counties in the country. Being a major center of commerce is also an important driver to Kenya's economy. The stretch of Mau Forest Complex in the North is one of the major water towers in the country where several rivers originate from, and also forms a basis of livelihood for a vast population in the region through farming and livestock practices and also wildlife. The slope of Mau escarpments provides fertile ground for farming for crops such as wheat and barley, making the county the breadbasket of the country. Unless proper action is taken, persistence in climate variability and change will continually impact on all these benefits in the county.

And thus, this study was aimed at assessing the impact of climate change on surface water resources in Narok County. The county was selected due to the significant contribution to the country's economy from the various sectors; water, tourism, and farming.

1.6 Significance of the study

Water is a vital commodity. This study seeks to assess the impacts of climate change on surface water resources, in Narok County. Findings from this study will be crucial in several sectors and may be adopted for planning and sustainable development by various water managers and also in the National Development Agenda. They will not only provide useful products but also methodologies that can be used in the strategic water management in the County, which should be adopted and amalgamated in the National Water Master Plan application and achievement of Kenya Vision 2030 and African Union Agenda 2063.

To add on results from this study will: provide policymakers with perception on the proper guide to planning and allocation of water resources; provide a proper guide of possible means of climate change adaptation, reduction, and eradication for the development of the country; disaster risk alertness and structural management and planning and provide advice to both the water and climate sectors for quality planning, and quantify the impacts of climate change at a catchment level.

Findings from this study will provide useful information on the use of the Water Evaluation and Planning Model (WEAP), and this should be adopted in the water sector section for the implementation and application of this model in the planning and management of water resources in Kenya for use at different scales, in line with the Kenya Vision 2030 and blueprint project, and the application in other counties and catchments as well.

This study will also provide a basis for further research on the application of other hydrological models for impact studies in the region, and the full functionality of the WEAP model by incorporating additional factors and data requirements.

1.7 Limitations of the study

The scope of this study is to investigate the impacts of climate change on surface water resources at a county level. However, this study does not incorporate the impacts of climate change on; water quality, groundwater recharge, demography, and other socio-economic and technology-based developments. Aiming at the main objective of the study, the study will prioritize on the application of the Water Evaluation and Planning sys (WEAP), to address the emerging water-related issues, considering different climate change scenarios in Narok County.

1.8 Study area characteristics

The main area of study is Narok County, in the Rift Valley Region of Kenya.

1.8.1 Location

The County of Narok is one of the 47 counties and is located south of the equator between Lat. 0° 50´S and 1° 50´ S and Lon. 35° 28´E and 36° 25´ E within the East African region, along the Rift Valley region of Kenya. The area spans from near the equator to the southern border of Kenya-Tanzania with an area of 17,944.1Km^2. The main administrative town is Narok town, which is also the center of all activities. This county has been ranked 11th in the country in terms of the area thus making it among the most important counties in the country to deliver. However, the Kenya National Bureau of Statistics (KNBS) 2019 census report of the region estimates a population of 1,149,379. Figure 1.2 shows the location of Narok County and the drainage features.

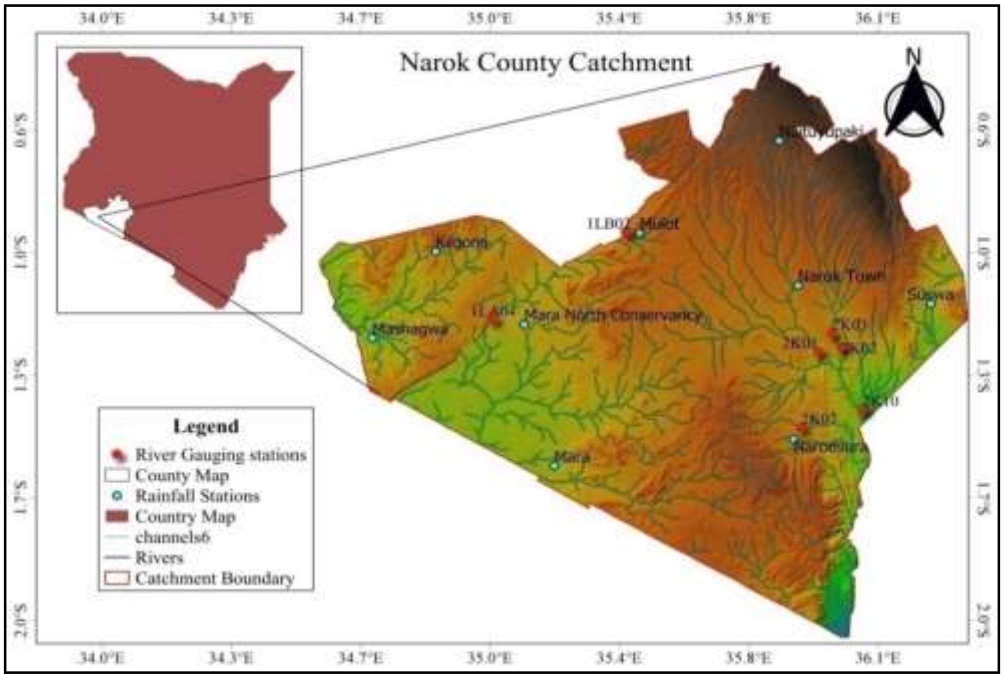

Figure 1.2: Location of Narok County Catchment with Rainfall stations and RGSs
(Source: Author, 2020; derived from QGIS- DEM data obtained from USGS).

1.8.2 Climatology of the study area

Narok County has a tropical type of climate. The region is largely influenced by the position and movement of the Inter-Tropical Convergence Zone (ITCZ) synoptic system, that also influence the occurrence of seasonal rainfall (March-April-May (MAM) and September-October-November (SON), over East Africa in intensity, magnitude, and distribution (Omeny and Oyieke, 2008; Rwigi, 2014).The proximity of Lake Victoria and the Indian Ocean also modifies the climate other than the local orography.

According to Nyakwada *et al.* (2009), the major source of moisture over the East African region comes from both the Atlantic and Indian Oceans. The interactions through atmospheric circulations influence the regional climate, where easterlies from the Indian Ocean and Westerlies from the Atlantic and the Congo Air mass are known to greatly influence the seasonal rainfall over East Africa. The presence of Lake Victoria on the western side of Narok induces land-sea breezes following a thermal contrast between the land and sea, which contributes to rainfall all year round (Rwigi, 2014; Sabiiti, 2008).

1.8.2.1 Temperature

Figure 1.3 presents the mean monthly air temperatures for the selected stations in the study area. Temperature ranges from about 22˚C in the South-Eastern part of Kalema in February- March, to 13.3˚C in the Northern parts of Kisiriri during July. However, the region records an average temperature of about 18˚C. Generally, the coolest month is July, while February-March-April and October-November-December are the warmest months in almost all stations in the study area.

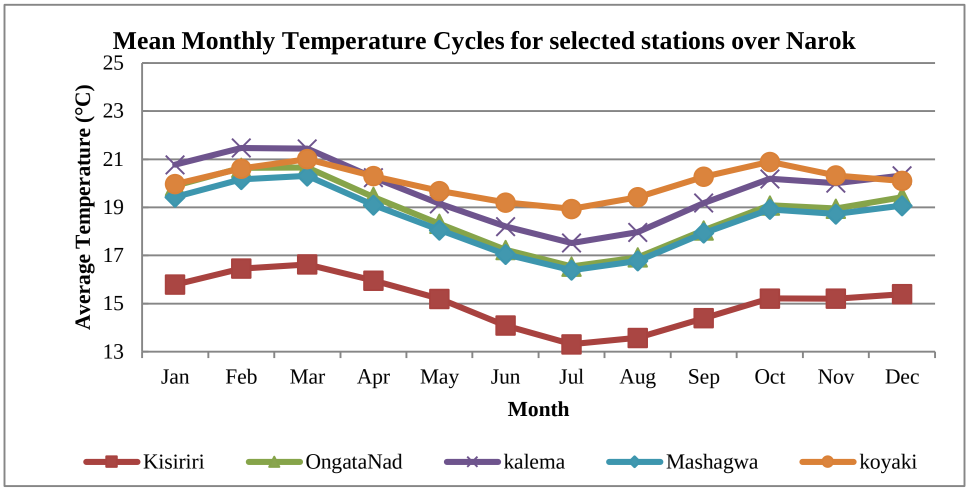

Figure 1.3: Mean Monthly Air Temperature distribution for the selected stations over Narok

1.8.2.2 Rainfall

Figure 1.4 shows monthly rainfall that was averaged over the period 1981-2018 at selected stations within the area of investigation. The region has two main wet seasons; March-April-May and Sep-Oct-Nov, though some stations in this region exhibit a trimodal rainfall pattern within Jun-Jul-Aug. The mean monthly rainfall ranges from about 12mm in July for Ongata Naado station, to about 191mm in April for Mashagwa in the west. Rainfall totals also vary in the region and range from about 650mm to 1300mm annually.

According to the NCIDP (2017), the March-April-May rainfall season is the main season and the region also receives high amounts of rainfall in all months, which supports the growth of vegetation and makes food for animals, and also assists farmers in planning for planting and harvesting. However, there exist several climatic zones ranging from humid, sub-humid, semi-humid, and arid and semi-arid zones.

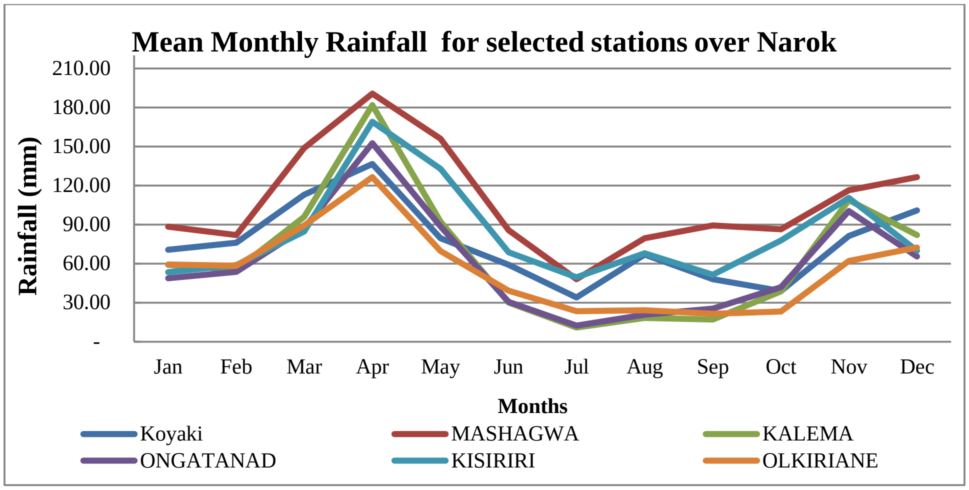

Figure 1.4: Mean Monthly Rainfall distribution for selected stations over Narok

1.8.2.3 Hydrology

Three main rivers drain the region; Mara, Ewaso Nyiro, and Migori rivers. Ewaso Nyiro River has its headwaters high in the Mau rising to the North of Olokurto and flows South-Eastwards to the edge of Nguruman into the Rift Valley. This river is fed by several tributaries such as Narok and Siyabei rivers which also have their headwaters from the Mau region. Mara River has its source near that of Ewaso Nyiro in the Mau and flows South-East in the Siria escarpment to form the “Mara Triangle”, then south towards Tanganyika and then westwards into Lake Victoria Nyanza near Musoma. Migori River rises near Abossi and drains the Transmara plateau, and flow South then West to join river Kuja near the Tanganyika border before flowing into Lake Victoria. Sondu River and Ewaso Kedong are the two peripheral rivers in the region that are important to the ecosystem. The Mau region in the North mainly drains into lakes Nakuru, Naivasha, and Elementaita. All the permanent rivers in the area derive their headwaters from the Mau region (Glover et al., 2017; NCIDP, 2017)

Figure 1.5 presents a hydrograph of Enkare and Ewaso discharge. There are two main wet seasons; March-April-May (MAM) and Oct-Nov-Dec (OND), with an additional mini peak season Jul-Aug-Sep, where the water levels in these rivers peak. The highest peak is recorded during March-April-May (MAM) season with a lag of one month to allow for infiltration and underground seepage.

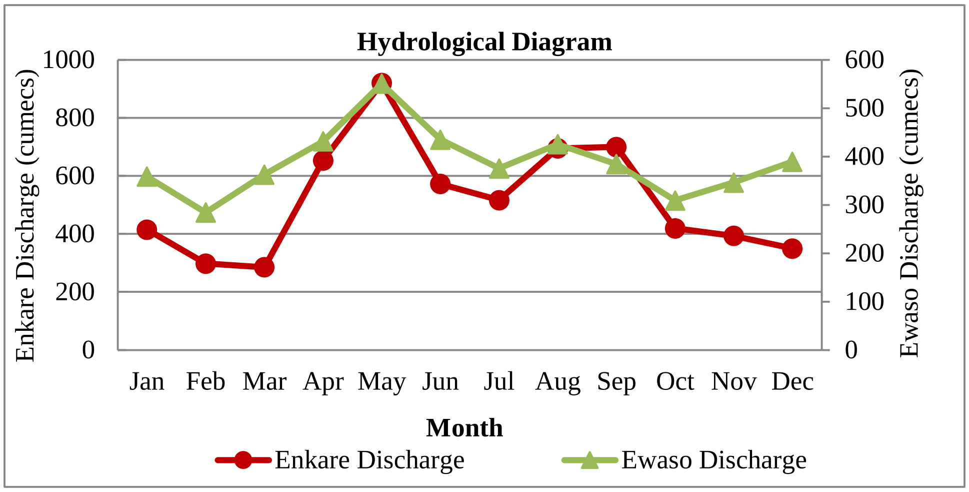

Figure 1.5: Mean Monthly hydrographs at Ewaso and Enkare RGSs

1.8.2.4 Geological characteristics and Soils

The main factors influencing soils in the region are geology, topography, and climate. The soils in the humid areas of Mau are mainly influenced by climate and vegetation. Soils in this region are deep volcanic. The soils within the Talek area are poorly drained due to the influence of topography. They are derived from the underlying phonolite. The South-East region of Narok have shallow soils derived from Basement System rocks and have a different chemical compound from that of Mau. Apart from the forested zones, most of the soils in the County are truncated and the top and sub-soils have gone leaving hard compacted pavements.

The Rift valley floor is mainly composed of Pleistocene sediments. Large areas of the central and Southern parts of Narok are immediately underlain by intensely metamorphosed sediments of the Basement system. The Western region around the Sirian escarpment has also low-grade metamorphic rocks of the Nyanzian and Kavirondian systems. Towards the Northern region, the alkali basalts are overlain by the Pliocene tuffs, agglomerates, and welded tuffs which together with a thick cover of Pleistocene ashes form the Mau Range. The South-Eastern part has more of the silts, gravel, and fluviatile pebble beds and sands (Glover *et al.*, 2017).

1.8.2.5 Land use Characteristics

The total land size of Narok County is 16.2 Hectares. There are several land uses ranging from agricultural, livestock, and wildlife production that is open to landowners. Mixed fruit farming is the major land-use in the region with portions allocated to wheat farming, tree crops and vegetables, and livestock farming in the fallow lands. There are also several game reserves in the region, and as a result, both tribal and human-wildlife conflicts have been on the rise in the recent past in the region mainly due to uncontrolled land use (NCIDP, 2017).

1.9 Data Availability and Challenges

There were several categories of data that were used in this study, which were collated from different sources which included; hydro-meteorological data, elevation data (DEM), and CORDEX climate projections. Hydrological data was obtained from the Water Resources Management Authority (WRMA), meteorological data from the Kenya Meteorological Department (KMD) which was substituted with CHIRPS and ERA5 datasets. CHIRPS datasets were obtained from the ICPAC data repository while the ERA5 dataset was obtained from the climate explorer webpage (http://climexp.knmi.nl/) (Accessed on February 5th, 2020). Topographical (DEM) data were downloaded from the USGS webpage (http://srtm.csi.cgiar.org/) (Accessed on February 5th, 2020) while the CORDEX outputs were obtained from the WCRP CORDEX domain *(https://esgf-data.dkrz.d)* (Accessed on March 10th, 2020).

The length of the datasets formed an important basis on the quality of the type of datasets used in this data. According to WMO (2009), quality records that have missing records should not exceed 10% of the total records and thus all the stations used in this study were picked depending on the length of records too. However, most of the hydrological datasets had missing records greater than 20% and were not included in the analysis.

The other datasets used in this study were obtained from several downscaling groups and were in the native model format grid and projection. These datasets had to be converted and placed into identical horizontal and vertical estimates before any analysis was performed.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents the Literature Review and gaps, an overview of climate and the climate models used, together with hydrology and the model applied.

2.2 ASPECTS OF CLIMATE VARIABILITY AND CHANGE

Weather is the state of the atmosphere at a given time and place, which can be described by variables such as temperature, precipitation, humidity, and clouds (IPCC, 2014b). The climate on the other hand is the equilibrium state of the atmosphere at a given place for a given period. It is the long term state or average state of the atmosphere (Bathke *et al.*, 2014), and can vary on timescales both longer and shorter than 30 years. Variability on timescales of few years to few decades is climate variability while variability on timescales longer than a few decades or longer than the standard climate averaging period is what is referred to as climate change. UNFCCC (2018) define climate as "a change of the climate that is attributed directly or indirectly to human activity, that alters the composition of the global atmosphere, and this is in addition to natural climate variability observations over comparable periods" With all these, climate change can best be defined as, the consequence of immobility of humanity, a perspective of the observer.

2.2.1 Observed Changes in Climate

Among the several platforms for monitoring climate, it is marked that climate has changed worldwide as shown by satellite platforms and observed records from weather stations. Major indicators of this change include; Temperature, precipitation, sea levels, snow and ice, and frequent occurrence of extreme events despite their non-uniformity in space and time as suggested by several studies including (Sikka and Islam, 2010). It is indisputable that the climate system is warming and is compelling. Global temperatures have risen to about 0.9°C. Temperatures today are warmer than they were in the mid-1800s. Since 1970 the rate of warming is unprecedented (Bathke *et al.,* 2014). Figure 2.1 shows the reconstructed global temperatures for the past 2000 years, where the trend shows that actually global temperatures have been increasing.

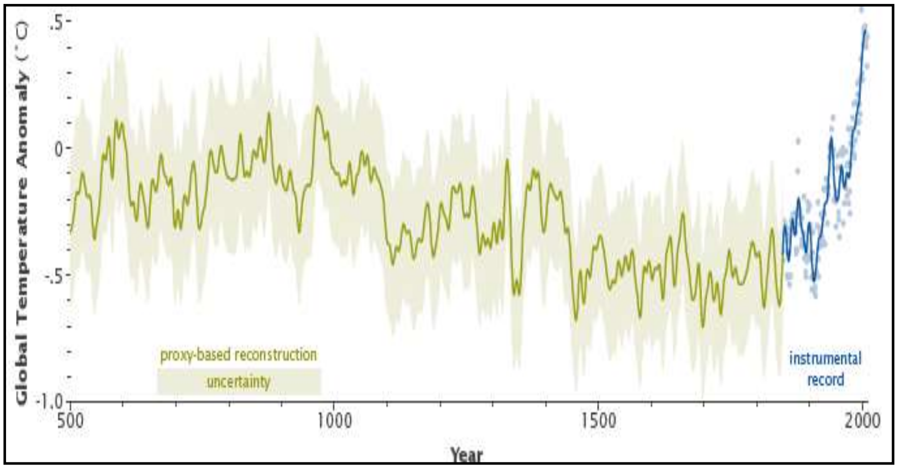

Figure 2.1: Global temperature record for the last 2000 years
(Source: NASA observatory, 2019)

With an average coverage of about 70% of the world's earth surface, oceans have a unique ability of storing heat. They also act as sinks atmospheric Carbon Dioxide. A study conducted by Rheine *et al.* (2013) shows that in the last few decades, oceans have warmed on the surface to about 6000ft deep, by the excess heat energy over the period 1971 to 2010 by a value of 0.18°F. According to NASA (2017), water levels in the oceans and seas have risen, and have absorbed much heat with the top warming up to as high as 0.4°F since as early as 1969, which has caused acidity in the water and alteration of the ocean circulation, including threatening the entire ecosystem. Sea level rise has also led to storm surges that have damaged buildings, loss of life, degradation of shorelines, and intrusion of salty seawater that has affected freshwater supplies (Bathke *et al.*, 2014).

The rates of warming and cooling has been variable globally. Some regions have had elevated temperatures causing more warming, while some have cooled unprecedentedly. Due to these factors, some of these regions have experienced drought condition due to excess warming resulting in reduction of precipitation, while some have been hit by wraths of frequent flooding (IPCC, 2014b). The frequency, intensity, and magnitude of precipitation have also been the norm in the recent past. Extreme climate conditions are increasing at an alarming rate. With temperature and precipitation as the key signals of climate change, several countries worldwide have proven that, the number of episodes from heatwaves have actually increased while cold snaps are diminishing (Bathke *et al.*, 2014).

According to Marvel and Bonfils (2013), atmospheric circulation patterns and the hydrological cycle have been greatly affected by shifts in global precipitation patterns. A natural ecosystem is directly linked to climate and changes in patterns and cycles of precipitation will heavily impact it. To add on, a focus into the future patterns of change is dependent on quality historical records (Bathke *et al.,* 2014; Easterling *et al.,* 2017; Vose *et al.,* 2017).

Different regions have had different observational changes depending on their locations. A study conducted by Vose *et al.* (2017) highlights the distinct changes of climate change in the United States. In their key findings, they found that, from 1986 the US has been warming with a record mean of about 0.7°C. For instance, different from other states the state of New Jersey recorded an increase of 2°C since 1985, which was almost double the average of the other states (Grossman, 2020). However, precipitation increased by 4% over the region for the period 1901-2015, with increased frequency and intensity, with very few states remaining dry. Other than 1973 and 1983, the year 2015 was extremely wet with a bigger percentage coverage recording high rainfall amounts, especially Northern parts of United States (Easterling *et al.,* 2017). This was also true for Vaughan (2013), who discovered that the rate of snowfall in this part of the United States had significantly reduced, leading to substantial alterations of hydrological regimes in river basins which had affected the reservoir storage and management.

A report by NOAA (2011), indicated that in the year 2011, the United States experienced several extreme events. There were extreme warming and the occurrence of heavy precipitation that submerged many regions such as Pennsylvania and the New York States following heavy storms. Vast regions along the Eastern coasts of Florida and England experienced severe drought conditions due to high temperatures, with extensive regions the same conditions. Substantially, a report by NASA (2017), indicated a shrinkage in the tonnage and a reduction in the number of both Arctic and Antarctic ice sheets since 1993. Greenland was the most affected than Antarctica and is projected to surfer the worst in the coming decades. Several regions around the world are experiencing the same conditions including; Alps, Himalayas, Andes, Rockies, Alaska, and Africa, which has also led to sea-level rise(Vaughan *et al.,* 2013).

Spatial and temporal discrepancies of climate variables are not an exception in climate studies. According to Collins (2011) and Niang *et al.* (2014), changes in climates was felt as early as mid-19^{th} century in Africa, and there has been an increase in observed surface temperatures. For instance, it is expected that the better part of the 21^{st} century will have significant precipitation changes (IPCC, 2014b; Kendon *et al.,* 2019), and more warming over the Sahel region, with a change of about 3°C. At least 70% of the countries in Africa are at a great risk of facing climate change impacts, as shown by the Africa vulnerability index. For almost two and a halve decades past, the region over the south of Africa including the Sahel have recorded decrease in precipitation amounts, with the Central region including parts of DR Congo recording an increase (Sultan, 2020). The drought vulnerability index despite the fact that there has been increased incidences of extreme events such as flooding and drought conditions (350 Africa, 2020).

It is a paradox that the African continent will be the hardest hit by climate change even if it is the least contributor to GHG emissions. It is evidently supported such factors as low adaptive capacity of member states, that exposes them to the harsh impacts of climate change, and the complexity of climatology within, induced by the largescale climate systems around. Climate is also highly variable especially around the tropics. The frequency of occurrence of extremes is on the rise, with many affected by droughts, storms and floods (IPCC, 2014a; Mannschatz *et al.*, 2015; Niang *et al.,* 2014). Droughts begun as early as 1965. The Sahel, South and West Africa are among the worst hit by severe dry and drought conditions. For instance, many countries including Lesotho, Eswatini and Zimbabwe have been entangled in the chain of famine. Other than scarcity of water availability big percentages of population in these countries are acutely facing a shortage in food supply and need humanitarian Aid (Nicholson *et al.,* 2018; OCHA, 2020).

Storms have also been part and parcel of occurrence in Africa. The Eastern shores have been majorly affected by tropical cyclones. For example, the Tropical cyclone IDAI and Kenneth in 2018 greatly affected the northern parts of Mozambique Channel and nearly 1.6 million people were affected including loss of lives and property. This also caused flooding in some parts in Malawi (OCHA, 2020).

Warming in East Africa dates as back in the 19th century and as early as 1965. Significant trends in patterns of warming is evident (about 0.7°C increase in Rwanda and 1.7°C Eritrea). The Greater Horn of Africa (GHA) is the most affected. Countries such as Somalia and Ethiopia are fighting to cope and eradicate famine and scarcity of water, and have reached a point of sourcing for humanitarian aid. It is also observed that, since the year 1960, precipitation has significantly changed over this region. There has been frequent incidences of flooding and droughts than the preceding years which is suspected to be as a result of a 1°C temperature warming over the Indian Ocean (OCHA, 2020; USAID, 2020). A bigger portion of GHA was also infested by desert locusts in the year 2020, which were breeding at a very fast rate despite the control measures to combat them. This invasion was linked to climate change where, the warmer temperatures and increased rainfall formed a conducive environment for their breeding (FAO, 2020).

Rainfall in Kenya is highly variable. There has been increased occurrence of such extreme events as floods and droughts, with significant intensities and magnitude, coupled with increased warming with a maximum of 0.3°C-1.3°C and a minimum of 0.7°C-2.0°C. this has been linked to ENSO event. For instance, 1997/98 was the wettest which caused flooding across the country (Muhati *et al.,* 2018). In the year 2020, there was an increase in volumes in the Rift Valley lakes that led to destruction of property and displacement of people within affected areas. There has been frequent flooding in various regions that has led to loss of life and property and infestation with desert locusts which have been breeding following a favorable climate of warm temperatures and precipitation (Aura *et al.,* 2020).

2.2.2 Detection and Attribution of Climate Change

With or without proof, several studies suggest that climate has changed and is continually changing with several possible liable mechanisms (IPCC, 2007). A report by Bathke *et al.*(2014) asserts that, currently, there is a small but significant positive imbalance of approximately 0.6W/m^2 between observed and terrestrial radiation emitted to space, and this has been the major driving force behind the observed increase in global temperature since the industrial revolution. Two major mechanisms that can change this radiation balance are; Natural (external) forcing and anthropogenic forcing. According to IPCC (2014b), there is a 95% confidence that human beings have greatly influenced the rate of atmospheric warming including oceans. An increase in atmospheric concentrations of GHGs and aerosols, land use, and land cover changes are the main dominant mechanisms of anthropogenic forcing. Climate oscillations, changes in solar activity, and volcanic activity are some of the natural mechanisms contributing to climate change (Bathke *et al.,* 2014).

The Radiative balance of the earth is predominantly affected by human activities. Changes in the amount and concentration of GHGs and other aerosols in the atmosphere are the major scales to base on. Climate warming has been majorly due to increased human activities since the pre-industrial era and there is a high confidence that the Radiative forcing from these human activities has surpassed natural factors like energy from the sun (Fahey *et al.,* 2017). The positive effect of cooling by the interaction of aerosol-cloud and aerosol radiation interact has significantly declined in recent decades. The human-induced aerosols play a crucial role in cooling. Over several decades, their contribution towards cooling has significantly reduced, surpassed by GHG forcing by human activities.

Other than atmospheric circulation, internal climate variability and changes in land use, anthropogenic aerosols have played a crucial role to GHG emission and climate change. For instance, warming over the United States especially the Northern and Western regions have been majorly due to anthropogenic activities (Tian *et al.,* 2015; Vose *et al.,* 2017). The Fifth Assessment Report (AR5) by the IPCC attributes the frequency and intensity of global temperature extremes to human influence (IPCC, 2007, 2014a).

A report by the Livestock long shadow, 2006 estimated that, 18% of the annual global GHGs are attributed to livestock and wildlife. A greater percentage of emissions came from the use of fossil fuels to generate energy in the UK (approximately 65%). Carbon industrial emissions contributed a 4% while at least 30% from agriculture and transport (FAO, 2018). Personal decisions such as car driving, air travel and home energy use contributes to about 40% of carbon in the UK, which can be cut down (Olivier *et al.*, 2017).

Being the least contributor to GHG emissions, Africa is one of the most vulnerable continents to climate change and climate variability despite the fact that agriculture and deforestation are currently on the rise and are key contributors. However, other than agriculture being the major economic activity, most countries are struggling to become middle-income and thus, industrialization and urbanization is the order of the day. This is accompanied by great emissions of carbon from the different sectors and is unwelcome to climate change several countries will be forced to see a low carbon pathway implementation in order to tackle this problem (Boko *et al.*, 2007).

About 80% of Kenya's population is dependent on agriculture for livelihood. A good percent of this also contributes to the GDP in the Kenyan market. Other than industrialization and urbanization, climate change has been attributed to the deforestation of Mau Forest Complex, which the government is trying to reclaimed since the year 2017, and plant more trees with an aim of reducing the amounts of carbon emissions that have come along with rapid industrialization.

2.2.3 Impacts of Climate Change on Hydrology and Water Resources

High levels of GHGs in the climate system induce a change in climate and this can affect the hydrological cycle and hydrological systems in watersheds. The water balance of a watershed is greatly determined by the climate within since it affects the moisture and energy input that controls a watershed (Rwigi, 2014).

In the coming decades, water resources will be overwhelmed by the changing climate and as such, streams will record low levels and water tables and aquifers will dwindle notably in dry regions such as the Arid and Semi-Arid regions. Water quality in both rivers and seas would be degraded following the increase in temperatures. Water levels in oceans and seas will rise, consequently affecting the water aquifers in the coastal borders following an intrusion from salty water. An increase in frequency and magnitude will also be observed and this could lead to flooding and landslides in many regions (Begum *et al.*, 2008). Other than the degradation of water quality, there will be an increase in water demands which will be proportional to increased rates of warming.

The atmosphere in warmer latitudes such as the tropics will tend to have more moisture held by warm air than higher cold latitudes, which will result in high rates of evaporation from water bodies, soils, and even plants, eventually resulting in more intense precipitation and snowfall events (Begum *et al.*, 2008; Farhan *et al.*, 2020). It is true that, as the climate changes the ratio and magnitude of rainfall will differ from one region to another. Some will have frequent and intense extreme event while other less frequent and mild(Rwigi, 2014; Vaughan *et al.*, 2013). As a consequence, the amount of water in catchment areas will also vary.

Forests are a major source of water in a catchment. Degrading forest reserves lead to alteration of the climate system which eventually leads to the disorientation of the hydrological cycle. Heavy precipitation will lead to increased erosion, siltation, reduced groundwater recharge, and minimum storage capacity (Rwigi, 2014).

Other than the obstruction in groundwater recharge, the changing climate will escalate drought and decrease the availability of water in many regions, which will also be compounded by insecurity issues in continents such as Africa. The aftermath of elevated temperatures incorporated with extreme events will also result in water pollution (Agamuthu *et al.*, 2019). The intrusion of saline seawater into freshwater resources from glaciers, snow, and ice melts will lead to scarcity of fresh and clean water (Harvey and Pilgrim, 2011; IPCC, 2007).

It will be substantial to obtain information on the extent of climate change at different scales to properly manage and plan water resources in any region, both short and long term about the economic activities within (Rwigi, 2014).

2.2.4 Impacts on agriculture and food security

Food security is when at all times people have full unrestricted and satisfactory reach to food and is detrimental to the livelihood of people. Future projections of precipitation and temperature indicates a change in climate that will greatly impact food security and food systems (FAO, 2020; IPCC, 2019). IPCC (2019) states "Climate change is affecting all four pillars of food security: availability (yield and production), access (prices and ability to obtain food), utilization (nutrition and cooking), and stability (disruptions to availability)". Carbon dioxide (CO2) being a major requirement together with favourable temperatures provides an ambient environment for quicker plant growth while reducing maturity periods. As a result, some regions will yield more produce following and increase in these conditions while some will record reduced yields depending on the same (FAO, 2020). Water spots will also diminish in areas that will have increased warming, and this will result in the withering of plants, which may eventually impair the agricultural sector.

Almost the whole African continent depends entirely on agriculture. In the past few decades, rainfall has been below average with several dry years. The productivity of produce is majorly dependent on geographical location. For instance, McGuire (2013) asserts that, the tropics and mid tropics are expected to give more yields following moderate temperatures, the amount of CO2 present, and precipitation. The productivity of crop yields and livestock has been greatly hampered by drought, heat stress, and flooding, which has greatly contributed to poverty and malnutrition in many countries therein.

East Africa has had its worst in the 21^{st} century not to mention, water scarcity and food crisis, and this has affected a bigger population therein. High temperatures have led to loss of soil moisture which have led to wilting. Future projection indicate even a much warmer environment and this is a threat to the agricultural sector (Bond, 2018; Vörösmarty *et al.*, 2005).

A vast population in Kenya is also dependent on rain fed agriculture and a good percentage of the produce contributes to the GDP. Projected increase in temperatures is likely to modify the productive agro-climatic zones and this will greatly affect the quality, quantity, availability and access of produce (Olaka *et al.*, 2019).

Findings from this study will greatly contribute to the agricultural sector in several ways; it will sensitize the idea that the already happening climate change will greatly affect food security in the country, and the most likely affected are the poor and young. Food security being one of the

Big Four agenda of the Vision 2030 goal in Kenya, it would be crucial to take quick action to minimize the impacts of climate change.

This study will also avail fine scale climate information and the sensitivity of a region to climate change and precisely suggest the pathways and actions to be adopted to protect the stature of food security.

2.3 CLIMATE MODELLING

This is the simulation of the interplay between the earth's climate system and components using computerized climate models and facilitates the understanding of how the atmosphere warms due to radiation imbalance in the long and short waves. It is also easier and simpler to comprehend the complexity of the climate system on seasonal, annual, decadal, and continental time scales (Haberle *et al.*, 2019). Predicting the evolution and changes in the climate system by studying the impacts caused by both the natural and anthropogenic factors (Rummukainen, 2013).

A comprehensive depiction of the components of the climate system and their interaction that provides a detailed description of the atmosphere is what best depicts a climate model (IPCC, 2007; Rwigi, 2014).They are grouped into two categories; Global Circulation Models (GCM) and Regional Circulation Models (RCMs).

2.3.1 Global Circulation Models (GCMs)

These are processed on feedback mechanisms, component interactions, and properties, numerically represented in a climate system, and are also crucial in assessing the possible quantity of GHGs and other particles in the atmosphere (Rwigi, 2014; Wilson *et al.*, 2010). However, GCMs have been unable to address the fine-scale details of local climates and hydrological scale simulations, even though they have been widely used to represent the atmosphere and water bodies on a macro-scale, considering the sequence of climate worldwide. Since they are global models, their resolution is courser (IPCC, 2007; Rummukainen, 2013; Teutschbein and Seibert, 2010).

The next subsection presents the Regional Circulation Models. They have been widely applied in climate studies following their fine-scale resolution in representing climate (Rwigi, 2014).

2.3.2 Regional Circulation Models (RCMs)

Though they have the same processes as those contained in the GCMs, they have a much finer resolution and capture a smaller area representation of the earth, typically a 50km horizontal resolution. They finely represent earth's features from the information obtained from GCMs aided by their high capability in climate system representation (Jones *et al.,* 2005; Rwigi, 2014; Teutschbein and Seibert, 2010). Model projections from these RCMs runs have been done on time scale modes i.e. baseline period, recent past, and future scenarios (Christensen *et al.*, 2010; Rwigi, 2014). Impact analysis of climate change on the entire ecosystem through modeling framework has been done by analyzing the differences in these modeled climates e.g. a change in the 30-year seasonal or annual mean (Rwigi, 2014). Figure 2.2 below shows a downscaling scheme from the global to catchment scale.

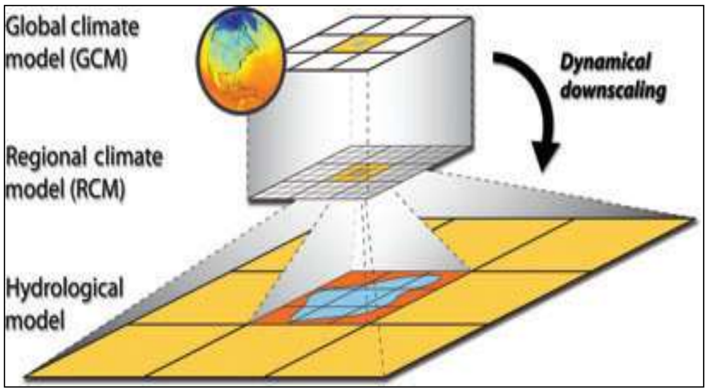

Figure 2.2: Downscaling scheme from global to catchment
(Adopted from Tseutchbein and Seibert, 2010)

2.4 CLIMATE CHANGE EMISSION SCENARIOS

Storylines of how the future may evolve with a given state of conditions and situations is what best describes a scenario. They are tools with which driving forces that influence the future emission outcomes can be analyzed and the associated uncertainties assessed, hence becomes images of how the future may unfold, and also create an understanding of how regional climates may change, and affect the sensitivity of systems, and identify and evaluate adaptation strategies (IPCC, 2007; UNFCCC, 2018). Getting a picture of how global warming will impact the future climate has several factors taken into account and among them; the amount of GHG emissions, technology development, global and regional economic circumstances, population growth, changes in energy generation, and land use (Anchukaitis *et al.*, 2017; Landis *et al.*, 2014).

Towards the end of the 19th century, IPCC develop Special Emission Scenarios (SRES) to assess future trajectories in demographic and socio-economic factors, with an inclusion of GHG emissions. However, they were superseded a new set of Emission Scenarios named the ‘Representative Concentration Pathways (RCPs)’ in 2014 which were trajectories to describe the concentration of GHGs in the atmosphere and the subsequent amount of energy (radiative forcing) in Watts per square meter. Four new sets of pathways were developed; RCP2.6, RCP4.5, RCP6.0 and RCP8.5 describing a possible attainable future that is dependent on their volume (GHG emission) until 2100 (Ebi *et al.*, 2014; Haasnoot *et al.*, 2019; IPCC, 2014a; Landis *et al.*, 2014). Table 2.1 below shows the description of the Representative Concentration Pathways and the Radiative forcing.

Table 2.1: Representative concentration pathways and the Radiative Forcing (RF) amounts

Representative concentration Pathway (RCP)	**Description**
RCP1.9	Maintaining a 1.5°C warming and below in the long-term
RCP2.6	Before circling back to 2.6W/m^2 by the year 2100, this scenario projects the level of Radiative forcing to reach a value close to 3.0W/m^2.
RCP3.4	An intermediate scenario in mechanisms to deliver a 2°C objective.
RCP4.5	A scenario where there is a stabilization of RF in the mid-century (2050) and before 2100, which comes with strong efforts of adaptation measures as a master plan and blueprint to reduce GHG emissions.
RCP6.0	The scenario indicates that stabilization of Radiative forcing will only be poised after 2100, by putting effective measures and strategies that will effectively curb emissions of GHGs.
RCP8.5	A high emission scenario with economic activity continuing as usual into the future with GHG emissions uncurbed.

(Source: (IPCC, 2019; Misiani, 2015)*)*

In 2018, another set range of pathways were developed to characterize developments in the social and economic sectors. They were named the 'Shared Socioeconomic Pathways (SSPs)', to establish the behaviour of a future world without policies, and the achievement of combined efforts of RCPs and SSPs (Hausfather and Peters, 2020; IPCC, 2019). The trend of these SSPs is based on narratives coupled with "business as usual" world; SSP1- "equality and sustainable focused growth", SSP2- "future trends based on historical patterns", SSP3- "fragmented world of resurgent nationalism", SSP4- "inequality overshoot" and SSP5- "a world of rapid and unconstrained growth in economic output and energy use". Two more pathways were added; RCP1.9, and RCP3.4 focusing on maintaining a 1.5°C warming and below in the long-term and RCP3.4 an intermediate scenario in mechanisms to deliver a 2°C objective (Hausfather and Peters, 2020; IPCC, 2019). Figure 2.3 shows a graphical representation of the RCPs in comparison with the present and past trends and Figure 2.4 shows the cumulative emission of CO2 from 2005 to 2050 with a 'business as usual' scenario.

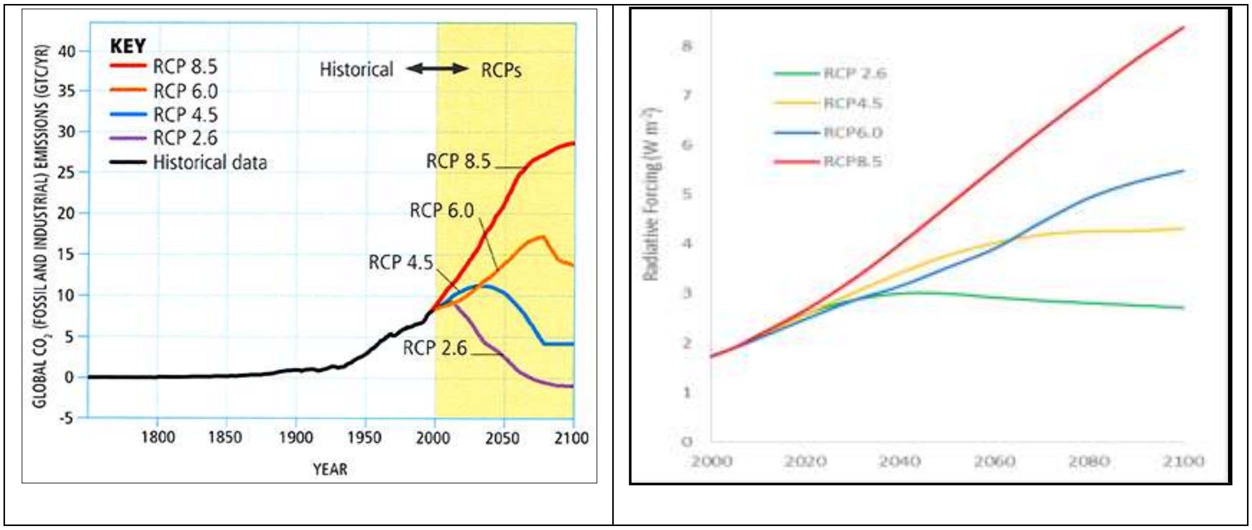

Figure 2.3: Representative Concentration Pathways
(source: (Kawase et al., 2011; Van Vuuren et al., 2011)

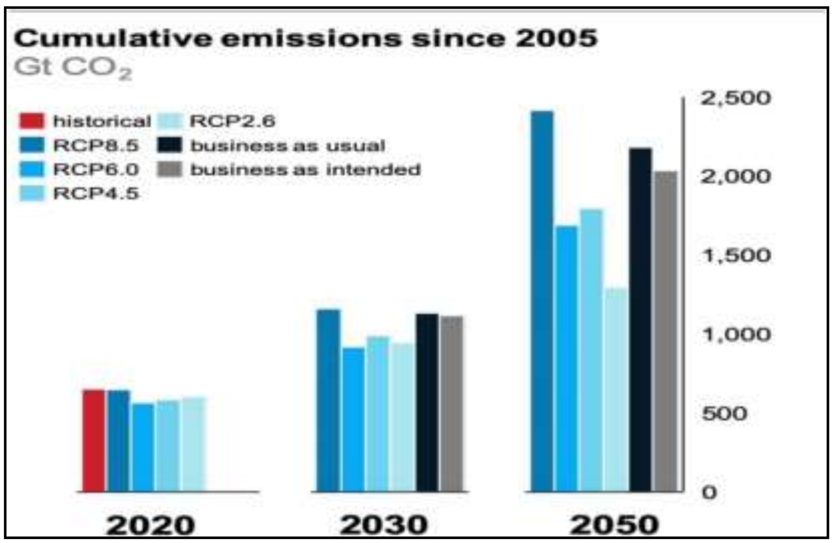

Figure 2.4: cumulative CO2 emissions since 2005, through 2020, 2030 and 2050.
(Source (Schwalm et al., 2020)

Other than the GCM scenarios, synthetic scenarios have also been widely used by researchers for climate impact studies. They are generated by simple alteration to existing conditions in such variables as precipitation and temperature and can represent climate over a comprehensive range as proxy scenarios. A change in the climate variable is obtained by a simple adjustment in the mean of the variable e.g. ΔT= +1°C, +2°C and +4°C and ΔP = 0, 10% and/or 20% (Sikka and Islam, 2010).

Several studies have also adopted this method including (Aramaki *et al.*, 2005; Begum *et al.*, 2008; Jusoh, 2007; Khasawneh, 2015; Xu, 1999; Yates, 1996).

2.5 Sustainable Low Carbon Development Pathway (SLCDP)

Low carbon pathway development is the development that strictly considers reduction of GHG emission rates and opts for solutions that minimize these gasses in the atmosphere such clean energy, with a sole aim of obtaining a low carbon future (Morita *et al.*, 2001). Sustainable Low-carbon Development Pathway is to identify pathways to low emission and climate-resilient economies to achieve sustainable development. The process involves consideration of an alternative and efficient substitute of low-carbon energy that is chosen over fossil fuels while observing factors for development such as economic growth in any given region such as a state, country, or continent (Bulkeley *et al.,* 2010; EREC, 2008).There are three main phases of low-carbon development; primary stage, development stage, and maturity stage (Shrestha and Shakya, 2012; Urama, 2011).

Several countries are on the race to achieve green growth by adopting low carbon development pathway(s), and are trying to switch to clean cleaner energies while they look for climate change mitigation solutions(ESMAP, 2020; Hirsch *et al.,* 2015). According to the Forbes (2020) magazine, many countries are tirelessly working smart every day to look for innovative solutions. It says "as climate change and other environmental issues takes centre stage, and impact all areas of lives, responsible companies are taking initiative to reduce the carbon footprints". Countries such as Brazil and Nepal are struggling to good books, by trying to adopt good practices for low carbon pathway by switching to cleaner fuels and recycling as their major steps respectively, even after it has been suggested that this century should keep its temperatures below 2˚C to avoid the harsh aftermaths of climate change (Hanna and Hurmelinna-Laukkanen, 2019; Hirsch *et al.*, 2015).

As much as countries are struggling to achieve their long-term goals, most of them have had huddles and several barriers including; poverty, political instability, lack of proper information, lack of resources and financial help, inaccessibility to good technology and rapid urbanization, which have adversely hampered their development. These are also the top challenges the world is facing today towards achieving the long-term goals. Eradication of these barriers will be a roadmap to achieving a low carbon future (ESMAP, 2020; Hirsch *et al.*, 2015).

Other than having a rich resource diversity of natural resources, Africa's economy and population is growing fast mounting pressure on these resources, and thus on the verge of overexploitation and depletion and most countries will have to be resilient to protect their resources (Reinhardt *et al.,* 2018).

2.5.1 Low Carbon Development pathway in Kenya

With an aim of revolutionizing the country into a middle income country, the Kenya Vision 2030 blueprint focuses on availing a safe and comfortable environment. These can only be met by addressing climate change issues and conservation of natural resources. A low carbon pathway resilient development pathway is a crucial step for Kenya and the best option to meet the vision 2030 goals. Transitioning to a low carbon resilient pathway however will be ideal to safeguard a country's development and livelihoods from the consequences of climate change (Kwena *et al.*, 2015; NCCRS, 2010).

For several decades Kenya has been struggling with managing and reducing the risks and the repercussions of climate change. As an emerging economy, it is struggling with the challenge of tracking its development towards poverty eradication on one hand and the other responding to environmental threats like climate change and reducing rising GHG emissions following a surge in population increase in urban centers and economic growth (Newell *et al.,* 2014). Approximately 67% of emissions in the country arise from agriculture, livestock, forestry, and transport sectors. Prioritized low carbon actions need to be taken, at least to lower GHG emissions to halve by 2030 (Nzau, 2013).

As much as Kenya struggles to achieve its goals, there are a number of barriers that impede its transition to achieving a low carbon; poverty, financial constraints, technical and information barriers, policy and political barriers (Newell *et al.*, 2014). It would require double efforts in order to revolutionize the energy sector into a low-carbon pathway whilst considering the county's economic development and reduction of GHG emissions, encompassing the social-economic and political forces, international climate mitigation commitment and both foreign and domestic investment patterns, including local political actions (Johnson *et al.,* 2017).

Sustainable development, adaptation, and mitigation are the best mechanisms to a low carbon resilient pathway. A number of reformation strategies such as; Restoration of degraded forests, reforestation, afforestation and agro-forestry, smart agricultural farming practices, re-use and recycling of materials and transitioning to cleaner and efficient renewable energies e.g. geothermal power, and LPG and bus rapid transit with rail corridors are among the major reforms to be implemented in the development pathway (Nzau, 2013; Sokona, 2020). This transition will benefit the several ways including; improving the lives of the poor and vulnerable, reduce disaster risks, build adaptive capacity, enhance sustainable development, demonstrate global leadership in fighting against climate change, contributing towards constitution implementation and attracting international finance, technology and capacity building (Stieber *et al.,* 2012).

2.6 HYDROLOGICAL MODELLING

Water is an important resource in life. Ray and Brown (2015) describes hydrology as the interplay between the channeling and properties of water and the ecosystems which is also vital for the sustenance of life on earth. Changes in the hydrological system due to rapid urbanization, industrialization, and land cover changes; along with climate change has greatly impacted the hydrological cycle around the world, which calls for thorough investigations on water modeling and thus, a clear picture of the world can best be elaborated without any sophistication by a simple model (Devia *et al.,* 2015).

The synergy between climate and watersheds which is more elaborated by numerical processes in a catchment area creates a whole picture of hydrological modeling. Several processes in a catchment such as infiltration, evaporation, and runoff can be numerically assessed by a hydrological model including the interaction of these processes (Hansen e*t al.*, 2007; Rwigi, 2014). Modeling also gives an insight on the hydrological processes and can be applied in present situations and also future circumstances which can be crucial in finding solutions to real-world problems, and as such, it has been possible to detect the extent and the impacts of human activities, and also how the whole water situation may unfold in the future (Devia *et al.*, 2015; Rwigi, 2014).

A hydrological model can illustrate the metamorphic changes in the hydrological cycle such as the conversion of precipitation into a surface flow and infiltration, and runoff into evaporation, and thus, before being justified in hydrological application, they must be calibrated and validated using temperature and rainfall as input parameters (Droogers *et al.*, 2008; Rwigi, 2014).

The main aim of this investigation was to assess how climate change has affected the water resources in Narok County. It examines how the quantity of water from streams and rivers will range under the various climate change scenarios, by applying the Water Evaluation and Planning tool (WEAP).

2.6.1 Water Evaluation and Planning Model (WEAP)

This is a water planning tool that was developed by the Stockholm Environmental Institute (SEI) Boston Center, for Integrated Water Resource Management (IWRM). It is used for water resource evaluation and allocation planning, to meet different demands and water supply needs.

It is also a tool for the management of scenarios and can be used for assessing the impacts of climate change on water availability (Seiber and Purkey, 2015; WEAP, 2015).

Assessing the impacts of climate change on water resources in a catchment will always involve the application of a hydrological model. As clearly highlighted by, modeling gives an insight on the hydrological processes both at present and the future, and this can help find solutions in the real world problems. Different hydrological models have been applied indifferent watersheds for different purposes both conceptual and physically based (Devia *et al.*, 2015)

Rickards *et al.* (2020) applied The Global Water Availability Assessment (GWAVA) model to assess the impact of climate change on the hydrology of the Upper Narmada basin. To evaluate a broader picture of climate change and water resources, they considered several factors including water abstractions, dams and irrigation coupled with climate modelling using projections from Global Circulation Models (GCMs). They found that, in the next half century, climate change will greatly affect hydrology in the basin and are like to cause increased monsoon flows. However, this model has a number of drawbacks; lack of user friendliness, extensive data requirements and global scale resolution that makes it only apply in large watersheds. It is therefore necessary for the model to include rapid advances such as local scale applicability and few data requirements.

Flamig *et al*. (2020) used the Ensemble Framework for Flash Flood Forecasting (EF5) model to model flash-flood-scale basins in the United States. They found that, accuracy in streamflow projections is linked to three models through kinematic routing and without optimized parameters. However, this characteristic however ideal it sounds, is tedious and does not provide a user friendly interface for simulations. The model also exhibits huge positive biases in most watershed for the worst case scenario and unnecessarily takes longer time simulating streamflow. It is a global model that needs application in bigger catchments with extensive data requirements. And thus there is need for rectification of these uncertainties in order for the model to function fully and widely.

Msaddek *et al.* (2020) used the Hydrologic Engineering Center Hydrological Modelling System (HEC-HMS) to simulate the Land-use and Land Cover Change (LULCC) impact on water balance in the Upper OumErRabia basin in Morocco. They found that, discharge in river volumes and peak flows were greatly affected by agricultural water demands and increased land cover (forests) and the water balance was altered. However, they discovered that, the full functionality of the model dependent on land-use land-cover (LULC) within the basin, a field-based data approach, availability of PET measurements for accurate results and a snow effect on stream flows. This approach however is only suitable in large watershed basins rather than small basins. It is also time consuming and needs a skillful approach for hydrological modelling.

Rwigi (2014) applied Soil Water Assessment Tool (SWAT) to assess the impact of climate change on surface water yields in the Mau Forest Complex in Kenya. Together with PRECIS climate models, he found that since 1970s, temperatures in Mau have been increasing and stream flows decreasing. He also found that forest cover was decreasing in the region, another factor that could be associated with decreased stream flows. In his study, he found the model ideal for climate model and recommended for application in different catchments including a trial on alternative models. The same tool was used by Mueni (2016) who assessed the vulnerability of Upper Tana catchment to climate and found that, there was a likelihood of the region having decreased water availability during the long rain seasons (MAM) and an increase in OND. She also indicated that there was a likelihood of the future having more yield in that basin. However, SWAT functionality is dependent on extensive data input including socioeconomic factors and land use changes. It is also not a user friendly tool. The manual calibration of parameters makes it even more tedious a modelling approach. There is need to review the model into a user friendly interface for ease of use and application.

Given the evidence above, the choice of Water Evaluation and Planning Model (WEAP) was picked, for hydrological modelling of Narok county surface water resources due to a number of benefits; It is a readily available, affordable, and easy to use tool in solving water resource issues in the community both at the local scale and globally (Li *et al.*, 2015), by combining both water resource management and policies on the availability of water and its quality in ecosystems (Oti, 2019; Seiber and Purkey, 2015), it also does not require extensive datasets for impact assessment and it offers a wide range of scenario creation and analysis that can be used for analysis depending on the needs (SEI, 2015). A range of water issues can also be analyzed by scenario-based approach through WEAP including climate variability and change, conditions in a watershed, demands, environmental and ecosystem needs, infrastructure, and costs (Azadani, 2012). Figure 2.5 illustrates the conceptual framework of the WEAP hydrological model.

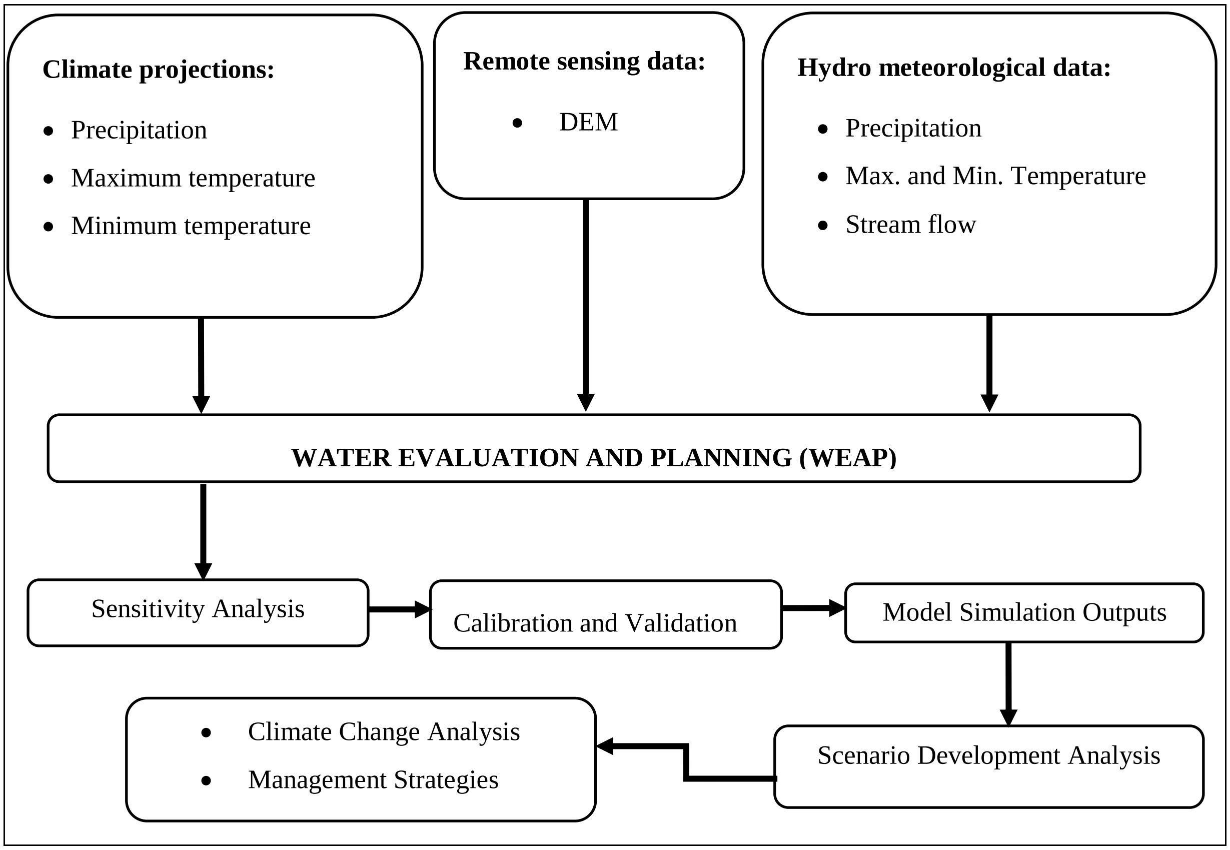

Figure 2.5: WEAP model conceptual framework

2.6.2 Application of the WEAP model in Water Management

The model has been applied worldwide by various users on multiple water management projects. Some examples are as follows;

Mahat and Brown (2019) used WEAP to assess future water shortages in the United States. They considered two things; increasing population size and changing climate. They found that the two will combine and may apparently have a negative impact on water availability in many areas in the U.S and that, water shortages will neither be improved by improved efficiency in water use, but reduced agricultural irrigation will contain shortages, together with a reduction in groundwater drawing and environmental flow losses. The same idea was suggested by (Droogers *et al.*, 2012). However, they did not consider the application of current climate models in projecting climate and water demands. This is well considered in the present study.

Hao *et al.* (2015) suggested that, climate and demographic changes are the key factors that are leading groundwater depletion and rise in energy demand and that they have created a complex challenge to policymakers. They suggested several sources of water demands; agricultural, domestic, and industrial. They found that an effective and efficient way of adapting to climate change would be through the construction of more water storage spaces such as reservoirs and improved agricultural technologies such as improving crop and irrigation patterns. However, their study did not take into account the Regional Climate Modelling approach to obtain the current situation in the watershed. Instead, they used a National Climate Change Assessment Report, which did not factor in the consequential outputs of climate change on water resources. This is however well-considered in the present study.

A report by Rayej (2012) suggested that, other than the social-economic factors, climate and demographic changes will likely increase the water-related energy consumption in the future. This was likely to stress the existing infrastructure following an increase in water and energy-related demands. They concluded that conservation and demand reduction are the only means to reduce energy demands without an impact on financial obligation neither the environment. The same idea was also advanced by (Gupta *et al.*, 2015).

Alameddine *et al.* (2018) found that, within the next few decades, projected climate change will worsen following a surge in the world's population. The majority of people living in dry regions will face the worst. They also found that there will be persistent pressure on river basins and as result, there was a need to come up with an efficient water management system to curb the rising needs of water demand. They suggested two factors as means of adaptation strategies to contain the water challenges; technological and social-economic improvements. This is the same idea employed in the present study.

Kou *et al.* (2018) used the WEAP model to study the water situation in Xiamen's city. They discovered that population distribution and rapid growth are the main factors escalating water shortages. The study analyzed cycles in water demands and use from the current period to the year 2050 considering several scenarios, and from the projections, the city will be under pressure due to the unavailability of water after 2030. And thus, their government had to put in more efforts to curb this. The present study uses a similar idea to come up with a solution to the availability of water in the study region.

Berredjem and Hani (2017) discovered that, other than climate variability, population increase and industrial and agricultural sector booming initiates new water demands. They applied WEAP to simulate water yields for both current and future scenarios up to the year 2050, by incorporating several water demands from agricultural, municipal, and industrial usages. The present study takes no exception to this fact by employing the same concept in modeling.

A study conducted by Haji (2011) on how climate change has affected surface water resources in the Upper Vaal River Basin in South Africa found that there was an expansive demand for water needs in the region favored by a growing population. Quoting from Bates *et al.* (2008) and Trifunovic (2006) he says that, major factors contributing to water stresses include climate change, demographic changes, and poor conservation practices. He conducted the study using two climate change models; ECHAM4 and CSIRO following the SRES B2 emission scenarios, to project the water demands. In his findings, the future indicted to be likely hotter and wetter. However, this study did not take into account any model sensitivity analysis. The study also used an older version of climate models. The present study used CORDEX model outputs for climate change simulations with an integration of Representative concentration pathways (RCPs).

Amisigo *et al.* (2015) explored the impacts of changing climate agricultural demands and on water resources in the Volta Basin, Ghana. They mention two things; variability of climate and change, which are great, affected several factors such as an increase in both population and economic activities. They also found that these water resources will be slackened in the future by climate change and hence advised proper mechanisms such as groundwater evaluation and efficient socio-economic measures for development. However, this study did not in any way consider climate projections or employ climate models but instead used CLIRUN to project stream flows. The present study takes care of several scenarios together with current climate projections for deep analysis of climate change.

Mounir *et al.* (2011) documented that though water is essential for life on earth fundamental for living, it is a scarce resource. He adds that many regions in the world depend on it for agriculture and a means to achieve sustainability. Other than imposing policies, several factors such as variability of climate and improved irrigation technology are additional challenges. Quoting from Conway (2009) he says, it has been challenge water managers and relevant authorities to take care of the planning, allocation, and use of the water resources in different areas. This study enlightens the need to study the consequences of a changing climate especially on water resource availability

Toure *et al.* (2017) observed that the water table is sensitive to climate change and a series of human activities. In this study, two scenarios were developed to calculate groundwater recharge; social-economic and population growth for water demands along with GHG emission scenarios; RCP4.5 and RCP8.5. They found that surface discharge can be used to recharge the underground water table through artificial recharge technique, and is the most efficient way, though it may have an impact on downstream users.

Hussen *et al.* (2018) exclusively analyzed the availability of water resources in Ethiopia under a changing climate. They applied the Regional Climate CORDEX outputs for three emission scenarios; RCP2.6, RCP4.5, and RCP8.5 and four-time slice between the years 2015 and 2035. Basing on several assumptions, they formulated a set of scenarios to assess the availability of water in the catchment. The same is the idea that was also employed by (Mayol, 2015; Shumet and Mengistu, 2016).The present study takes no exception to this fact.

In the Hassan *et al.* (2019) report on the water situation in Shebelle Basin, Somali, an attempt was made to evaluate the situation of water availability. He found that increased agricultural water demand, accelerated population growth and infrastructure disparity of rainfall distributions are going to exacerbate. He notes further that, it was wise to consider the possible water demands in the future, to make clear and concise conclusions and resolutions. This calls for a proper assessment of water demand availability within a catchment, which is a proposed recommendation in the present study.

Kishiwa *et al.* (2018) on their study on the assessment of the availability of surface water in the Pangani River catchment, Tanzania found that, by mid-centuries around (2060's), there will be a surge in unmet demands that will greatly impound the agricultural sector and this was most likely due to a change in the climate. The same approach was employed by Arsiso *et al.* (2017), who also found that rapid urbanization in Ethiopia is leading to the release of large amounts of GHGs in the atmosphere. And this can only be combated by planting more trees and creating awareness to people, especially farmers, water harvesting to meet the future unmet demands and building additional reservoirs to increase flow release. This is one of the recommended methods of climate adaptation strategies in the present study.

Akivaga (2010) used the WEAP model to simulate and analyze scenarios on water resource management in Perkerra catchment in Kenya, by employing several scenarios. He found that there are sharp flow peaks downstream and at dam nodes. Demand coverage could only be improved by constructing dams, which stabilizes flows and allows the supply of water to towns hence increasing water availability at the irrigation scheme, but only by proper regulation of reservoir abstraction. However, the accountability of the impacts of climate change on water resources was not considered in this study. This is well taken care of in the present study.

In a study to find sustainable water futures under a changing climate in the Turkwel basin, Hirpa *et al.* (2018) found that, scarcity of water in the basin is majorly driven by climate change and that, the current and probable future water demands will be a big challenge in planning and allocation of water resources not only at regional level but worldwide. They further noted that the expansion of irrigation in the region strongly influences the water resource system in the basin since it has already been weakened by drought due to climate variability. However, they concluded that groundwater depletion due to excessive abstraction following growth in population and expansion of irrigation will lead to higher risks of unsatisfied water demands. This is the strategy employed in the current investigation with a focus on surface water resources.

From the Nyika *et al.* (2017) report, water systems have complex component interaction. Amidst the uncertainties of climate and constrained natural resources, the development and operation of water as a resource is important. They found that increased water demands are majorly due to high population growth and prolonged drought, and the most efficient way to meet unmet demands was water re-use. The same idea was employed by Metobwa *et al.* (2018) and Mutiga *et al.* (2010). However, this calls for a necessity to study the factors that could hamper the water-related resource availability, which is the main objective of the current study.

Ojwang *et al.* (2017) found that, by the year 2035 there will be a surge in water demands within the city of Mombasa mainly due to socio-economic factors. They also add that the quantity of water through Rainwater Harvesting systems within the same city will not in any way be impacted by a change in the climate. They also tried to develop scenarios by assigning classes using images and simulating water by incorporating ensemble projections. However, this study failed to recognize the influence of climate change on the hydrology in this area. The present study takes no exception to this fact.

The literature review identified the following research gaps;

(i) Lack of research studies in Kenya and the study area on the arising impacts of a changing climate on the availability of water at present and the likelihood in the future was revealed. Only a few studies focusing on the problem of water demands and allocation, without due attention to changes taking place within different watersheds

(ii) Lack of research studies in the area of study on how the study area is sensitive to a change in climate and also lack of proper consideration and application of emission scenarios.

(iii) There are few studies that have examined the ramifications of climate change on water resources in the country and County level, which forms the main agenda of the present study.

This study aims to try to examine and evaluate how Narok County's surface water resources can be affected by a change in climate, which had not been investigated in any previous studies in the region. Besides, no efforts have been suggested or been put forward on assessing neither the consequences of change in climate on water resources nor the sensitivity of the region to the climate in the catchment, other catchments, and in Kenya as well. The present study however investigated the impacts of a changing climate on water resources at a county level using the WEAP hydrological model, by employing a number of both Synthetic and GCM scenario projection, with different time slices.

CHAPTER THREE

3.0 DATA AND METHODOLOGY

In this section, data types used and the methodologies applied to achieve the main objective of the study are presented.

3.1 DATA

Several sets of data were employed in this study which included; discharge, rainfall, maximum and minimum temperature. These datasets were on monthly basis for the period 1981- 2018. Below is a comprehensive description of the datasets and their sources.

3.1.1 Hydro-Climatic datasets

These were mainly observed climate data (Rainfall, maximum and minimum temperature), obtained from Kenya Meteorological Department (KMD) for Narok Met station, and river discharge from the Water Resource Authority (WRA). The data were obtained on monthly timescale for the period 1981-2018. Table 3.1 and table 3.2 shows the location and distribution of representative rainfall stations and RGS used in the study respectively.

3.1.2 Climate Hazard Group Infrared Precipitation with Stations (CHIRPS)

This is a global precipitation dataset spanning 50°N-50°S with a high resolution that uses rainfall estimates by Tropical Rainfall measuring Mission Multi-Satellite Precipitation Analysis (TMPA) as a means of calibration. It also uses interpolated gauged products from high-resolution climatology and incorporates station data. It provides blended gauged satellite data estimates from CHIRP for each 0.05° grid point, provide high resolution datasets that spans a vast region over land. They are advantageous in that, they have high resolution and also low bias on the sets of data. This study utilized daily precipitation from CHIRPS to validate the model outputs, gridded at a resolution of 0.05x0.05, approximately 5*km*x5*km* over land areas, which was then converted to monthly annual time series. This was obtained from the IGAD Climate Prediction and Application Centre (ICPAC).

Randomly generated fifty-eight stations of rainfall data from CHIRPS were used for rainfall analysis and temperature analysis, and were validated using observed data from Narok met synoptic station. Only seven stations are presented together with their location and distribution over the study area. The selection criteria were dependent on the distribution of RGS within the region and the quality and length of the records (>30 years) where, stations with more than 10% missing data were not considered for analysis. Table 3.1 and Table 3.2 show the station identification, location and distribution of hydro-climatic datasets used in the study together with the percentage of data missing. Figure 3.1 shows the spatial distribution of rainfall stations used in the study.

Table 3.1: Representative meteorological stations used in the study

No.	Station Identification		Location			Distribution			Missing Range (%)
	Name	**Code**	**Lat.**	**Lon.**	**Elev. (m)**	**Start**	**End**	**Length (yrs.)**	
1.	Narok Met.		-1.093	35.8670	1890	1981	2018	37	5.4
2.	Koyaki	-	-1.3683	35.1489	1555	1981	2018	37	-
3.	Mashagwa	-	-1.2432	34.7317	1536	1981	2018	37	-
4.	Ongata Naado	-	-1.2450	35.9983	1751	1981	2018	37	-
5.	Kisiriri	-	-0.8970	35.8752	2218	1981	2018	37	-
6.	Olkiriane	-	-1.211	35.7050	1869	1981	2018	37	-
7.	Kalema	-	-1.6425	35.9681	1693	1981	2018	37	-

Table 3.2: River Gauging Stations used in the study

No.	RGS Station Identification		Location of RGS			Distribution			Missing Range (%)
	Name	**Code**	**Lat.**	**Lon.**	**Elev. (m)**	**Start**	**End**	**Length (yrs.)**	
1.	Enkare Narok	2K03	-1.2306	35.9750	1903	1959	2014	55	12.72
2.	Amala	1LB02	-0.9407	35.4171	1889	1955	2017	62	19.35
3.	Ewaso Nyiro	2K01	-1.2813	35.9388	1869	1959	2018	59	8.47
4.	Mara	1LA04	-1.1907	35.0584	1653	1970	2015	45	26.01

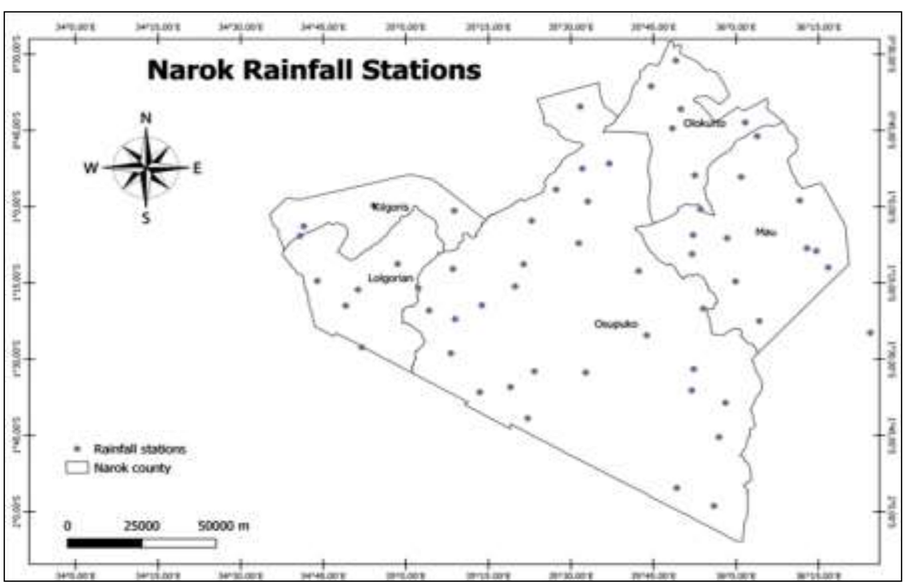

Figure 3.1: Location of Rainfall stations used in the study area
(Source; derived from QGIS)

3.1.3 The European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 data

This provided a 30km grid span with an 80km height temperature datasets from the land, atmosphere, and ocean for 37surface levels. This study utilized maximum and minimum temperature from the ERA5 to validate the model outputs the ERA5 datasets were gridded at 0.5x0.5 resolutions over land areas from 198 to 2018.

The CHIRPS and ERA5 datasets were Ground-truthed by performing correlation analysis on with the observed station datasets to validate their accuracy.

3.1.4 Climate Projection Datasets

CORDEX is a project that incorporates the dynamical downscaling of Global Climate Model (GCM) datasets to regional scales using specified domains over the entire globe. The coverage of the African domain is 45.76°S to 42.24°N and 24.64°W to 60.28°E with a resolution of 0.44°(Endris *et al.*, 2013a; Misiani, 2015). A total of 6 RCMs forced by the lateral and surface boundary conditions were used to downscale data over the African region, for the period 1981-2055, following RCP4.5 and RCP8.5. This study used the monthly CORDEX outputs to assess the climate change scenarios over Narok County. A list of CORDEX General Circulation Models extracted over Africa as used in this study is as shown in table 3.3 below.

Table 3.3: Global Climate Models used with CORDEX

No.	GCM Name	Institute Name	Country	Calendar
1.	MPI-ESM-LR	Max Plank Institute(MPI-M)	Germany	Standard
2.	NorESM1-M	Norwegian Climate Centre (NCC)	Norway	365 days
3.	CanESM2	Canadian Center for Climate Modelling Analysis (CCCma)	Canada	365 days
4.	EC-EARTH	Irish Centre for High-End Computing (ICHEC)	Europe	Standard
5.	GFDL-ESM2M	National Oceanic Atmospheric Administration (NOAA)	USA	365 days
6.	MIROC5	Model For Interdisciplinary Research On Climate (MIROC)	Japan	365 days

Source: (https://esgf-data.dkrz.d)(accessed on March 10th, 2020)

3.1.5 DEM

A Digital Elevation Model of 90m resolution was used and was obtained from the USGS website. The projection of the study area was re-projected to a World Geodetic System (WGS) of 1984, zone 36S.

3.2 METHODOLOGY

The methods used to obtain the objectives of this study are presented in this section. The first part presents methods used to organize the data used, to meet the standards such as estimating missing values and quality checks. The other part presents methods for evaluating specific objectives to attain the main objective of the study.

3.2.1 Estimation of missing data

There are many uncertainties allied with observed datasets ascribed to several factors; observation errors and instrument errors. It is therefore essential to test for homogeneity in these datasets before analysis. This study employed the arithmetic mean method and regression analysis to estimate gaps in the hydro meteorological datasets. Missing records were done by mean arithmetic rainfall and temperature estimates and regression analysis for discharge data. The two methods are highlighted in the next sub-section;

3.2.2 Normal Ratio Method

Records of stations in the same homogeneous regions that are highly correlated are areally averaged using the normal ratio method. This however requires that stations have long periods of records that is crucial in generating viable values of stations (Mueni, 2016). The Normal Ratio method may be maybe expressed as follows;

$$\mathrm{x_{Aj}} = \frac{\mathrm{x_{Bj}}}{\mathrm{\bar{x}_B}} * \mathrm{\bar{x}_A} \qquad \text{Eqn. 3.1}$$

Where; $\boldsymbol{x_{Aj}}$ is the missing record of station A in thej^{th}, $\boldsymbol{x_{Bj}}$ is the record for station B with reliable records in the j^{th}year,$\boldsymbol{\bar{x}_B}$and$\boldsymbol{\bar{x}_A}$ are the long-term averages of for station B and A respectively based on the period of records available at A.

The normal ratio method was used to fill in missing records in the observed rainfall and temperature records.

3.2.3 Regression Analysis

This involves finding a linear relationship between two variables to find the missing record. Missing values were obtained by correlating the values of stations with complete records. The slope coefficient from the model relationship was then applied for estimating missing values. The following equation was used for performing simple regression analysis.

$$\hat{y}_\mathrm{i} = \mathrm{a} + bx_i \qquad \text{Eqn. 3.2}$$

Where; $\hat{y}_i$is the missing value estimated, x_i is the variable corresponding to the missing record, $a$is the y-intercept and b is the slope of the regression line.

Since most River Gauging Stations had higher percentages of missing records, regression analysis was used to estimate missing records in discharge data in conjunction with the normal ratio method.

3.3 Data Quality Control

Inconsistencies in climatological records are a norm and can be a result of several contributing factors including technology, microclimate, instrument type, or factors such as changing instruments and their location. Data collection, transmission and processing, and estimation of data can also contribute to heterogeneous records (Nyakwada, 2009; Sahin and Cigizoglu, 2010). It's, therefore, crucial to check for the quality of those climatological records before any analysis is done.

The most commonly used methods of testing the quality of data include the run test, single and double mass curves. This study employed the double and single mass curves for quality control. A brief discussion of the mass curves included in the next sub-section.

3.3.1 Single and Double Mass Curves

Single Mass Curve analysis involves plotting cumulative climatological records against time and their patterns used to test for the quality of records. Nearly error-free homogeneous records display a single straight line while other patterns indicate heterogeneity in the records. Heterogeneity in the climatological records can also be corrected by double mass curve analysis.

The idea behind double mass curve is that, cumulative values of heterogeneous stations is plotted against cumulative values of homogeneous stations. The sole aim is to correct heterogeneity but can also be used to check consistency in streamflow data. Inconsistency in hydrological records may arise due to a number of factors; collection mechanism, changes in storage and use of water, coupled with hydrological processes in a basin. Further details of these methods are documented in several pieces of literature including; (Gao *et al.*, 2017; McLean, 2016; Nyakwada, 2009; Searcy and Hardison, 1960; WMO, 2009).

This study used both single mass curves to test the quality of climatic records (rainfall, maximum and minimum temperature, and discharge). Double mass curve analysis was used to check for consistency and correct heterogeneity in hydrological records. Consistent quality datasets were then used for further analysis in this research.

3.4 Assessing the Temporal and Spatial Distribution of Rainfall and Discharge in Narok County.

To achieve this specific objective, several steps were performed on both climate and hydrological data. Principal component analysis (PCA) was performed on the rainfall data, to delineate the point stations into homogeneous rainfall zones. Three methods were also adopted under this objective, namely; temporal analysis, spatial analysis, and spectral analysis. The temporal analysis involved plotting time series of observed climate and discharge values, spectral analysis was mainly computing the spectral estimates of the distribution of rainfall by plotting the density against period, while spatial analysis was to estimate the spatial distribution of rainfall in the region, mainly on spatial maps. An analysis of the hydro-climatic characteristics of the region involved the following steps: assessing the variability of rainfall in the region; identifying the long-term monthly patterns of both rainfall and discharge; time series analysis of discharge and rainfall.

Several activities and methodologies were to be done. Firstly, the rainfall data were subjected to PCA which is discussed in the next sub-section.

3.4.1 Principal Component Analysis (PCA)

This involves dimensionally reducing large datasets into small datasets that can be clearly understood and interpreted while retaining much information. Variance is maximized when new uncorrelated variables are created. The principal components (PCs) solve an eigenvector problem to find new variables from the data.

There are different ways of performing PCA that are dependent on the input matrix of observation is arrayed (Ouma, 2000; Richman, 1986). If a parameter understudy is (e.g. rainfall anomalies) fixed, then it’s possible to generate the correlation data matrix between locations over a set of periods (S-mode) or between periods over a set of locations (T-mode). S-mode is the correlation of variables in a time series and yields grouping of locations in terms of change in time, while T-mode is the correlation between fields and is used to analyze spatial fields in different times hence yields groupings of periods with similar patterns (Barreira, 2010; Compagnucci *et al.*, 2001; Ogallo, 1989; Ouma, 2000).

Both T-mode and S-mode were performed on the standardized monthly anomaly rainfall data in this study to delineate the different climate zones within the study region and identify representative station in each location. In an S-mode, the variables are the values. Each station is correlated with each component in the component matrix, which can be visually displayed on maps for spatial analysis or climatological zoning. It is therefore possible to represent most information contents of the data by using only the significant Principal components (PCs).

Large mesoscale systems such complex topographical patterns and the presence of inland lakes have their circulation patterns, which has an influence on regional climate and rainfall distribution (Ouma, 2000). Grouping locations into zones with similar rainfall patterns is therefore important, and in this section, the method that was used to delineate homogeneous zones using monthly rainfall is presented.

Several statistical methods based on Eigenvalues and Eigenvectors have been used in delineating regions into climatic zones. Among these techniques include the use of Empirical Orthogonal Function (EOF), whose solutions are described normally through Common Factor Analysis (CFA) and Principal Component Analysis (PCA). Eigenvectors help in understanding the direction of transformations while Eigenvalues explain the strength of these transformations. A review of these methods can be found in (Kithiia, 2012). The advantages of these methods based on Eigen Values include;

(i) Their ability in the reduction of dimensions of a given data matrix by searching for uncorrelated new variable sets that have the maximum variance of the initial dataset.

(ii) The detection of a homogeneous group of variables as in the same kind of climate classification.

(iii) The simplification of investigation of the spatial or temporal behavior of meteorological variables e.g. cycles, periodicity, and prediction models through the use of relatively few representative stations for each homogeneous zones.

Several statistical books have covered the theory of the Eigenvalue method such as Harman (1967) and Joliffe (1986) among others. Authors such as (Gitau, 2010; Nyakwada, 2009; Okoola *et al.*, 2009; Ouma, 2000) have also applied these techniques and of the two, CFA has not been much applied in meteorological applications due to its complexity. The principal behind EOF is the concept of variances and thus CFA assumes that the variable observed is influenced by several determinants in which some of which are shared by other variables in the set, while others aren’t shared and are unique to the variable only. The part of the variable that’s influenced by the shared determinants is called common, while the other part is called unique (Ouma, 2000). This unique part results in a variable not having a perfect correlation with itself and hence emphasis is placed on the covariance between variables within the input matrix rather than variances. The basic factor model maybe put in the form given by Harman (1967) as;

$$Z_j = \sum_{k=1}^{n} a_{jk} F_k + U_f B_i + \cdots (j = 1, 2 \dots N) \quad \text{Eqn. 3.3}$$

Where; Z_j is the variable j in the standardized form, a_{jk} is the standardized multi-regression coefficient, F_k is the hypothetical factor k, B_i is the unique factor for variable j and U_f is the standardized regression coefficient of variable j on unique factor j.

The major problem arising from CFA is determining the unique component, which is a rigorous and tiresome mathematical process that requires superior computer facilities, and hence many studies have neglected it, thus reducing the CFA to PCA.

The Model for PCA may be expressed as;

$$Z_j = \sum_{k=1}^{n} a_{jk} F_k \quad \text{Eqn. 3.4}$$

Where the symbols have their usual meaning. In this case, the uniqueness is ignored and the correlation of a variable with itself is considered to be perfect unity i.e. no account is taken of observational or instrumental errors. Due to the disadvantages of CFA above, PCA was preferred in this study.

This method has been applied by several authors to demarcate the country into homogeneous rainfall zones including (Indeje *et al.*, 2000; Kimani, 2019; Ouma, 2000). This study however aimed at demarcating Narok County into homogeneous rainfall zones using annual rainfall totals from 1981-2018. PCA was applied in this region for several reasons; to factor out the spatial and temporal patterns in rainfall, identify dominant modes by grouping the rainfall parameters into groups concerning their mass loadings, which explained homogeneity of regions, and most importantly to identify and account for the most recent changes in rainfall patterns

3.4.1.1 Determining the Number of Significant Components

The dimensions of a given dataset are reduced by PCA from the description of new variables (PCs) that have the following properties;

(i) Uncorrelated two different components

(ii) Each component is derived from the Empirical Orthogonal Variable (EOV), which has the highest variance totals of the original data (Ouma, 2000).

The definite number of components to retain can be determined by performing several tests; Kaiser’s Criterion, the Scree Test method, Logarithmic of Eigenvalue (LEV), and sampling errors of Eigenvalue. Kaiser’s Criterion and Scree Test methods were used in this study to determine the number of significant PCs to retain.

3.4.1.2 Kaiser’s Criterion

This is the simplest method of determining the significant PCs by Kaiser (1959), which assumes significant PCs are those whose corresponding Eigen Values are greater than or equal to 1. It retains only those PCs that extract variance at least as much as the equivalent of one original variable.

3.4.1.3 The Scree Test method

In this method, each raw Eigen Value is plotted against the model number, which results in an exponential curve which decreases as the number of modes increases. The most significant PCs are those before the graph breaks and become nearly linear (Nyakwada, 2009; Ouma, 2000). According to Cohen (1988) rotating data before graphing gives a more distinct break in the curve.

3.4.1.4 Rotation of Principal Components

The advantage behind unrotated components is that they can extract maximum variance from a dataset and are insensitive to the number of retained principal components, making it easy for data interpretation (Ouma, 2000). However, other than their shape dependence, the Principal components are unstable and may portray an inaccurate relationship during sampling in the input data, which may alter their unity to modes of variation. A detailed discussion of these characteristics is found in literature such as (Richman, 1986).

Two modes of rotation of principal components exist; orthogonal and oblique. The orthogonal rotations rigidly rotate a predetermined number of PCs, several degrees to better explain the data while retaining the orthogonality of the vectors to each other. An oblique rotation makes it easy for the identification of data groups in rotated vectors. Examples of the orthogonal rotations include; Quartimax, Varimax, Transvarimax, Equamax, and Parsimax (Richman, 1986) while Oblique rotations include Quartimin, Covarimin, Oblimax, and Direct Oblimin among others (Ouma, 2000).

In this study, the orthogonal class of rotation through Varimax rotation was used in rotating the PCs. Mapping the significant rotated components then delineated the climatic zones.

3.4.1.5 Choice of Representative Stations for the Homogeneous Regions

Rainfall data were grouped into independent climatological zones by the PCA method. However, picking representative stations is another process and there are several methods including the unweighted arithmetic mean method, principal communality, weighted averages among others. A detailed discussion of these methods can be found in (Ogallo, 1989; Ouma, 2000). This study adopted the Principal Communality method to pick representative records for each homogeneous group, as derived from rotated PCA.

3.4.1.6 Principal Communality

Communality for any given location in a homogeneous zone may be expressed as;

$C_j = \sum_{k=1}^{n} \left(a_{jk}\right)^2 \ldots (\mathrm{j} = 1, 2 \ \ldots \mathrm{n})$ ………………………………………………………… Eqn. 3.5

Where; n is the number of significant PCs, C_j is the communality, j is the location. The idea behind communality is that it gives a measure of the degree of interrelations amongst the various variables. The location with the highest value in any homogeneous region may be reflective of the location that's highly correlated with all other stations within the homogeneous zone. The communality principle has been widely used to pick representative locations within each homogeneous zone (Kimani, 2019; Nyakwada, 2009; Ouma, 2000).

3.4.2 Time Series analysis

Time series analysis involves plotting the observed data against time. It is a crucial process in hydrology for detecting trends, periodicities and cycles, seasonality (Chen *et al.,* 2007; Rwigi, 2014) or shifts in records, hydrological forecasting and extrapolation, and interpolation (Mueni, 2016). Time series analysis was used to establish historical patterns in the rainfall and discharge datasets, and to analyze the trend in the future climate projections of both rainfall and temperature datasets under different climate scenarios over Narok County region.

However, several authors have also applied this method in their research works including (Mueni, 2016; Muhati *et al.,* 2018; Omoj *et al.,* 2016; Opiyo, 2014; Rwigi, 2014).

3.4.2.1 Mann Kendall Trend Test

This is a non-parametric test that was first derived and used by Mann (1945) and Kendall (1975) that indicates the direction of a significant trend (Omay, 2015). It is also based on an alternative measure of correlation called Kendall's tau (τ). This test was used to detect trends in this study in stream flows, surface air temperature and rainfall. Trends could result in the long time changes in both climate and hydrological datasets following a change in the driving forces such as land use/change characteristics in a catchment (Mueni, 2016).

The Mann Kendall test is given by equation 3.7 as follows.

$$\mathbf{S} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbf{sgn}(x_j - x_i) \quad \text{…………………………………………………….. Eqn. 3.6}$$

Where; S is the standardized test statistic, x_x and x_j are sequential data values, n is the length of the data record and

$$\mathbf{Sgn}(x_j - x_i) = \begin{cases} +1 \text{ for } (x_j - x_i) > 0 \\ 0 \text{ for} (x_j - x_i) = 0 \\ -1 \text{ for } (x_j - x_i) < 0 \end{cases} \quad \text{…………………………………………………. Eqn. 3.7}$$

The resampling technique was used to identify the strength and level of significance of the trend, together with the strength of Kendall's correlation coefficient, given by equation 3.8 as follows.

$$\tau = \frac{2S}{(n(n-1))} \quad \text{………………………………………………………………………. Eqn. 3.8}$$

Where; τ is the Kendall correlation coefficient, S is the standardized test statistic and n is the record length of the dataset. When the value of τ is positive, it signifies an increasing trend while a negative value of τ gives a decreasing trend while $\tau = 0$ is a stagnant trend (no trend). In this study, the level of significance of P=0.05 was used to indicate a significant trend. Any value that was less than this ($P \leq 0.05$) was considered insignificant.

However, this method has also been widely used for testing trends by several authors including (Mueni, 2016; Ngaina and Mutai, 2013; Omay, 2015; Ouma, 2015).

3.4.3 Spectral Analysis

Spectral estimation refers to a time series in terms of wavelengths associated with oscillations rather than individual data values. It gives a decomposition of the process into dominant frequencies and detection of periodicities and repeatable patterns. According to (Okoola, 2000), almost all locations have a common pattern of weather; recurrences of warm and cold events. However, spectral analysis has been used extensively to examine whether a time series of any meteorological dataset exhibits any periodic function. There are three methods commonly used for computation of cyclic variations; Auto-correlation Function (ACF), First-Fourier Transform (FFT), and the Maximum Entropy method (Cooley *et al.*, 1967; Jenkins and Box, 1968; King'uyu, 1994).

This study employed the FFT technique to estimate the spectral peaks in the annual time-series rainfall over Narok County. The peaks were tested at a 95% confidence level and the white noise hypothesis by the Turkey-hamming window.

Spectral distribution function F (λ) and spectral density f (λ) function which is the Fourier transform of the auto covariance function, γ (λ) are used to detect the cyclic variations in a time series (Omay, 2015; Omondi *et al.*, 2009). The plot of F (λ) against period (t), resulting in peaks that are in form of wavelengths. Fourier analysis presents the spectral distribution function and the density function as a sum of sine and cosine, which is the basis for spectral analysis, which is given by equation 3.10 below.

$\gamma(t) = \int_0^{\pi} \cos(\lambda \mathrm{t}) \mathrm{dF}(\lambda) = \int_0^{\pi} \cos(\lambda \mathrm{t}) \mathrm{df}(\lambda)$ ………………………………………… Eqn. 3.9

Where; $\gamma(t)$ is the auto covariance coefficient, $\mathrm{dF}(\lambda)$ is the spectral distribution function, $\mathrm{df}(\lambda)$ is the spectral density function and *t* is the time units.

From the spectral density $\mathrm{df}(\lambda)$, the auto covariance function $\gamma(t)$ can then be computed as follows;

$\gamma(t) = \int_0^{\pi} \cos(\lambda \mathrm{t}) \mathrm{f}(\lambda) \mathrm{d}(\lambda) = \int_0^{\pi} e^{i\lambda \mathrm{t}} \mathrm{f}(\lambda) \mathrm{d}$ …………………………………………... Eqn. 3.10

The spectral density function $\mathrm{f}(\lambda)$, can also be computed from the auto covariance function as follows;

$f(t) = \frac{1}{2\pi} \gamma(0) + \frac{1}{\pi} \sum_{t=1}^{\infty} \gamma(t) \cos(\lambda \mathrm{t})$ …………………………………………… Eqn. 3.11

Spectral analysis was used in this study to determine periodicities of dorminant significant cycles in the rainfall data, that are associated with climate systems.

3.4.4 Assessing the Temporal Variability of Discharge in the County.

The aim of this activity was to assess the temporal variability in the discharge records. Two methods were adopted; temporal analysis and temporal variability on the monthly observed discharge and rainfall.

3.4.4.1 Time Series analysis

Time series analysis was used evaluate the long term trends in the observed discharge and analyse the trends. Significant trends were tested at α=0.05 using the Mann Kendall non parametric test. A detailed discussion of this method is as presented in section 3.4.2 and 3.4.2.1 respectively.

Temporal variability was evaluated by the Coefficient of Variation (CV), presented in the next subsection.

3.4.5 Coefficient of Variation (CV)

This is a statistical measure of dispersion expressed as a standardized value of the ratio of the standard deviation to the mean, which is normally expressed as a percentage and is a useful indicator of spatial rainfall variation. It depicts the variability between data series and explains the degree of variation of a dataset in around the mean value. Zacky (2016) explains the allowable ranges of CV where a perfect range of CV should be less than 10 (0.1), 10-20 (0.1-0.2) good, 20-30 (0.2-0.3) acceptable and greater than 30 (0.3) is beyond the acceptable range. High variations of coefficient of variability indicates high level of disparity in the variable under estimation while lower values indicate lower disparity within the mean and are more precise.

Equation 3.6 shows the expression of CV in percent.

$$\mathrm{CV} = \frac{\sigma}{\mu} * 100\% \quad \ldots\ldots \quad \text{Eqn. 3.12}$$

Where; σ is the standard deviation and μ is the mean.

Coefficient of Variation was used in this research to depict the extent of temporal variability of rainfall and discharge to characterize the climate and deduce the evidence of climate change.

3.5 Assessing the Future Climate Change Scenarios over the County

3.5.1 Generating climate change scenarios

Climate projections were derived from CORDEX. It is a project coordinating the dynamical scaling of General Circulation Model (GCM) datasets over the entire globe using specified domains. Downscaled CORDEX Africa datasets that cover the domain 45.76°S to 42.24°N and 24.64°W to 60.28°E with a resolution of 0.44° with a total of six RCMs were used, from whence regional datasets covering Narok County were extracted.

To assess the change in climate over Narok County, CORDEX outputs were used on a monthly basis for the period 1981-2055, following RCP4.5 and RCP8.5. Three time slices were selected; the period (1981-1990) which was used as the baseline, the period (2006-2030) as the present and near future, and (2031-2055) as the medium-term near future period. This was also targeting Kenya's Vision 2030 development blueprint and beyond.

An assessment of the models was done by evaluating their performances against the observation. Research conducted by Endris *et al.* (2013b) and Mascaro *et al.* (2015) found that GCMs have their limitations, and therefore computing an ENSEMBLE of the model was better than using individual models. An ENSEMBLE was therefore computed and their performance was analyzed together with individual models. This was done to identify the best model that replicates the observations very well. Several statistical methods were used to assess the model performance including; time series analysis, correlation analysis, Root Mean Square Difference (RMSD), and Standard Deviation (SD).

Since time series analysis was noted to be a subjective way of identifying the best model, this study adopted a Taylor diagram, to provide a statistical summary of how well the models mimic the observation. They visually depict how well and close a pattern or sets of patterns are to the observed values (Taylor, 2005), which can be evaluated by their correlation, amplitude of variation (SD), and their centered RMSD. According to IPCC(2007), these diagrams are crucial in assessing complex aspects of different climate models and also evaluating their skills. How close each model simulates the observations is represented by a letter on the plot, and the closer the models are to the observations, the more reliable the models are in simulating the observations (Taylor, 2001, 2005).

Figure 3.2 illustrates a Taylor diagram and also indicates how it can be used to summarize the relative skill with which several global climate models simulate the pattern of annual mean precipitation in this study. The following equation gives a relation of the Taylor statistics;

$$\mathrm{E}'^2 = \sigma_\mathrm{p}^2 + \sigma_\mathrm{o}^2 - 2\sigma_\mathrm{p}\sigma_\mathrm{o}\mathrm{R} \quad \text{.......... Eqn. 3.13}$$

Where; E' is the Mean Square Error (RMSE) between the observed and predicted values, σ_s^2 and σ_o^2 are the standard deviation for the predicted and observed values and R is the correlation between predicted and observed values (Taylor, 2005).

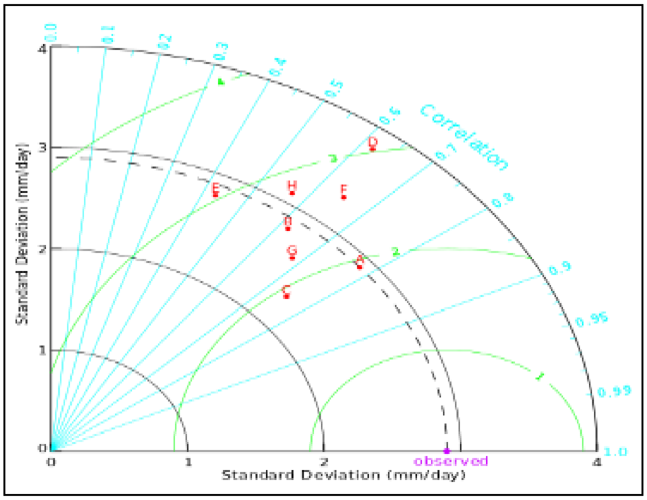

Figure 3.2: Schematic representation of the Taylor diagram
(Adopted from Taylor 2015)

However, to achieve this specific objective, the best model was then subjected to further analysis which involved plotting time series analysis of both rainfall and mean temperature and analysis of Probability Distribution and Density Function.

3.5.2 Time Series Analysis

This was used to analyze the trends in climate change scenarios over the region and assess the future behavior of rainfall and temperature series and identify the patterns in future climate series. Significant trends were tested using Mann-Kendall trend test with a threshold of α=0.05. However, these methods have been extensively described under section 3.4.2 and 3.4.2.1 respectively.

3.5.3 Probability Distribution and Density Function (PDFs).

Probability density function explains the likelihood of variable to change that only describes random variables. It also gives the probability of occurrence at a given point represented by *f(x).* Probability distribution function gives the probability of occurrence till that point and that the variable is below a defined threshold. It is denoted by *F(x).* Patterns are identified through skewness of data towards either left or right from the mean. Equation 3.14 shows the equation of Probability density function.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right] \quad \text{.......... Eqn. 3.14}$$

Where $\boldsymbol{\mu}$is the mean, $\boldsymbol{\sigma^2}$ the variance and $\boldsymbol{\sigma}$ is the standard deviation.

This method was used in this study to assess the patterns and shifts in the mean values of climate projections (rainfall and temperature), by evaluation of various time slices. However, results obtained from this objective formed the basis foundation analysis of assessing the impacts of climate change on water resources over Narok County.

3.5.4 Bias Correction

Even though RCMs provide spatial and physical coherent outputs, and have a higher spatial resolution than GCMs on a regional scale, they still retain model errors and biases from GCMs forcing. These can be amplified by including other parameters such as hydrological analysis (Turco *et al.,* 2017). Therefore, it is a crucial step before any analysis is done, to correct RCM biases (Ai *et al.,* 2018), to bring them closer to observations by calibration and validation before (Aramaki *et al.*, 2005; Rwigi, 2014).

There are many bias correction methods for both rainfall and temperature. Rainfall bias correction techniques include; Linear Scaling (LS), Daily Translation (DT), Delta Change correction (DC), and Empirical Quantile Mapping (EQM). Temperature bias correction methods include; Linear Scaling (LS), Daily Translation (DT), Variance Scaling (VARI), Distribution Mapping (DM), and Empirical Quantile Mapping (EQM).Details of these methods can be found in (Liu *et al.,* 2011; Luo *et al.,* 2018; Wu *et al.,* 2014). This study adopted linear scaling as a bias correction method for the CORDEX model outputs (temperature and rainfall) before any analysis was done. The corresponding observed data from the study area was used as the basis of extraction using the CMhyd tool. The description of linear scaling is given in the next sub-section.

3.5.4.1 Linear Scaling of Precipitation and Temperature

This is the simplest method of bias correction. In this method, the corrected values are linearly and closely matched with observed values. Basing on monthly values, precipitation and temperature values are rectified with a factor of multiplication and addition respectively. The factor is the difference between monthly observed and model simulated values (Luo *et al.*, 2018). The equation is as follows;

$$\mathrm{P_{cor,m,d}} = \mathrm{P_{sim,m,d}} * \frac{\mu(\mathrm{P_{obs,m}})}{\mu(\mathrm{P_{sim,m}})} \quad \text{Eqn. 3.15}$$

$$\mathrm{T_{cor,m,d}} = \mathrm{T_{sim,m,d}} + \mu(\mathrm{T_{obs,m}}) - \mu(\mathrm{T_{sim,m}}) \quad \text{Eqn. 3.16}$$

Where;$P_{cor,m,d}$ and $T_{cor,m,d}$ are corrected precipitation and temperature on the d^{th} day of the m^{th} month, $P_{sim,m,d}$ and $T_{sim,m,d}$ are the simulated precipitation and temperature on the d^{th} and $m^{th}$and μ represents the mean value.

3.6 Assessing the Impacts of climate change on the surface water resources in the county

The main aim of this investigation was to examine the impact caused by climate change on stream flows and rainfall in Narok County. The upper region comprises of Mau Forest, one of the crucial water catchments in Kenya, while the lower part has the Maasai Mara Game reserve. The study also examined how the quantity of surface water resources varied under the different climate change scenarios, and the sensitivity of the region to a changing climate system. This objective was achieved by applying a physically-based hydrological model, Water Planning, and Evaluation system (WEAP). The model is extensively described in several research works by several authors including (Azadani, 2012; Haji, 2011; Kou *et al.*, 2018; Mayol, 2015; Oti, 2019), among others.

To assess this objective, four time slices were considered; 1981-2005, 2006-2030, 2021-2030 and 2031-2055. Stream flow patterns were simulated and water yields quantified, considering two approaches; by use of Representative Concentration Pathways (RCP4.5 and RCP8.5) and Synthetic scenarios (±temperature and ± Precipitation).

3.6.1 WEAP Modelling

In this section, the requirements needed for WEAP hydrological model are presented, including model setup, data requirements, calibration and validation, and application and simulation options. Modeling a watershed in WEAP involves the following steps (Oti, 2019; WEAP, 2015);

(i) Definition of the study area. This includes setting up the timeframe (initial and last year) of scenario, spatial boundary, and system components.

(ii) Creation of Current Accounts. This describes the situation of available water resources in the area of study and is important since it forms the basis of the modeling process.

(iii) Creation of scenarios. This is the core attribute and heart of the WEAP model and is based on future assumptions. Scenarios allow possible adoption of possible water management processes and can be used to address "what if situations", like "what if climate change alters hydrology in the region?", and can take into consideration factors that change with time.

(iv) Evaluation of scenarios regarding water resource availability in the study area, costs, water quality and quantity, and other policies. These results form a crucial step in the water sector since it can help in planning and decision making.

The modeling process in WEAP entails building and running the model to simulate catchment processes under different climate scenarios.

3.6.1.1 WEAP model set up

Using the area defined area of study, the model was set up in the schematic view and the catchment set up including the infiltration channels to the catchment, rivers, and gauges on these rivers. The current account, key assumptions, time steps, and scenarios were also defined. Climate data was entered for the catchment including the area of the region and latitude. Gauged stream flow was also entered under the supply and resources. An initial run of the model was done at a selected gauging station on Ewaso Nyiro River, to establish if the parameters were correctly loaded, and establish the suitability of the model and prepare it for calibration and validation, to improve on the model simulations and reduce any uncertainties. To perform calibration and validation of the model, Ewaso Nyiro RGS was chosen and monthly time steps chosen with a three-step procedure as follows;

(i) Sensitivity analysis
(ii) Parameter calibration
(iii) Model validation

3.6.1.2 Model Sensitivity Analysis

This was done manually for the period 1985-1990 using monthly observed discharge data from Ewaso Nyiro RGS (2K01). Each model was used to calculate the observed function between the observed and simulated values. This is also the first process that is done to most hydrological models before calibration, to fix calibration parameters within suitable thresholds (Rwigi, 2014; Van Liew and Veith, 2010). Model sensitivity analysis was done in order the parameters according to their degree of sensitivity before model calibration was done.

3.6.1.3 Model Calibration and Validation

To appropriately simulate historical observations, the calibration process of parameters is done. Monthly observed Stream flow data from 1985-1987 of Ewaso RGS was used for calibration and the discharge from 1988-1990 used for validation. The PEST tool within the WEAP interface was used combined with a manual approach. To aid the process of calibration, the PEST tool had to modify some parameters while others were manually adjusted. Validation was done to evaluate the suitability of the model for hydrological analysis, and is done through some given criteria for model assessment. According to (Moriasi *et al.,* 2015), assessment of model performance is based on several statistics including; Coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), Percentage Bias (PBIAS) among others. This study adopted all three evaluation statistics to assess the performance of the WEAP hydrological model before being applied in hydrological modeling. A brief description of the three is given as follows;

(i) Coefficient of determination (R^2)

This is a statistical value that shows how close the simulated model values relate to the observed values, mainly estimated by the trend line. It is a number between 0 and 1 and is computed to compare the variability of estimation errors (SS_E) with the variability of the original value (SS_T) (Rwigi, 2014), using the following equation;

$$R^2 = 1 - \frac{SS_E}{SS_T} \qquad \text{Eqn. 3.17}$$

Where;R^2 is the coefficient of determination, SS_E is the sum square of errors and SS_T is the total sum of squares.

An optimal value of 1 indicates the best performance of the model, with more reliable predictions, while values of $R^2 \geq 0.5$ and close to 1 indicates less variance and are considered acceptable. However, since this statistic is highly sensitive and insensitive to outliers and proportional differences between simulated and observed values respectively, it calls for other statistical measures to be used for model assessment (Moriasi *et al.*, 2015; Rwigi, 2014).

(ii) Nash-Sutcliffe Efficiency (NSE)

This was first proposed by Nash and Sutcliffe (1970), and based on observations, it is used to measure the accuracy of model simulations by estimating the ratio of observed flow produced by the model (Moriasi *et al.*, 2015; Rwigi, 2014). It is given by the following equation;

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad \text{Eqn. 3.18}$$

Where; NSE is the model efficiency, O_i is the observed discharge value, P_i is the predicted discharge values, $\bar{O}$ is the mean of observed discharge values and n is the total number of observations.

The value of NSE is between -∞ and 1, with 1 being the best value. 0 and 1 are also values that are considered acceptable. From research works done by Moriasi *et al.*, (2015) and Rwigi (2014), values $\leq$ 0are considered unacceptable since they indicate that the observed mean is more accurate than the simulated mean. The following criteria for evaluation of model performance was also seconded; $0.5 < NSE \leq 0.65$ (satisfactory performance), $0.65 < NSE \leq 0.75$ (Good performance) and $0.75 < NSE \leq 1.0$ (very good performance). The NSE is unique from the Coefficient of determination (R^2) in that, the coefficient of determination compares the variability of estimation errors (SS_E) with the variability of the original value (SS_T), while NSE measure the accuracy of model simulations by estimating the ratio of observed flow produced by the model.

3.6.1.4 Percentage Bias (PBIAS)

At times, there is a tendency of simulated values being larger or smaller than observed values and thus, PBIAS can indicate the performance level of a model (Moriasi *et al.,* 2015; Rwigi, 2014).It is expressed by the following equation;

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i}\right] * 100\% \quad \text{Eqn. 3.19}$$

Where;O_i is the observed flowP_i is the simulated flow and PBIAS is the deviation of Stream flow discharge. This is always expressed as a percentage.

A PBIAS of 0 indicates a perfect model with no underestimation or overestimation of model values. Positive and negative values can also be used to evaluate model performance. However, an additional criteria was suggested to evaluate the model performance; $\pm15\% \leq PBIAS < 25\%$ (Satisfactory performance), $\pm 10\% \leq PBIAS < \pm25\%$ (Good performance) and $PBIAS < \pm 10\%$ (very good performance)(Moriasi *et al.,* 2015; Rwigi, 2014).

3.6.2 Catchment simulations

There are five methods within the WEAP model to model catchment processes (Azadani, 2012; Seiber and Purkey, 2015); Rainfall-Runoff (simplified coefficient and soil moisture methods), Irrigation Demands only method, MABIA, and Plant Growth methods, that are highly dependent on the purpose of analysis and data availability. This study used the Rainfall-Runoff (soil moisture method) to compute runoff in the region from the climate data. All the calculations were done on a monthly time step from the current year account to the last year of the scenario.

3.6.2.1 Rainfall-Runoff (soil moisture method)

This method simulates catchment runoff with two soil layers. The upper soil layer simulates runoff, shallow interflow, soil moisture changes, and Evapotranspiration. The base flow and moisture in the soil are simulated in the lower layer. This method is also one dimensional and uses two control volumes (buckets) for a catchment unit. The catchment is classified into sections they represent well the soil types and land uses, for j and N sub-catchments, assuming that climate in that catchment is constant. The mass balance water Equation is given by;

$$\mathrm{Rd_j}\frac{\mathrm{dz_{1,j}}}{\mathrm{dt}} = \mathrm{P_e(t)} - \mathrm{PET(t)K_{c,j}(t)}\frac{5\mathrm{Z_{1,j}} - 2\mathrm{Z_{1,j}^2}}{3} - \mathrm{P_e(t)Z_{1,j}^{RRF_j}} - \mathrm{f_j k_{s,j} Z_{1,j}^2} - \left(1 - \mathrm{f_j}\right)\mathrm{k_{s,j} Z_{1,j}^2} \text{ ... Eqn. 3.20}$$

Where; $\mathrm{Rd_j}$(mm) is the land cover fraction, $Z_{1,j}$ is the relative storage and is a fraction of effective root zone, $\mathrm{P_e}$ is the effective precipitation which includes snowmelt from snow parks within each watershed, $\mathrm{m_c}$ is the melt coefficient, PET is the Penman-Monteith crop Potential Evapotranspiration, $\mathrm{k_{c,j}}$ is a fraction for each land cover, $\mathrm{k_{s,j}}$ is the root zone saturated conductivity (mm/time), and $\mathrm{f_j}$ is the portioning fraction (Horizontally and vertically) based on the soil type, land cover, and topography. Figure 3.3 presents the concept of the Soil Moisture Method and the equations involved.

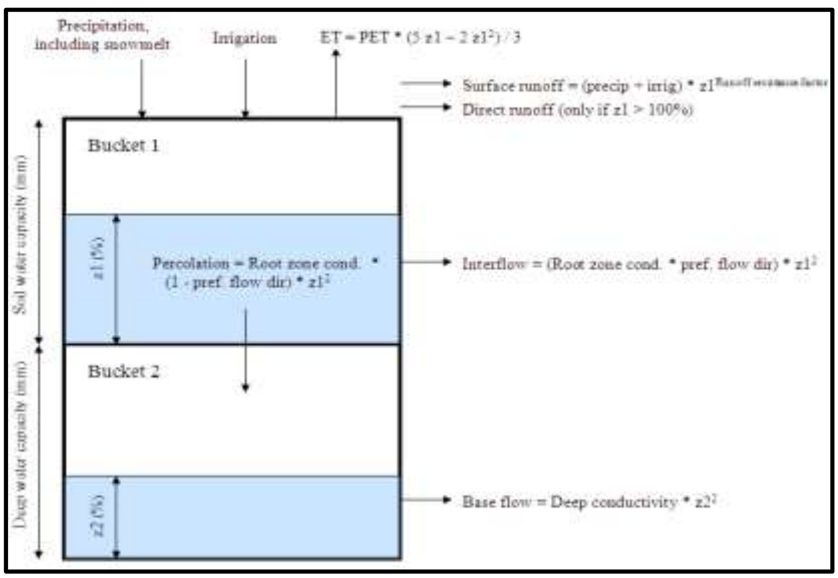

Figure 3.3: Representation of the Soil Moisture Method and equations
(Adopted from Seiber and Purkey, 2015)

3.6.3 Creation of Synthetic Scenarios

Scenarios mimic the future situations of systems like how well they will also respond to various conditions such as climate change and thus can be used to assess the impact of climate change and develop climate adaption strategies (Azadani, 2012; Jusoh, 2007). A synthetic scenario approach assists in estimating the amount and extent of climate change by altering a climatic variable to identify the critical threshold, which facilitates the analysis the sensitivity of a system to climate change (Aramaki *et al.*, 2005; Khasawneh, 2015). Synthetic scenarios are created by altering the existing climate conditions (reference year period/current account) and applied to generate future climate scenarios. Typically, they are based on the changes in annual means in both temperature and precipitation from simple adjustment e.g. ΔT=±1°C, ±2°C, ±4°C, and ΔP=0, ±10%, ±20%.

Synthetic scenarios were created to investigate how sensitive the hydrological system in the county is to climate change. Four scenarios were created to evaluate and compare the potential cause by climate change impacts in the county, which were analyzed for the period 2021-2055.

Most Global circulation models depict an increase in the annual mean temperature projection by (0.8°C-1.5°C) by 2030, 1.0°C-2.8°C by 2050, (1.6°C-2.7°C) by 2060s, and 3°C by 2100, while rainfall will vary from 2-11% by 2060 and 12% by 2100, indicating possible increase (Butterfield, 2009; Gebrechorkos *et al.*, 2019; KNAP, 2016; Sagero, 2019; USAID, 2018). In this regard, three hypothetical scenarios of a +2.5°C temperature increase combined with a change of ±10% in precipitation was applied to historical data from 1981-2000, to develop climate change scenarios for further analysis as summarized in Table 3.4 below. A base (reference) scenario of no change was also included.

Table 3.4: Synthetic climate change scenarios

Scenario	ΔTemperature (°C)	ΔPrecipitation (%)
Reference (base case)	0	0
Scenario 1	+2.5	0
Scenario 2	+2.5	+10%
Scenario 3	+2.5	-10%

3.6.4 Quantifying water availability due to climate change and Impact assessment

The availability of water in the area of study was quantified in all scenarios basing on the simulated outputs from the WEAP hydrological model. This was based on the difference in amount of water yields in the different time slices (2006-2030, 2021-2030 and 2031-2055), in comparison to the reference or base case scenario.

Impact assessment was done by analyzing projected stream flows using majorly rainfall and temperature as climate data inputs, and the quantity was compared with both base case and future scenarios. Quantification and impact assessment was done on two approaches;

(i) Impact of climate change on the quantity of water (water yields) using the GCM scenarios following the RCP4.5 and RCP8.5 pathways.

(ii) Impact of climate change by use of Synthetic scenarios.

The projected change in water quantity was compared to baseline to evaluate the level of change in both scenarios. This was given by the following relation.

$$Relative\ Change = \frac{(Simulated\ Mean) - (Baseline/Reference\ Mean)}{(Baseline\ Mean)}\ x\ 100\%$$ .... Eqn. 3.21

Where simulated mean are the simulated water yields and reference is the observed base case of streamflow in both GCM-scenario generated and Synthetic scenarios.

The water available in each scenario was then quantified in order to evaluate the sensitivity of the study area to climate change.

3.6.5 Conceptual Framework

Figure 3.4 below shows the conceptual framework. Standardized anomalies of rainfall, temperature, and discharge were used for objective 1 and two and the output from objective 2 were used to achieve objective 3. The final output was to evaluate the impact of climate change on water resources by using the WEAP hydrological model.

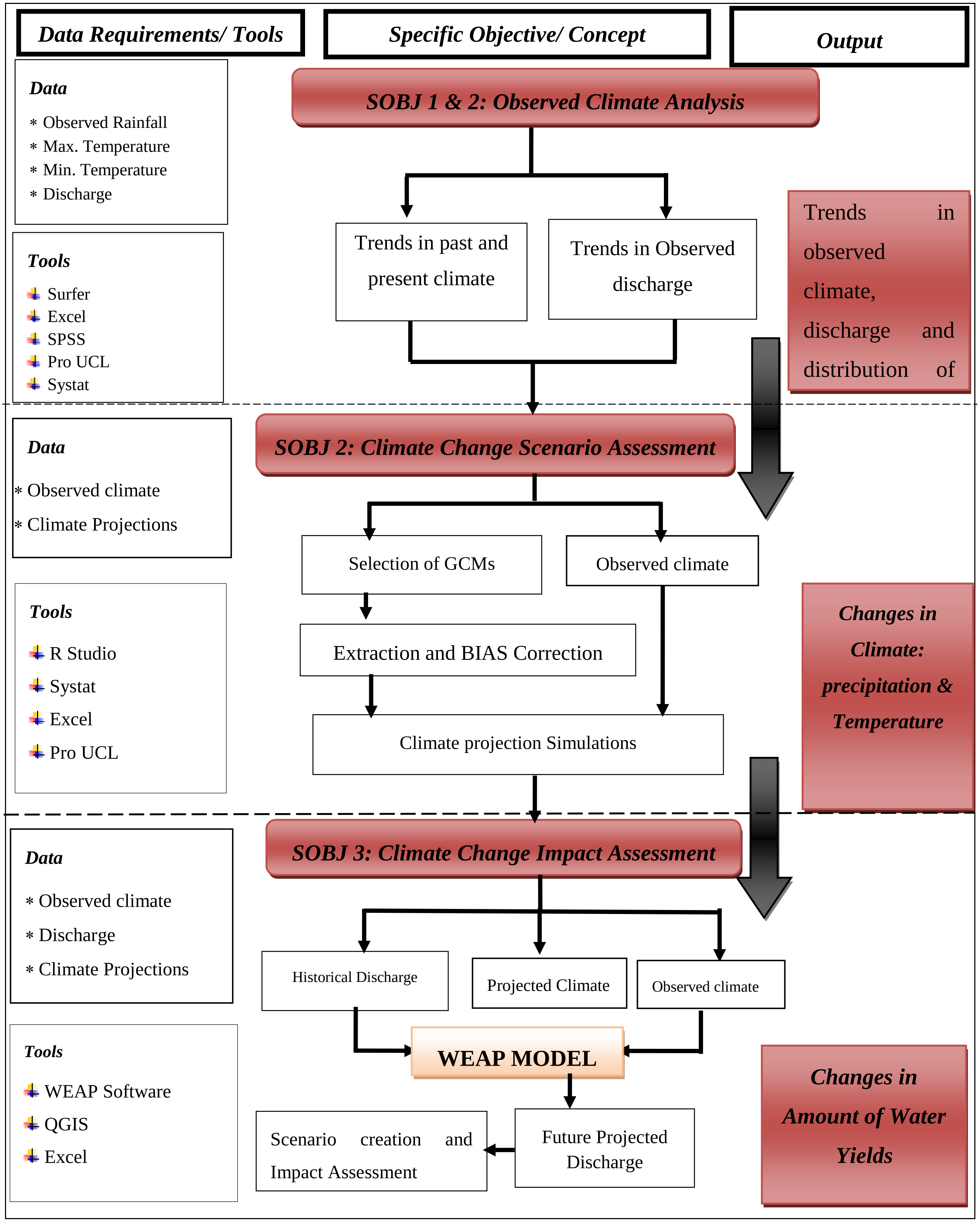

Figure 3.4: Conceptual Framework of study

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

In this section, the results obtained from the various methods used in this study to achieve the main objective are presented.

4.1 Results from Data Quality Control

This section presents results obtained from homogeneity tests for rainfall, temperature (maximum and minimum), and discharge.

4.1.1 Results from Single mass curves for Rainfall and Temperature

Cumulative values were plotted against time (years), for the period 1981-2018. Figure 4.1 presents the single mass curves of observed rainfall, temperature and discharge datasets. The climate dataset plots of gave straight lines indicating that the datasets were homogeneous and were used for further analysis. Most discharge data were heterogeneous and double mass curve analysis was used to test for consistency as presented in the next subsection.

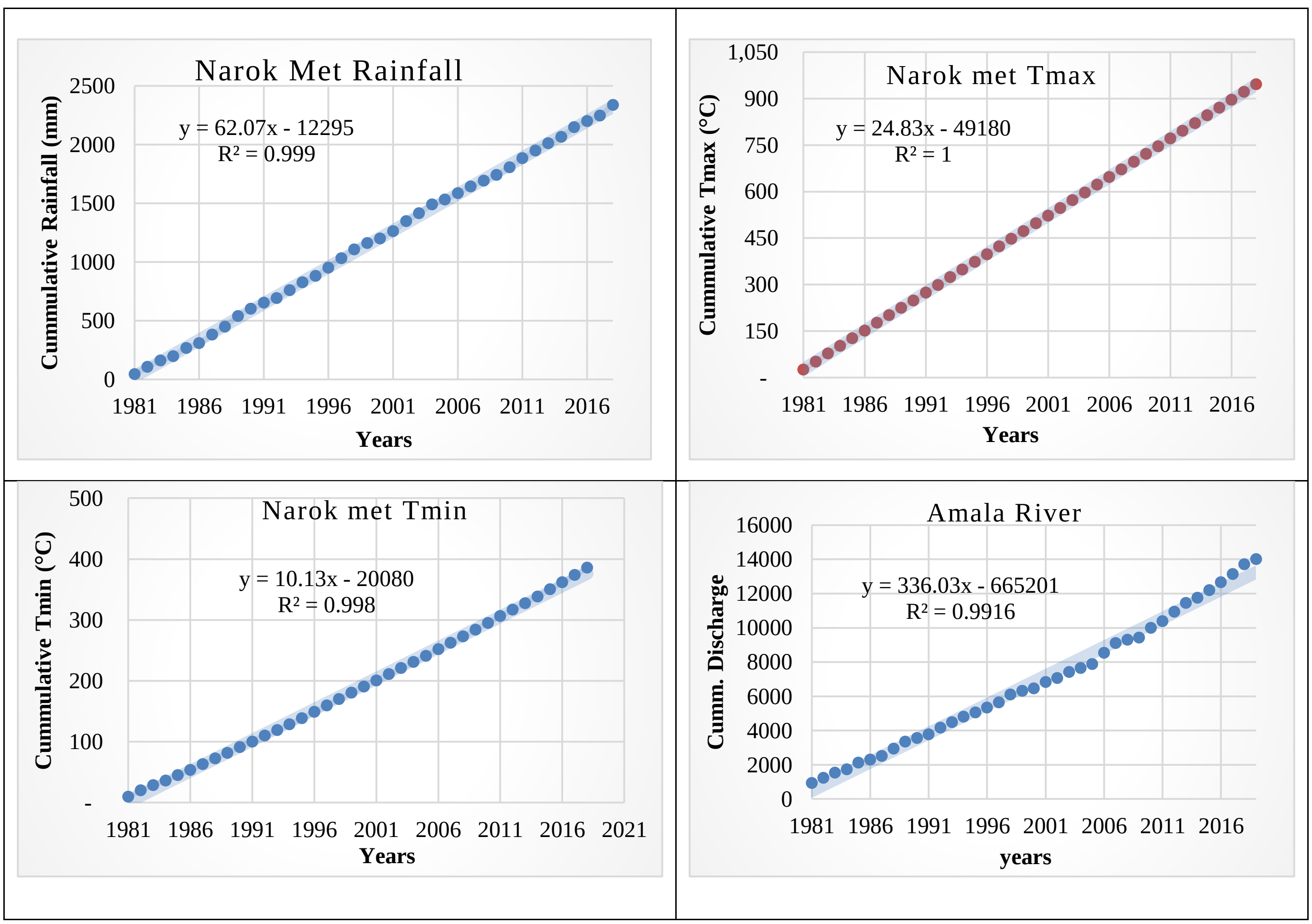

Figure 4.1: Single mass curves for Narok Met Rainfall, Maximum and minimum temperature and Amala River.

4.1.2 Results from Double mass curves for River Discharge

Figure 4.2 presents the double mass curves for Narok rivers. Most RGSs had missing records. The results indicated that all the stations had heterogeneous records except for Ewaso Nyiro RGS. They did not have straight-line plots but rather indicated irregular lines. However, heterogeneous stations were not included as part of the analysis. Only station with at least less than 10% missing data were used (Ewaso Nyiro River).

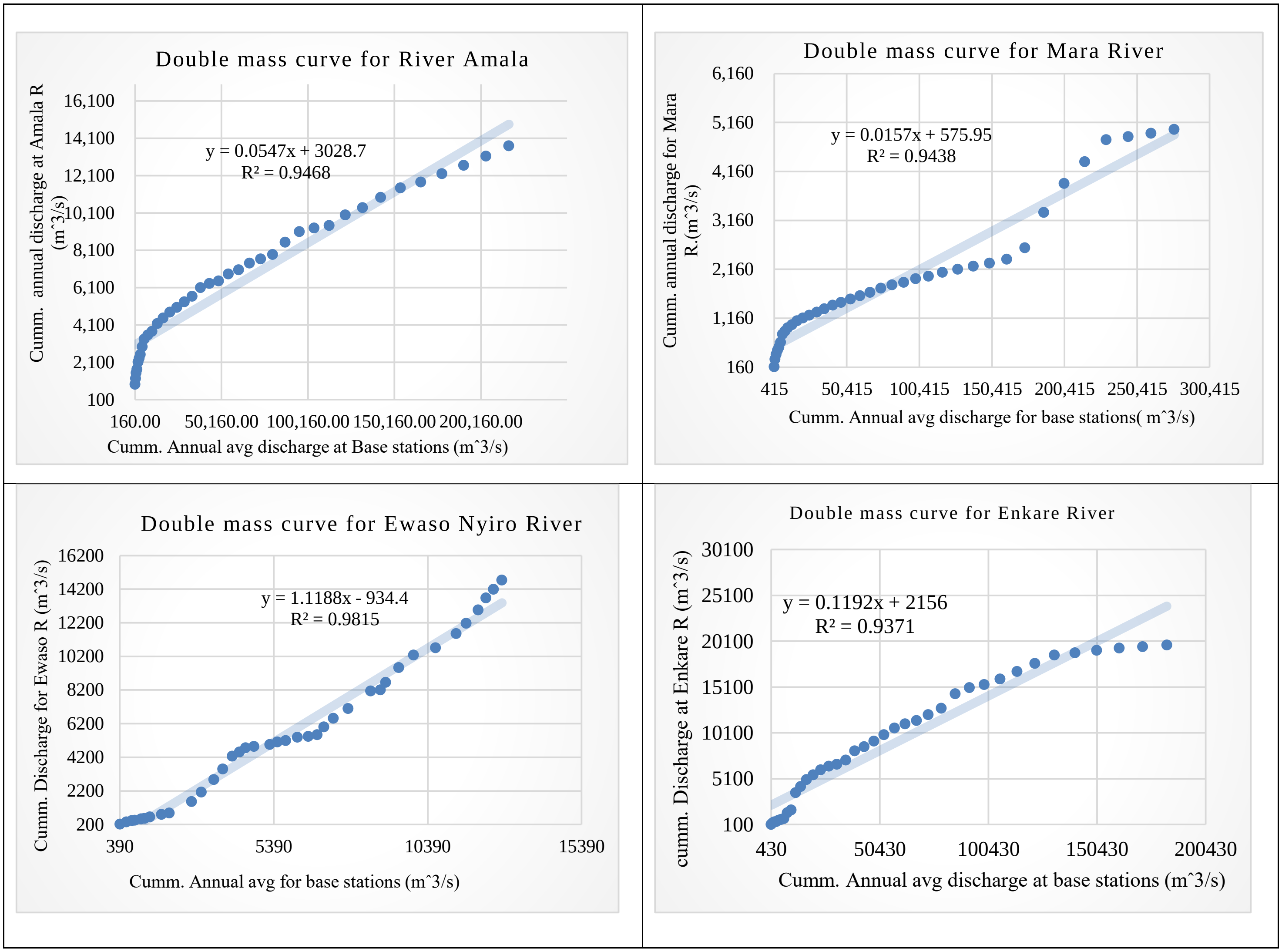

Figure 4.2: Double mass curves for Rivers Amala, Mara, Ewaso Nyiro and Enkare Narok

4.1.3 Validation of the CHIRPS and ERA5 datasets (Ground truthing)

Regridding was done from spatial resolution to a 1° x 1° lat/lon resolution to match the models between 50°N and 50°S and extracted over a grid box covering Narok County. Point stations were then randomly extracted in QGIS as proxy rainfall stations over Narok County. A comparison between the observed annual rainfall and CHIRPS data over Narok for the period 1981- 2018 indicated that, there was a good relationship between the two datasets. The correlation coefficient (R^2) for rainfall was 0.75 (75%), 0.68 (68%) for maximum temperature and 0.65 (65%) for minimum temperature. These thresholds were good and indicated that the satellite data from CHIRPS can be used as proxy data for rainfall and temperature over the study area. Figure 4.3 illustrates the relationship between CHIRPS datasets and observed for rainfall over the period 1981-2018, while Table 4.1 indicates a comparison between the observed maximum and minimum temperatures with ERA5 datasets over Narok County for the same period.

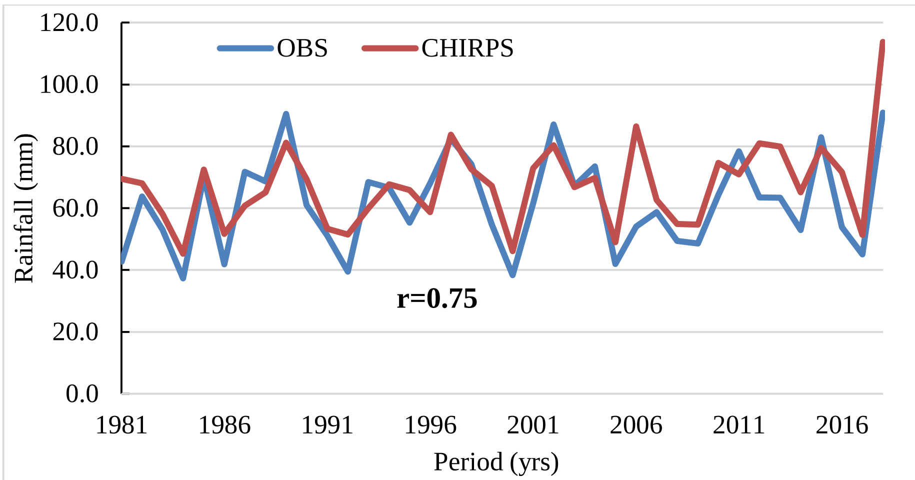

Figure 4.3: Comparison between the observed and CHIRPS rainfall (mm) datasets and the correlation for the period 1981 to 2018 over Narok County

Table 4.1: Validation Coefficients

Parameter	Correlation coefficient (r)
Maximum Temperature	0.68
Minimum Temperature	0.65

4.2 Assessing Temporal and Spatial Distribution of Rainfall and Discharge in Narok County.

This subsection presents the discussion obtained from Principal Component Analysis (PCA), delineation of the study area into homogeneous rainfall zones, computing the spatial, temporal, and spectra estimates of rainfall over the region.

4.2.1 Regionalization from Rainfall data

PCA was performed on the annual rainfall and the rotated PCA factor loadings were mapped against the stations to analyze the spatial distribution of rainfall in the study area. T-mode and S-modes were employed to arrange the data for analysis. In T-mode, each station was a column of data arranged as a continuum of all the years, month-by-month starting from 1981-2018, while in

S-mode, factor loadings from significant components in each zone were mapped to give groupings of locations on spatial maps. The region was delineated into various homogeneous climatological zones basing on the annual rainfall data. Results from RPCA are usually mapped to give regions that experience similar rainfall patterns in the temporal anomalies, better explained by physical underlying reasons of these regions (Ouma, 2000), such as topography, presence of water large bodies, and other circulation thermally induced such as mountain/valley winds and the sea/land breeze (Kimani, 2019). The table below indicates the results obtained from the RPCA of the annual rainfall over Narok County.

Eigenvalues and Eigenvectors are obtained from the decomposition of data into uncorrelated components. The sole aim of unrotated Principal components was to obtain a smaller number of orthogonal factors. Rotation is necessary to maximize the difference between variance captured by the components and allow these factors to be correlated and thus only results from rotated PC are discussed.

Figure 4.4 illustrates a Scree Test plot with the five significant factors as identified, which were retained for rotation. Table 4.2 illustrates the statistical characteristics of PCA analysis on annual rainfall over the study area from Kaiser's Criterion, in which the five significant factors accounted for 94.3% of the total variance.

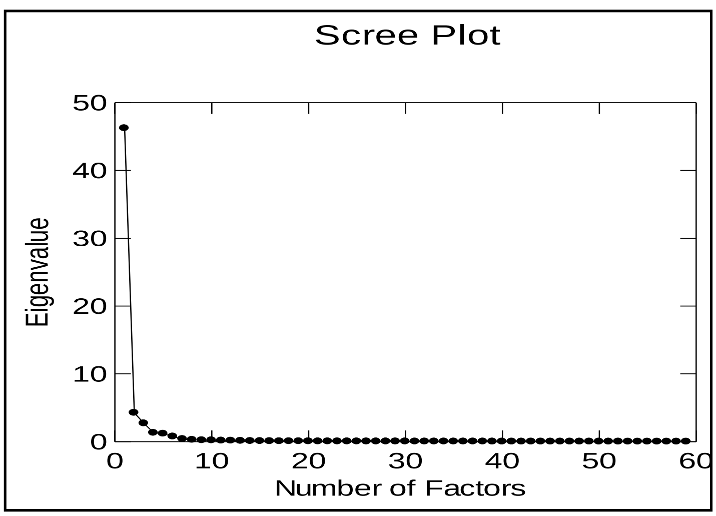

Figure 4.4: Scree Test for the dominant PCs for the annual rainfall

Table 4.2: Statistical characteristics of the annual rainfall from PCA

		NON ROTATED			ROTATED		
SEASON	FACTORS	EIGEN VALUE	VARIANCE EXPLAINED (%)	CUMMULATIVE VARIANCE (%)	EIGEN VALUE	VARIANCE EXPLAINED (%)	CUMULATIVE VARIANCE (%)
ANNUAL	1	46.23	78.35	78.35	18.01	30.53	30.53
	2	4.25	7.20	85.55	10.78	18.27	48.80
	3	2.70	4.58	90.13	17.84	30.23	79.03
	4	1.30	2.20	92.33	3.33	5.64	84.67
	5	1.18	1.99	94.32	5.70	9.67	94.34

Figure 4.5 presents the spatial distribution of five rotated components over the region. The spatial distribution of the 1st rotated principal component accounts for 30.5% of the total variance was dominant in the southern and southwestern regions around the Mara triangle. The unique characteristic delineated by this region may be caused by the presence of Lake Victoria, the Zonal and meridional arm of the ITCZ, and the influence of the moist Congo air mass (Ouma, 2000).

The 2nd rotated component that accounts for 18.3% was seen to be dominant over the northern part around the Mau Narok region, capturing the topographic effect of the high altitude and the Mau forest.

The 3rd rotated principal component was dominant over the Eastern stretch from North East to South East around the Suswa region, which accounted for 30.2% of the total variance. This is due to the topographical effects of mount Suswa and the highland regions around the region.

The 4th rotated principal component only accounted for 5.6% and was dominant over several patches over the region including central, south, east, and north. The 5th rotated component accounted for 9.67% with dominance over the western region around Kilgoris.

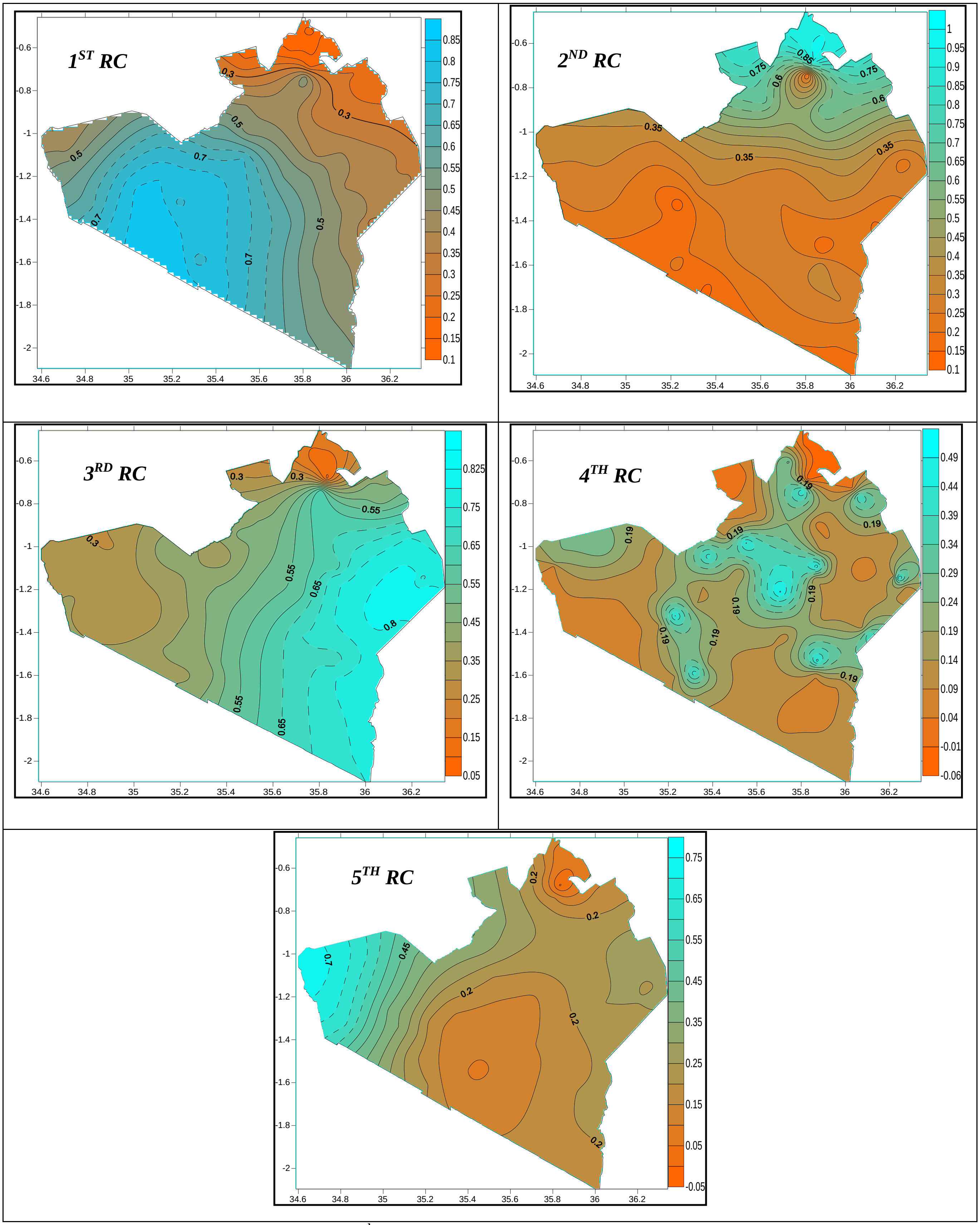

Figure 4.5: Spatial patterns for the 1st-5th Rotated components of the Annual Rainfall

Observing the spatial patterns of the five rotated factors, six homogeneous regions were obtained as displayed in figure 4.6, the statistical characteristics in table 4.3, and the physical underlying features/ characteristics of each zone in table 4.4 as shown below. Factor loadings are correlation coefficients between variables and factors. The square of each loading is the proportion or percentage of variance in that variable and was a basis of choosing representative stations in each group.

Table 4.3: Statistical characteristics from PCA of the Annual Rainfall

ZONE	STATIONS	SQUARED FACTOR LOADINGS	REP. STATION BY COMMUNALITY	ZONE	STATIONS	SQUARED FACTOR LOADINGS	REP. STATION BY COMMUNALITY
1	Koyaki	0.970	Koyaki	4	Ongata Naado	0.9754	Ongata Naado
	Ololmogi	0.965			Narok Met	0.9750	
	Aitong	0.963			Olenkuluo	0.9741	
	Mararianda	0.963			Kelongisa	0.9681	
	Megwara	0.961			Seyabei	0.9669	
	Mara 2	0.959			Rotian	0.9581	
	Sekenani	0.956			Enoosupukia	0.9572	
	Nkoilale	0.952			Olesharo	0.9555	
	MNC	0.950			Oleleshwa	0.9529	
	Esiot	0.947			Suswa	0.9491	
	Mara 1	0.943			Oloikarere	0.9419	
	Olkinyei	0.942			Mau	0.9183	
	Siana	0.936					
2	Mashagwa	0.970	Mashagwa	5	Kisiriri	0.954	Kisiriri
	Olorien	0.967			Olorropil	0.944	
	Sitoka	0.962			Mau Narok	0.941	
	Moita	0.959			Naituyupaki	0.939	
	Keiyan	0.952			Olchoro	0.936	
	Oldonyo Orok	0.952			Twendet	0.932	
	Kilgoris	0.936			Olpusimoru	0.915	
	Angata	0.916			Olokurto	0.892	
	Emarti	0.910					
3	Kalema	0.966	Kalema	6	Olkiriane	0.960	Olkiriane
	Maji Moto	0.966			Ololunga	0.946	
	Naroosura	0.956			Melelo	0.928	
	Olngarua	0.952			Lamek	0.925	
	Morijo	0.941			Ilmotiok	0.918	
	Mausa	0.921			Mulot	0.911	
	Olorte	0.907			Lemek	0.909	

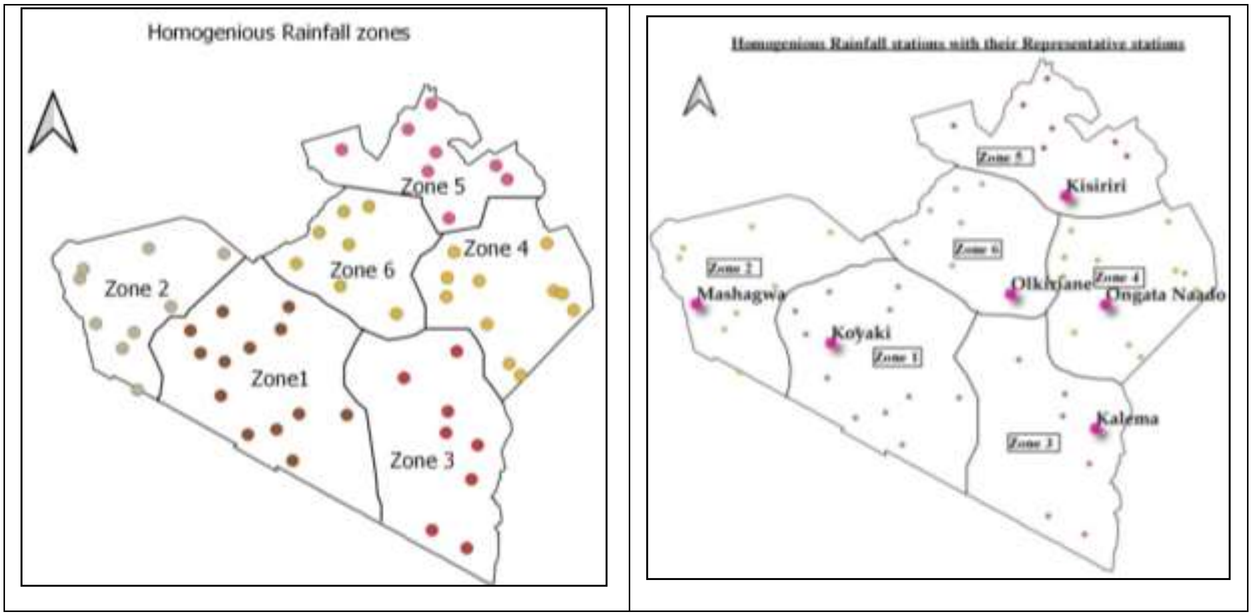

Figure 4.6: Homogeneous rainfall zones (a) with their representative stations (b)

Table 4.4: Characteristics and Features underlying the Homogeneous Zones

Zones	Possible Underlying Reasons
1	The diurnal variation of Lake Victoria Circulation and the interaction of the Zonal and Meridional arm of ITCZ.
2	Influence of the tropical climate and the effect of the high altitudes of the Kenyan Highlands and the Rift valley.
3	Influenced by the topography in the Naroosura area and the moist South Easterly air mass from the Indian Ocean.
4	Influence of the high altitude from Suswa highlands and circulation from the SE and Northern regions.
5	Effect of the Mau Forest Complex micro-climate and the high altitudes of Kenyan highlands.
6	Influenced by the topography of high altitudes of the Kenya highlands, warm moist Congo Air Mass, and the Zonal and meridional arms of the ITCZ.

4.2.2 Characteristics of Rainfall

This section describes the rainfall characteristics of each homogeneous zone including the variability of rainfall, the monthly long-term mean of rainfall and discharge, and the annual means of zones, spatial patterns of rainfall in the region, and the spectral estimates. The annual long term mean was only performed on the highly variable station in each zone.

4.2.2.1 Long-term Monthly means of Rainfall

Figure 4.7 displays the long-term monthly means of the zones

Zone1: Rainfall in this region is tri-modal with MAM season recording the highest rainfall during the year, with a minor peak in the months of JJAS. The highest amount of rainfall (155mm) occurs in April, while the least in July and October of about 30mm.

Zone2: Most of the stations in this region receive the highest amount of rainfall in April with Keiyan recording the highest amount of 214mm. The region also remains wet from August to December, with Angata recording the lowest amount of rainfall of less than 30mm in July.

Zone3: This region is characterized by a bimodal rainfall pattern with two distinct wet seasons (MAM and OND) in all the stations. Olngarua receives high rainfall amounts (240mm), with Mausa recording the lowest amount in July of less than 7mm.

Zone4: There are two wet seasons in this region (MAM and OND). April records the highest amount of rainfall in most stations, with Mau recording the lowest amount of rainfall of less than 1mm in July and August.

Zone5: Rainfall in this region is highly variable. The region remains wet almost all year-round with the highest amount of rainfall recorded in the MAM season. There are three peak seasons distinct with MAM recording the highest amount of rainfall, while JJA and OND are mini peaks, with Mau Narok recording the highest amount of rainfall in almost all seasons.

Zone6: This region remains wet throughout the year with rainfall above 50mm. There are three main wet seasons, MAM, JJAS, and OND. Ilmotiok receives high rainfall amounts all seasons with Lemek and Olkiriane receiving the lowest amounts throughout the year in all seasons.

From the observation, most regions exhibit a bimodal rainfall pattern with two distinct wet seasons (MAM and OND). Three zones (zones 1, 5, and 6) exhibit a tri-modal pattern, with much of the rain in April. JJA and DJF remain dry in almost all stations with rainfall less than 50mm or even zero in some regions.

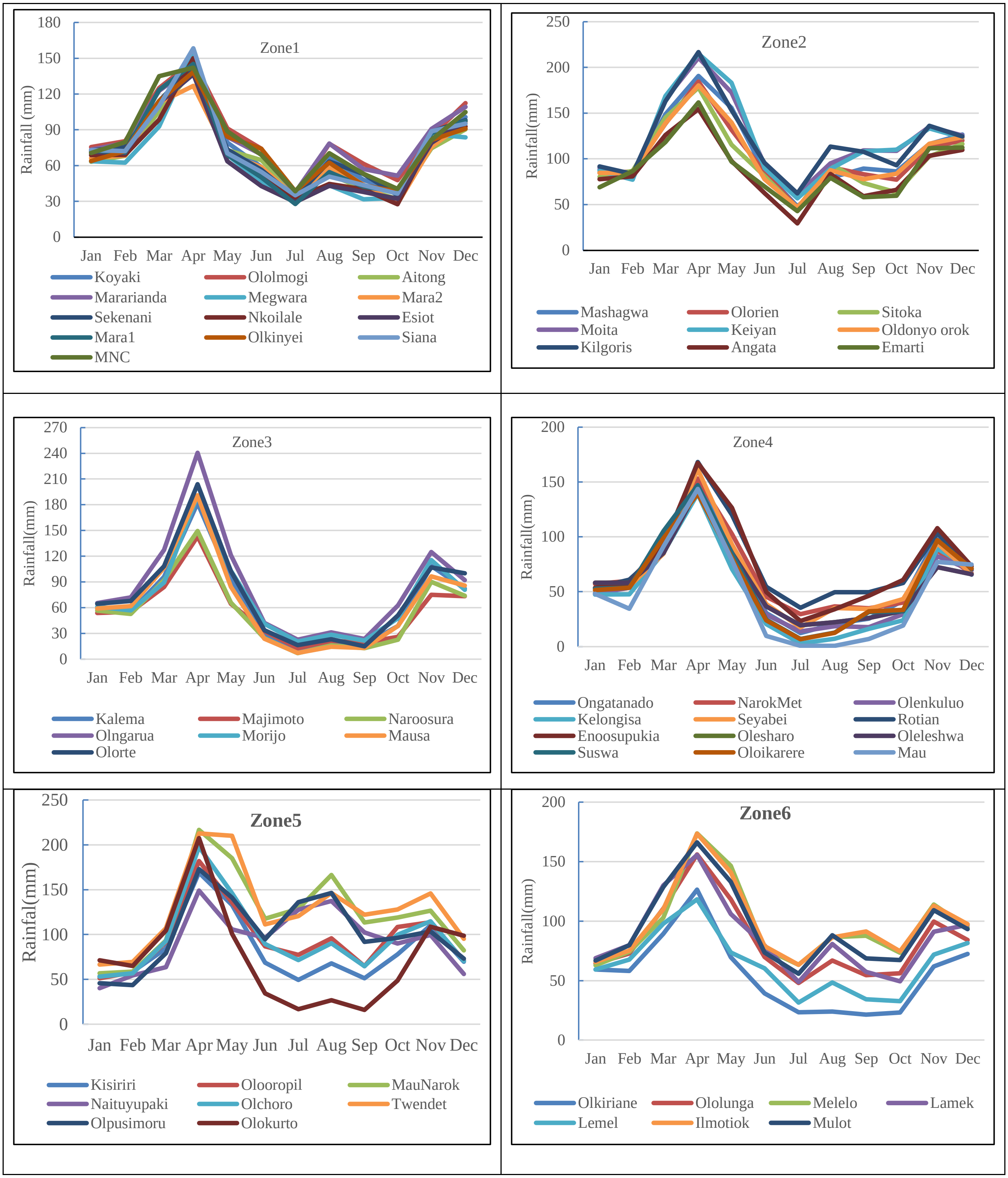

Figure 4.7: Observed monthly long-term mean for the Rainfall zones

4.2.2.2 Coefficient of variation (CV) of Monthly Rainfall

Figure 4.8 and Figure 4.9 indicates the variability of rainfall in each zone. Each zone had a unique characteristic, as discussed in the following subsection.

Zone1*:* Rainfall in this zone is highly variable throughout the year. Most stations recorded the lowest variability during the seasonal rains March-April (MAM) and Oct-Dec (OND). The lowest variability occurred in March for Mararianda and Mara North Conservancy stations, while the highest occurred in December and January for Megwara station. Rainfall in all stations in this zone is highly variable throughout the year.

Zone2*:* Just like in zone1, this zone observed low values of CV during the wet seasons of MAM and OND and high values during dry seasons DJF and JJA. The highest variability was observed in the month of January with Emarti (0.6) and Kilgoris recording high values, while Keiyan recorded the lowest (0.25) in the month of April.

Zone3*:* Almost all stations had the same variability of rainfall, with Naroosura recording the lowest value of 0.2 in July. December and January are the two months with the highest variability.

Zone4*:* In this zone, rainfall variability is similar for all the stations throughout the year. This is the zone that recorded the highest value of CV, where Mau region in January had a value of 1.28 compared to other stations in other zone. The lowest value is recorded in October for Mau Narok station. Most stations in this region recorded high values of CV almost the whole year. This could be due to variability of climate and of the location of this zone

Zone5*:* Rainfall is highly variable in this zone. The month of January depicts high variability of rainfall in almost all stations of nearly 0.9 except for Naituyupaki. The lowest variability is experienced during the wet seasons of MAM and OND. All stations have high variability in November towards December.

Zone6*:* This zone is also characterized by almost a similar pattern of rainfall in all the stations. Less variation is observed during the wet seasons' MAM and OND, as compared to JJA and DJF.

From figure 4.12, the highest variability is recorded during the dry months (DJF) and (JJA) in some zones, while the lowest variability is observed during the wet seasons of MAM and OND. This implies that rainfall is highly unpredictable during the dry seasons than wet seasons.

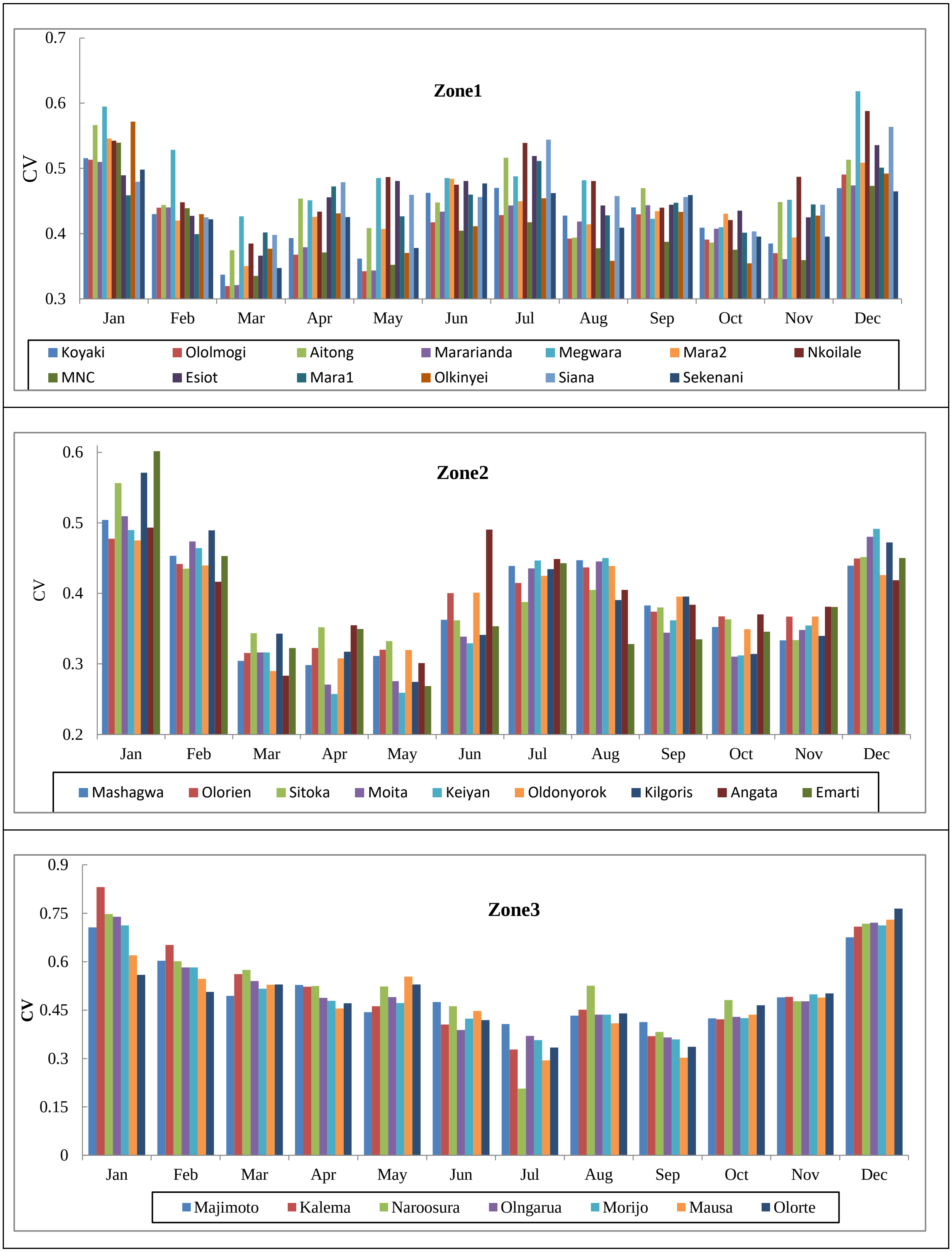

Figure 4.8: Coefficient of variability of monthly Rainfall totals for zone1 to zone3

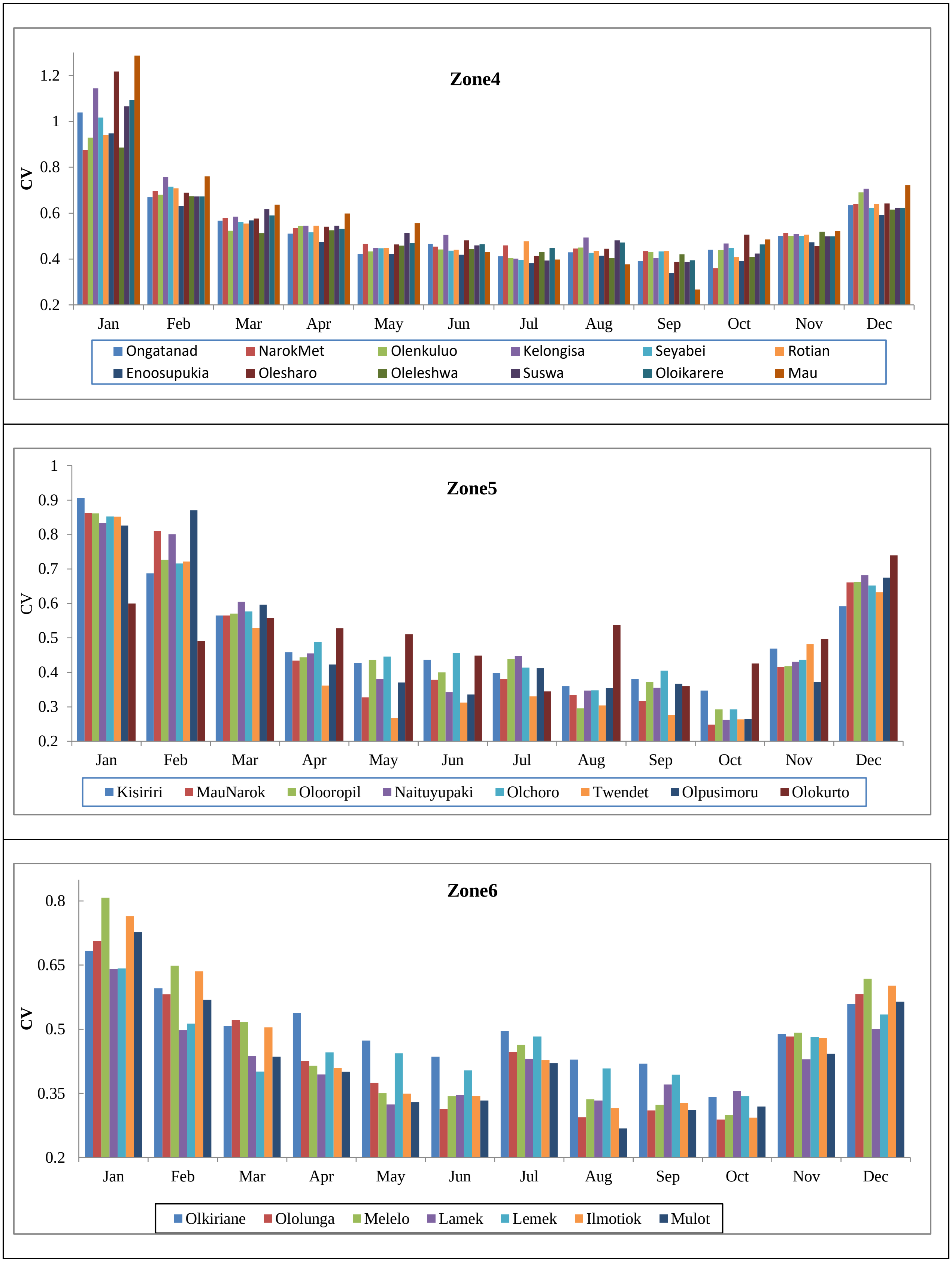

Figure 4.9: Coefficient of variability monthly Rainfall totals for the zone3 to zone6

4.2.2.3 Observed Temporal Characteristics of Rainfall Trends

In the section, results and discussions of temporal patterns of annual rainfall for the six zones are presented. The zones are several stations grouped which have similar characteristics and rainfall patterns. The main objective of the time series analysis was to detect the trends in the dataset and determine whether there is significant evidence of an increasing or decreasing trend, or whether there is no statistical evidence. The trends were tested at $\alpha=0.05$ and the threshold of normal rainfall was between +1 and -1. The time series of annual rainfall anomalies for the six zones are presented in Figures 4.10 and 4.11.

From figure 4.10, rainfall in zone1 has no statistical evidence of an increasing trend at $\alpha=0.05$. Rainfall is gradually increasing. Their number of episodes with above-normal rainfall is higher than dry and below normal rains. The years; 1989, 2006, 2010-2014had above-normal rains, with 2006 recording the highest amount of rainfall. 1984, 1992/93, and 2005 were the three years with below normal rainfall.

The trend in zone2 is similar to zone1. Rainfall is gradually increasing. It is observed that the year 1985, 2006, and 2010-2012 were the years with above-normal rainfall, while 1984, 1992/93, 2003, 2005, and 2016 were the years with below normal rains. All other years had rainfall within the normal range.

In zone3, same as zone1 and 2, the trend in rainfall over the years is not significant at $\alpha=0.05$. The frequency of above normal events in this zone is higher compared to the occurrence of below normal events. The years, 1989, 1997, 2002, 2006, 2010, 2012/2013, and 2015 were the years with above-normal rains. 1984, 1993, and 2017 were the few years that recorded below normal rains.

Figure 4.11 shows the rainfall trends in zones4 - zone6. In zone4, 1997/98, 2002, 2006, 2010, 2012/13, and 2015 were the years that recorded high amounts of rainfall above normal. In the same zone, the years 1984, 1987, 1991/92, 2000, 2005, 2009, and 2017 had rainfall below normal, recording the lowest amounts of rainfall. Though the rains were increasing, there was no sufficient evidence to show that the trend was significantly tested at $\alpha=0.05$.

Zone5 had the same trend with insufficient evidence to prove that the trend was increasing. Rainfall was increasing but at a slower pace. 1984, 1999, 2000, 2008/09 were the driest years that recorded rains below the normal average. 1988/89, 1997, 2002, 2006, 2010, 2012, and 2018 had rains above the normal range, shifting the trend to a slow positive and gradual increase, with a slight increase in 2018.

Zone6 had a similar description as all other zones except that the years 1989, 1997, 2006, and 2013/15 recorded high amounts of rains above the normal range. 1984, 1991, 1993, 2000, 2005, and 2008/09 had little rains below the normal average.

From the analysis of trends in Figures 4.10 and 4.11, it is also evident that there is insufficient evidence to explain for increasing rainfall trends though there is a gradual increase of rainfall in all ones in the region. Most stations received rainfall that was within the normal average, with almost an equal number of dry and wet episodes.

The frequency and length of both dry and wet spells are alarming. There are more frequent wet spells than there are dry spells. It is also seen that the length of the dry spells is longer than wet spells. Though there is no significant statistical evidence of increasing trends in the times series in all the zones, it is visible enough that the rainfall trends are gradually increasing. This is a clear signal of climate change over the region.

In the last few years, the intensity of rainfall has been unpredictable. These changes have several negative impacts on such sectors as social-economic, such as transport, health, agriculture, and energy, and most important the water sector. Heavy rains usually cause flooding in most regions. Floods destroy crops, roads, and human settlement, and this affects the livelihoods of humans in so many ways. The transport sector is halted by the impassable roads, stagnant waters can cause several diseases among them malaria to humans and sweeping away crops and animals can bring about hunger. The intrusion of dirty water into clean water resources is also another threat.

On the other hand, dry spells result in drought conditions, and this can bring about a scarcity of drinking water and also food since most of them will be dry for farming. According to WHO (2016), drought can affect the health and well-being of humans all over the globe. Drought has been a major issue, especially in African countries. The scarcity of food and water has negatively impacted the normal activities of people including the loss of lives of both humans and animals.

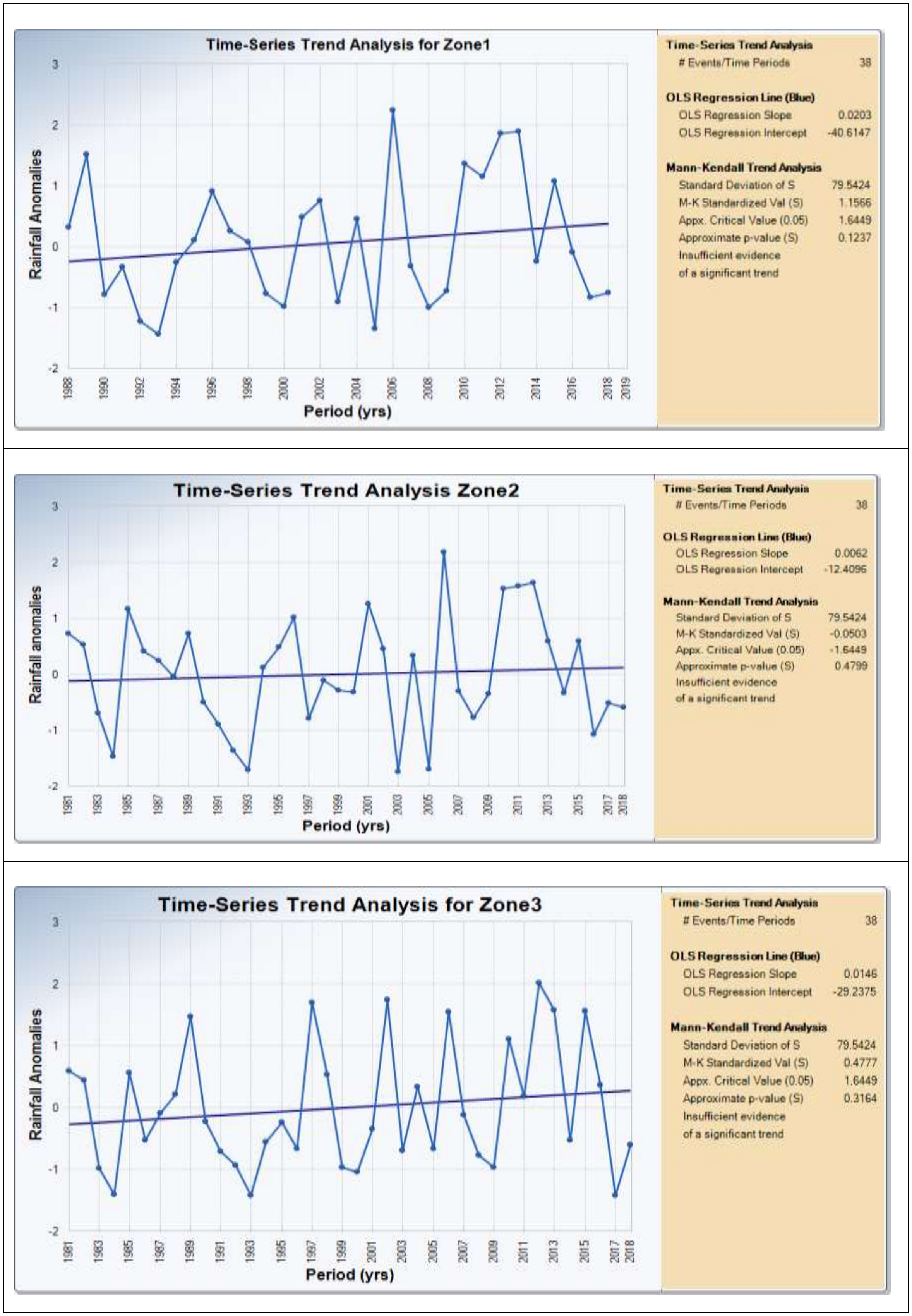

Figure 4.10: Time Series and Trend of Observed Annual Rainfall Anomalies of zone1- zone3

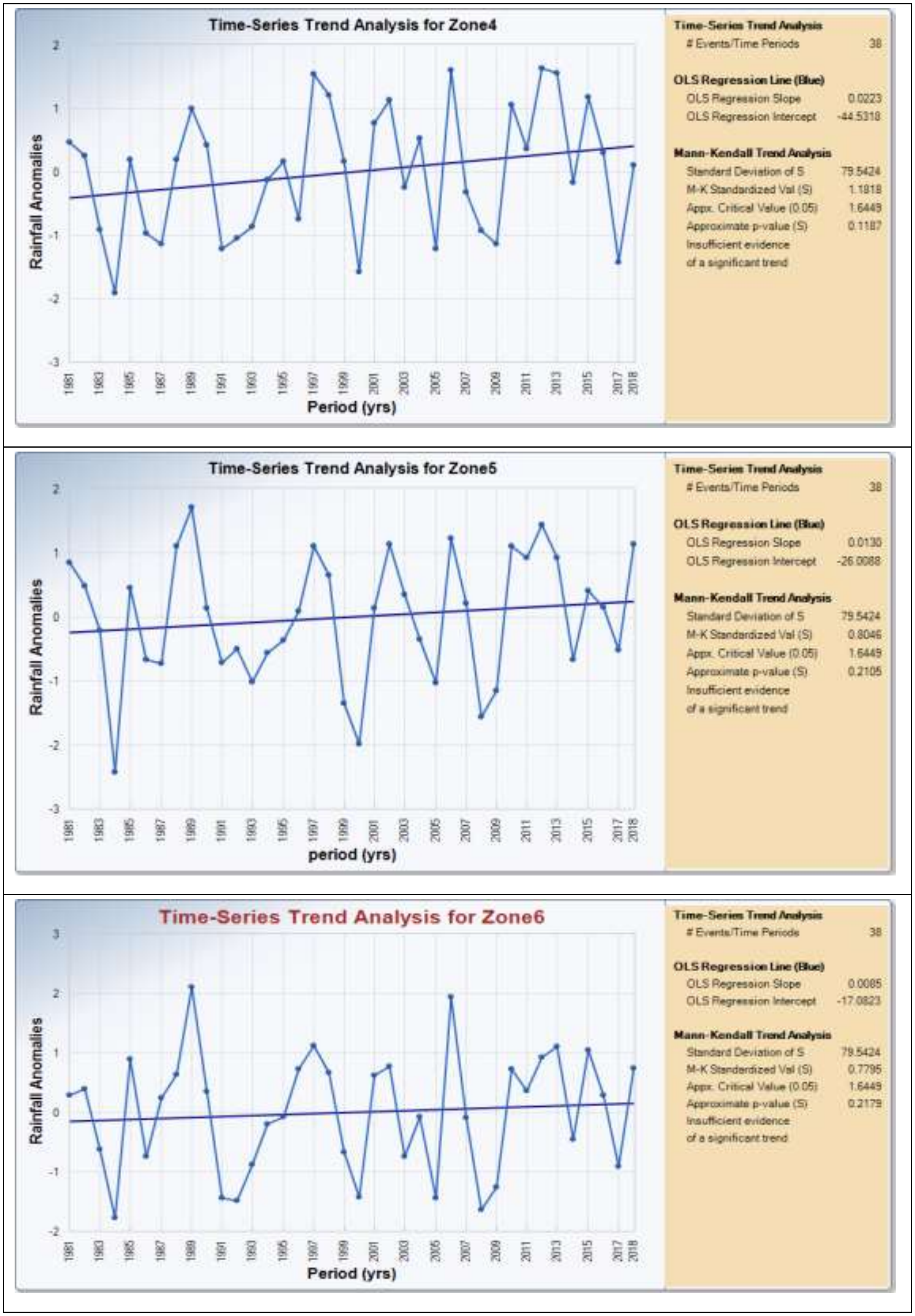

Figure 4.11: Time Series and Trend of Observed Annual Rainfall Anomalies of zone4- zone6

4.2.2.4 Spatial Analysis of Rainfall

Figure 4.12 presents the spatial rainfall patterns of long-term means (1981-2018). Two main Seasons were considered (MAM and OND), together with the annual distribution. This was done to evaluate the spatial extent and distribution of the annual and seasonal rainfall characteristics in the region.

From the observation, the annual rainfall distribution is mostly in the western region around Kilgoris. Rainfall starts from the West as it decreases towards the East. The western side also receives more rainfall of about 1400 mm annually, as compared to 650mm annual rain in the central region and Eastern parts. Much of these rains are majorly influenced by the presence of Lake Victoria and the topography of the surrounding region.

During MAM, rainfall starts from the West and the North as it decreases towards the East. The western part receives close to 400mm of rain the same as observed Northern region of Mau. The central region only gets a total of about 280mm of rain during the season.

Short rains begin in October-December. Most parts of the county receive rains of about 330mm except the central part which gets a total of 150mm of rain. The central region is mainly hilly and rocky. That makes it record low amounts of rainfall since the environment is not conducive to the formation of rainfall.

Areas receiving a good amount of rainfall in the region (West and North) are majorly influenced by several factors. The presence of Lake Victoria in the west and the Congo Air Mass are a good source of moisture that leads to the formation of rainfall in the region. The Northern region is majorly influenced by the presence of Mau forest and the orographic influence of the environment, other than the influence of the Congo Air mass and the Indian Ocean.

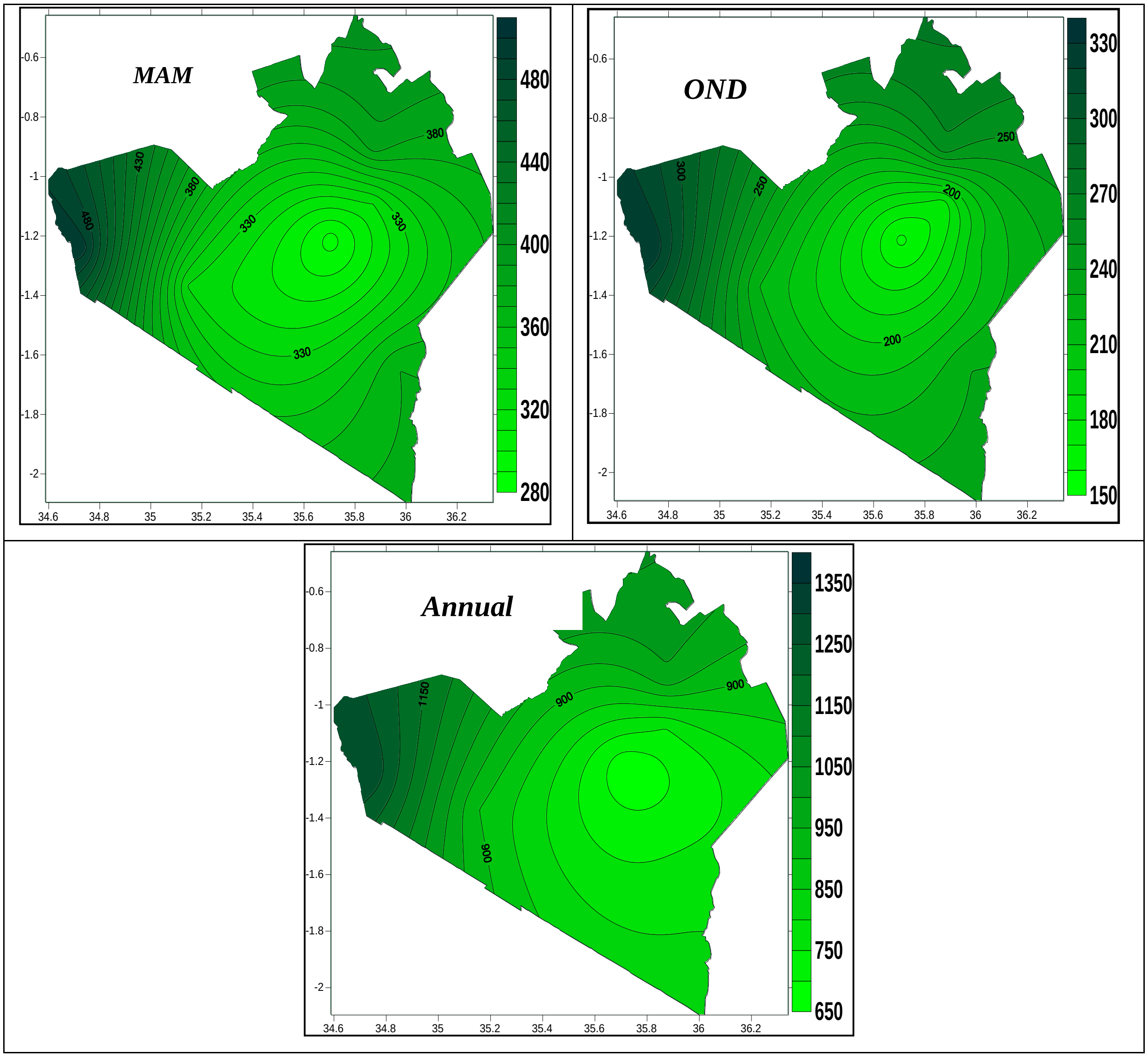

Figure 4.12: Observed Annual and Seasonal Spatial rainfall over Narok County

4.2.2.5 Spectral estimates

This subsection presents the results obtained from spectral analysis of the annual rainfall over Narok County. Spectral estimates are estimations of spectral densities of signals from a sample of time series in a dataset to show the frequencies and identify periodicities, basing on the peaks at frequencies that are linked to these periodicities in the same sample data. The spectral analysis technique was employed to the annual rainfall (1981-2018) over Narok to detect any periodicity or periodic shifts and identify any cycles in the rainfall records. The results obtained from spectral analysis in the annual rainfall over the region as presented in figure 4.13 indicated that dominant and significant spectral peaks were observed for the periods 2.0-3.2, 4-5.5, and 6.5-10 years. Several authors including (Indeje *et al.*, 2000; Mutemi, 2003; Omay, 2015; Omondi *et al.*, 2009; Ouma, 2015) have linked such observations to different climate systems including; QBO to 2.0-3.3 years cycles, ENSO to a 5.0-7.5 years cycle, and 10.0-11.0 years cycle to solar variability. From the analysis of spectral estimation, it was quite clear that, QBO and ENSO have a significant influence on the distribution of rainfall over Narok county.

Many authors have also made similar observations in different studies among them (King'uyu *et al.*, 2000; Omay, 2015; Omondi *et al.*, 2009; Ouma, 2015).

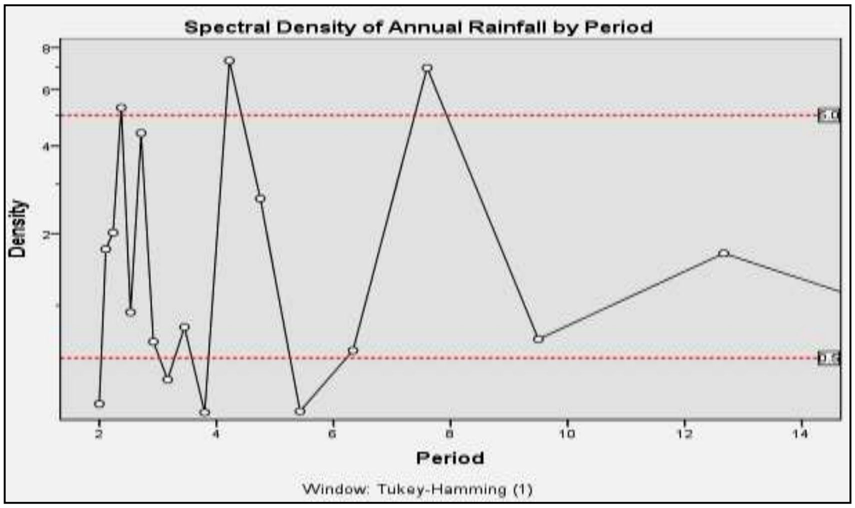

Figure 4.13: Spectral analysis in the total annual rainfall for Narok County

4.2.3 Assessing the Temporal Variability of Discharge

This section presents results obtained from temporal variability analysis of discharge. They include annual time series plots of discharge, seasonal cycles and the monthly variability.

4.2.3.1 Long-term Monthly means of Discharge

Figure 4.14 presents the results of the long-term monthly mean and patterns of the discharge from rivers in the region.

Amala River is located in zone6. The region has a tri-modal rainfall pattern indicating that it is wet almost throughout the year. The river records its highest peaks during March-April-May and August-September seasons in which the area records high rainfall amounts. The highest discharge is recorded in May with 521 cumecs.

Mara River is located in zone1. It is the most affected in terms of flow. The highest amount of discharge is recorded during the MAM wet season with only 173 cumecs of discharge. There are two dry seasons Jan-Feb and June-July. Low amounts of discharge are recorded during this period, with February recording the lowest amount of 87 cumecs.

Ewaso River is located in zone6. Rainfall in this region is tri-modal. Therefore, the rivers remain to record a higher discharge in most months throughout the year except February with less than 300 CMS. The month of May has the highest peak with 551 cumecs.

Enkare River also has its highest peak in May during the MAM season, with Aug-Sept also recording high levels. The river is also found in zone6, which has a tri-modal rainfall pattern, and that explains why there is a peak in August. Low levels are recorded in February and March, simply because of the high environmental temperatures.

It is observed that most rivers have their peak discharge during April during the long rain season (MAM) and short rains (OND). Some rivers however record peak discharge in the mini-peak season June-August (JJA), which follows a tri-modal pattern of rainfall in the region they fall. The peak also could be due to the time it takes for the surface runoff to reach the stream.

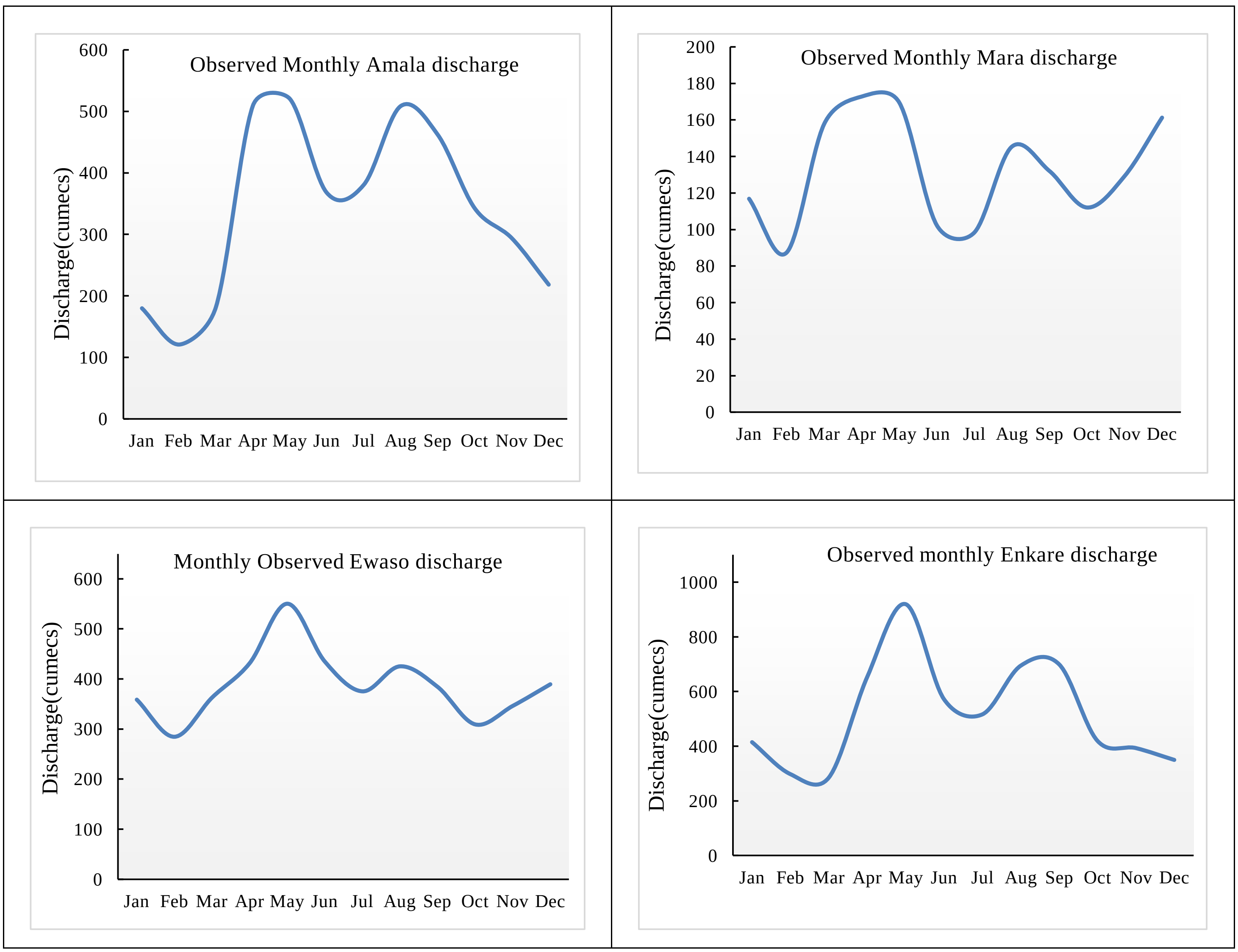

Figure 4.14: Observed monthly discharge from Narok Rivers

4.2.3.2 Coefficient of variation (CV) of Monthly Discharge

Figure 4.15 shows monthly coefficient of variability of Narok rivers. It is observed that, Amala River has the lowest variability in August. December, January, February and March exhibits high variability in flows with the period between May and September has the lowest. Discharge in Mara River is highly Variable throughout the year with July recording the highest with a CV of 1.7. the seasons that are highly variable in this river are Dec-Feb and July-Sept. Ewaso River has its highest between February and March. The month of April has the lowest value of CV (0.8). High values are also observed during dry months Dec-Feb and JJAS. For Enkare Narok, variability in streamflow is high in January, February, April, May, June and December. Low variability occurs March and between July-November.

From the analysis, it is observed that variability in stream flows in Narok county is high. Generally, streamflow is highly variable during the dry months DJF and JJAS, and low variability is observed in months like April, November. This however is directly linked to the wet seasons of MAM and OND and high variability during the dry seasons DJF and JJAS respectively. This variability could also be due to the geographical location of these rivers, and the activities taking place therein.

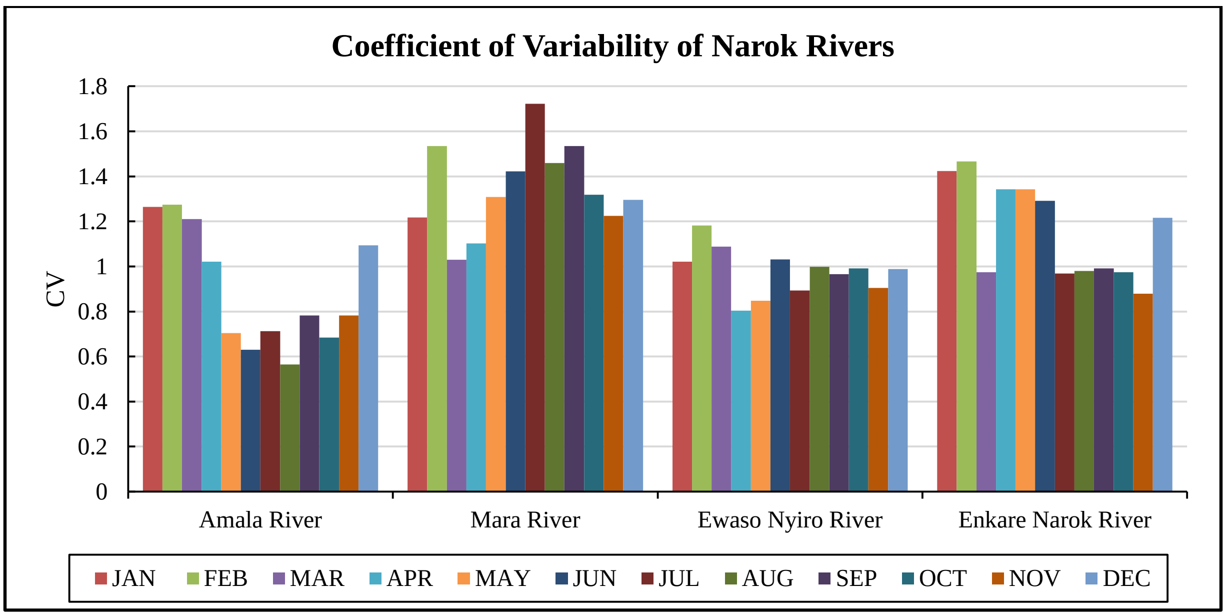

Figure 4.15: Coefficient of Variability of Narok Rivers

4.2.3.3 Observed Temporal Characteristics in Discharge

Figure 4.16 and 4.17 presents the time series and trends of discharge from the four Narok Rivers. The trends were tested at α=0.05.

Figure 4.16 present Amala and Ewaso Nyiro River discharge. Amala River is located in zone6 and receives its headwaters from the Mau forest catchment. The zone also has a tri-modal rainfall pattern and is wet almost all the year, which translates into large volumes of water in streams. Almost all the years have records above 200 cumecs except for the years 2000 and 2009 where there were low levels in the stream. However, there were high volumes of water in the years 2006, 2010, 2012, and 2018. This is in correspondence to the high rainfall recorded in those years. The discharge trend in the Ewaso Nyiro River is significant at $\alpha=0.05$ an increasing trend. This zone also is located in zone6 which has a tri-modal rainfall pattern. The years 2007, 2010, and 2013 recorded above-average rains, translating into high peaks in discharge. Following the trends in rainfall variability, the years that had below-average rains (1984, 1986, 1997, 2000/03 and 2008), also recorded low amounts of discharge.

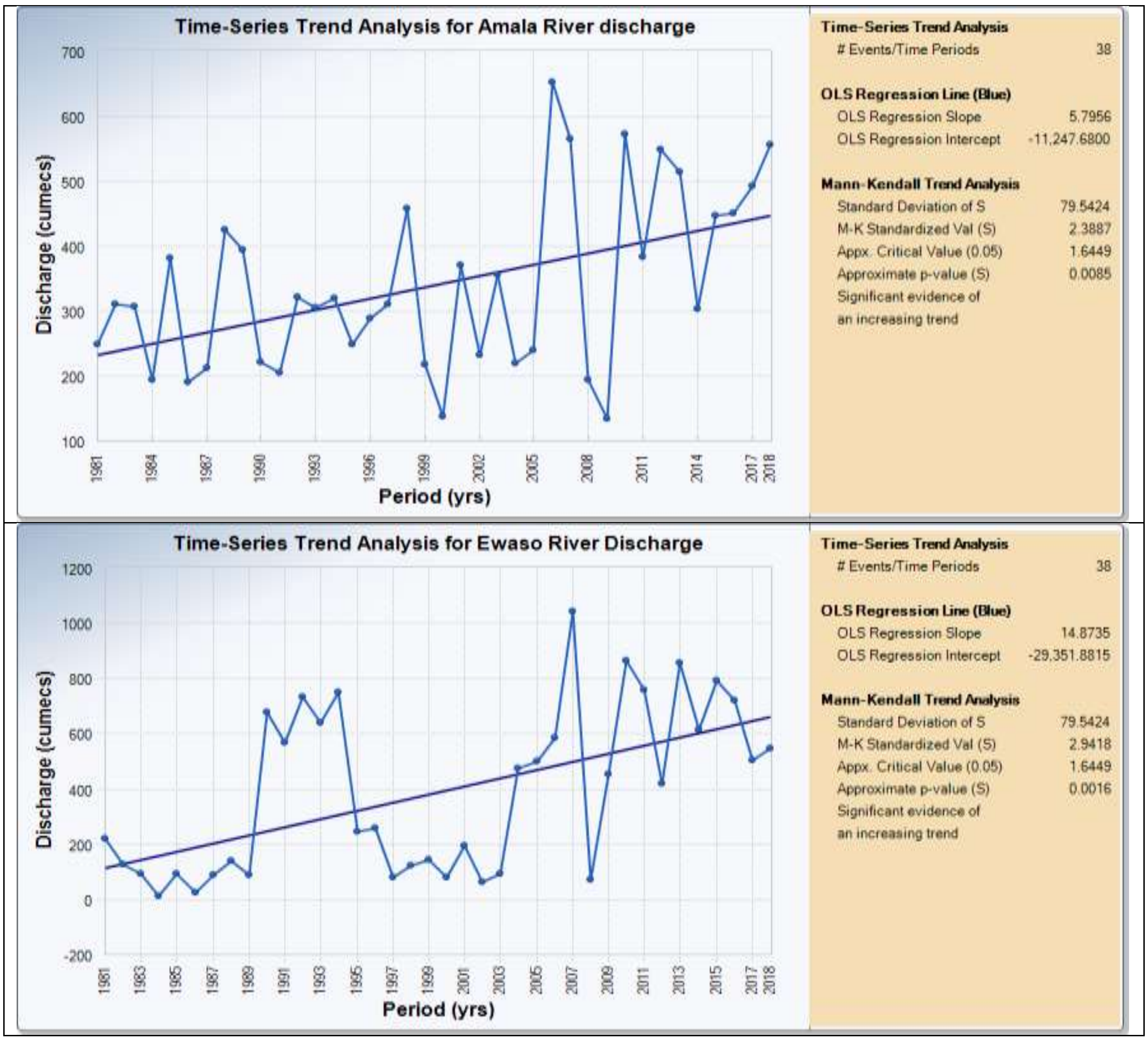

Figure 4.16: Time series and trend of Amala and Ewaso Nyiro Rivers.

As shown in figure 4.17, Enkare Narok river had an increasing trend at α=0.05. this river is located in the near central region in Narok County and is also situated in zone6. Just like all the other rivers, 1984, 1986, and 2017/18 were the years in which the river discharge was at its lowest. 1990 and 2007 had the highest peaks of discharge recorded that region. Even though there was no much data available for the Mara River, the highest level was observed in 2012, followed by a sharp decrease in 2016. All the other years had levels in these stream less than 100 cumecs except for 1981/82 and 1987. However, it is observed that high peaks in discharge correspond to the high peaks in rainfall above average. Most rivers have an increasing trend significant at α=0.05 except for the Mara River which had no evidence to support an increasing trend due to lack of data. Though the rivers in the region indicate an increasing trend, the amount of water in the streams is not enough to cater to the demands of various sectors in the region.

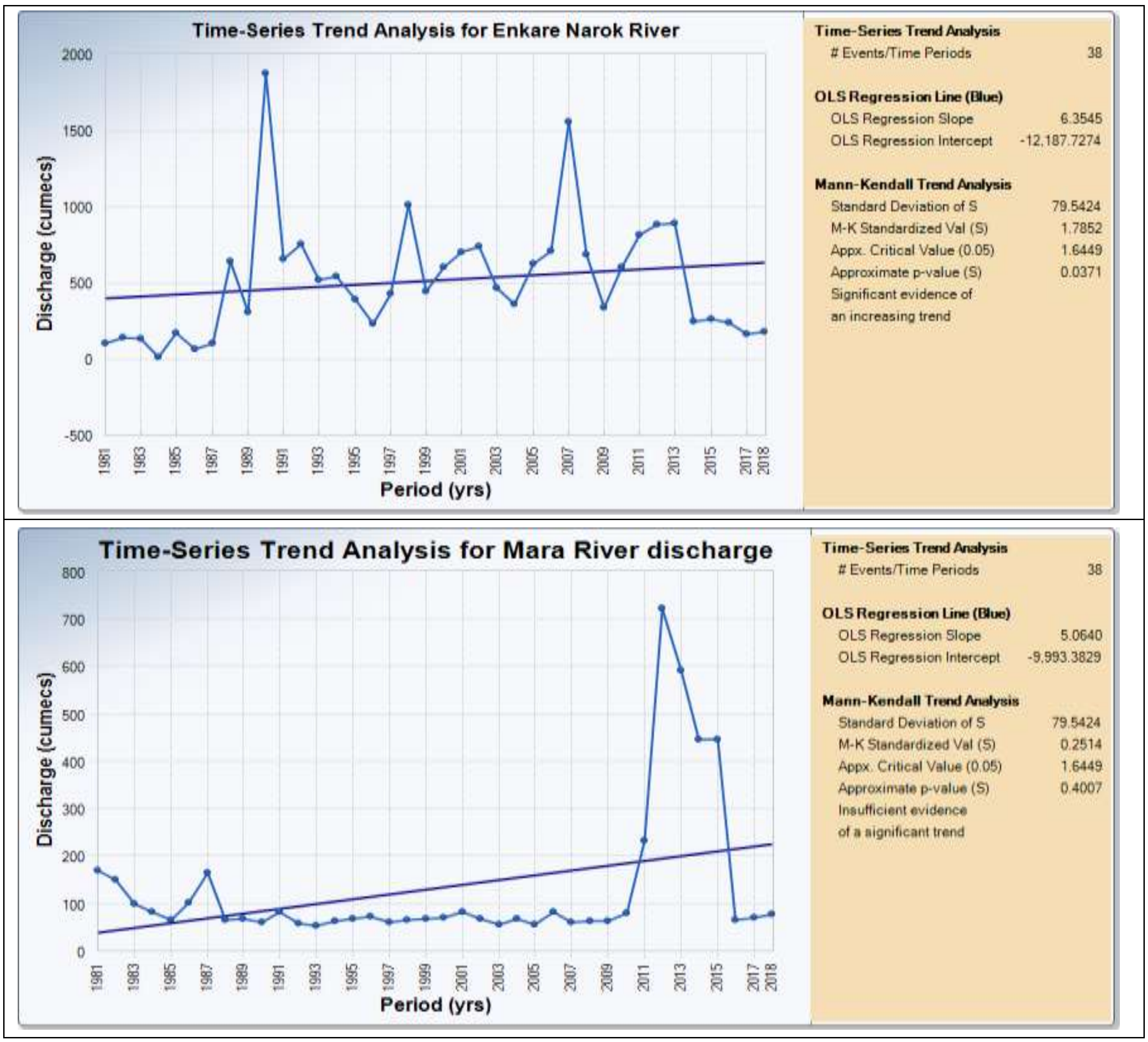

Figure 4.17: Time series and trend of Enkare Narok and Mara Rivers

4.3 Assessing the Future climate change scenarios over Narok County

This section presents results obtained from the analysis of climate change scenarios over Narok County. These include the graphical presentation of observed and climate models, a Taylor diagram, future climate trends of the different scenarios, and kernel distributions of rainfall and temperature for different climate periods.

Figure 4.18 presents a graphical representation of the historical rainfall for the observed (baseline), the CORDEX RCMs, and ENSEMBLE of all RCMs for the period 1981-2005 over the study area. However, since graphical analysis is known to be subjective in analyzing climate studies, a Taylor diagram was employed to determine the best model which bests simulates the observed values and can be used for climate modeling. The diagram also analyzed and summarized the performance of the models with several statistical indices such as correlation analysis, model bias, standard deviation and root mean square error (RMSE).

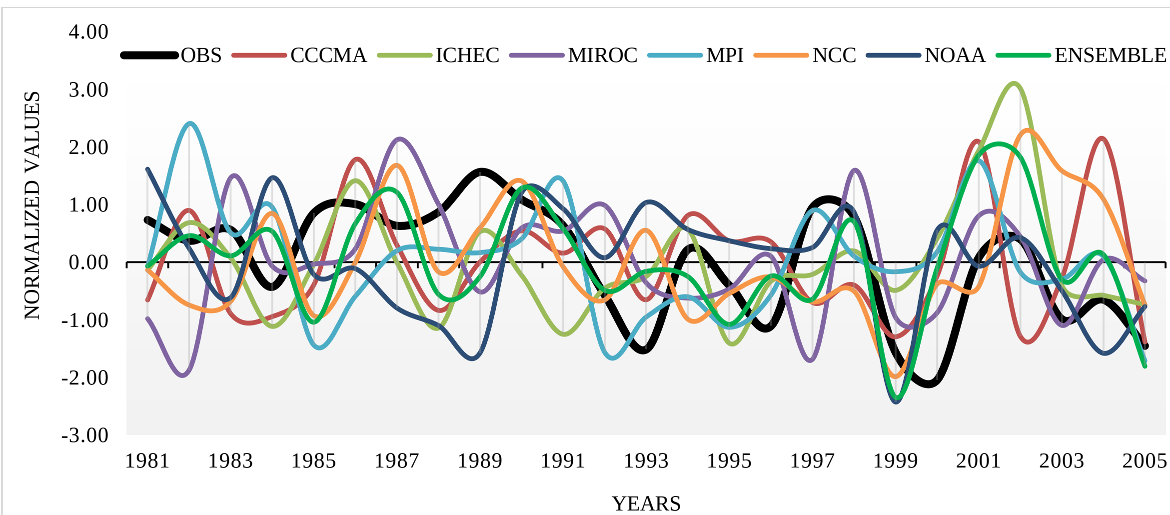

Figure 4.18: Time Series Analysis of the observed Rainfall, CORDEX RCMs, and ENSEMBLE of RCMs over the study area.

Figure 4.19 presents a Taylor diagram of all the models and their ENSEMBLE average against the observed value. It was observed that most of the models had a positive relation to the observed value. However, the ENSEMBLE average was seen to be the best and had a higher skill than individual models in simulating the observed rainfall over the region. The closest model that simulated closely the observed value was MPI. NOAA performed the worst of all models. There have been studies done within East Africa on climate modeling that also found the ENSEMBLE average to be better in simulating rainfall and have been used in various climate change studies for climate projections including (Endris *et al.*, 2013b; Mueni, 2016; Ouma, 2015).From the analysis of climate models, the ENSEMBLE average of the models was used to analyze climate projections, following the RCP4.5 and RCP8.5 pathways.

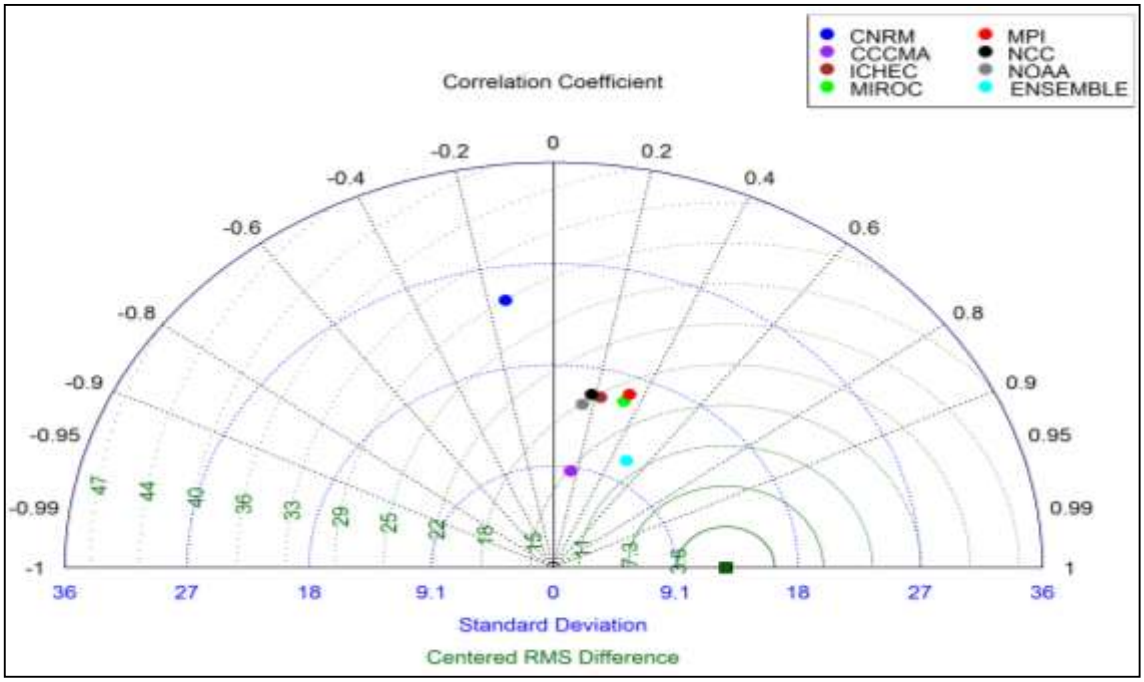

Figure 4.19: Taylor Diagram representing the performance of the CORDEX models, ENSEMBLE average of the models against observations over Narok County for precipitation.

4.3.1 Future climate change scenarios

This subsection presents the results of climate projections and trend analysis for both RCP4.5 and RCP8.5 over the study area. The best model which was the ENSEMBLE average was then subjected to trend analysis and Gauss kernel distributions methods. To assess the future scenarios, three climatological periods; present future (2006-2030) and near future (2031-2055) were analyzed in comparison to the baseline period 1981-2005 for both RCP4.5 and RCP8.5 over Narok County. Climatological trends were also performed for the period 2006-2055 for both rainfall and temperature.

Figure 4.20 presents the trend analysis for the future mean annual precipitation and temperature for Narok County for RCP4.5. Just like the observed climate series, the projected rainfall under RCP4.5 has no sufficient evidence to explain for an increasing trend at α=0.05 level of significance. Only two peaks are seen in the projections, to occurring in the year 2023 and 2048 in this scenario with rainfall above 250mm. all other years have rainfall within the normal range of 50-150mm. Though the trend is insignificant, it shows a gradual increase in rainfall until the year 2055. There is sufficient evidence that the mean temperatures over the region are increasing at an alarming rate in the RCP4.5 scenario. This is evident as seen in the diagram.

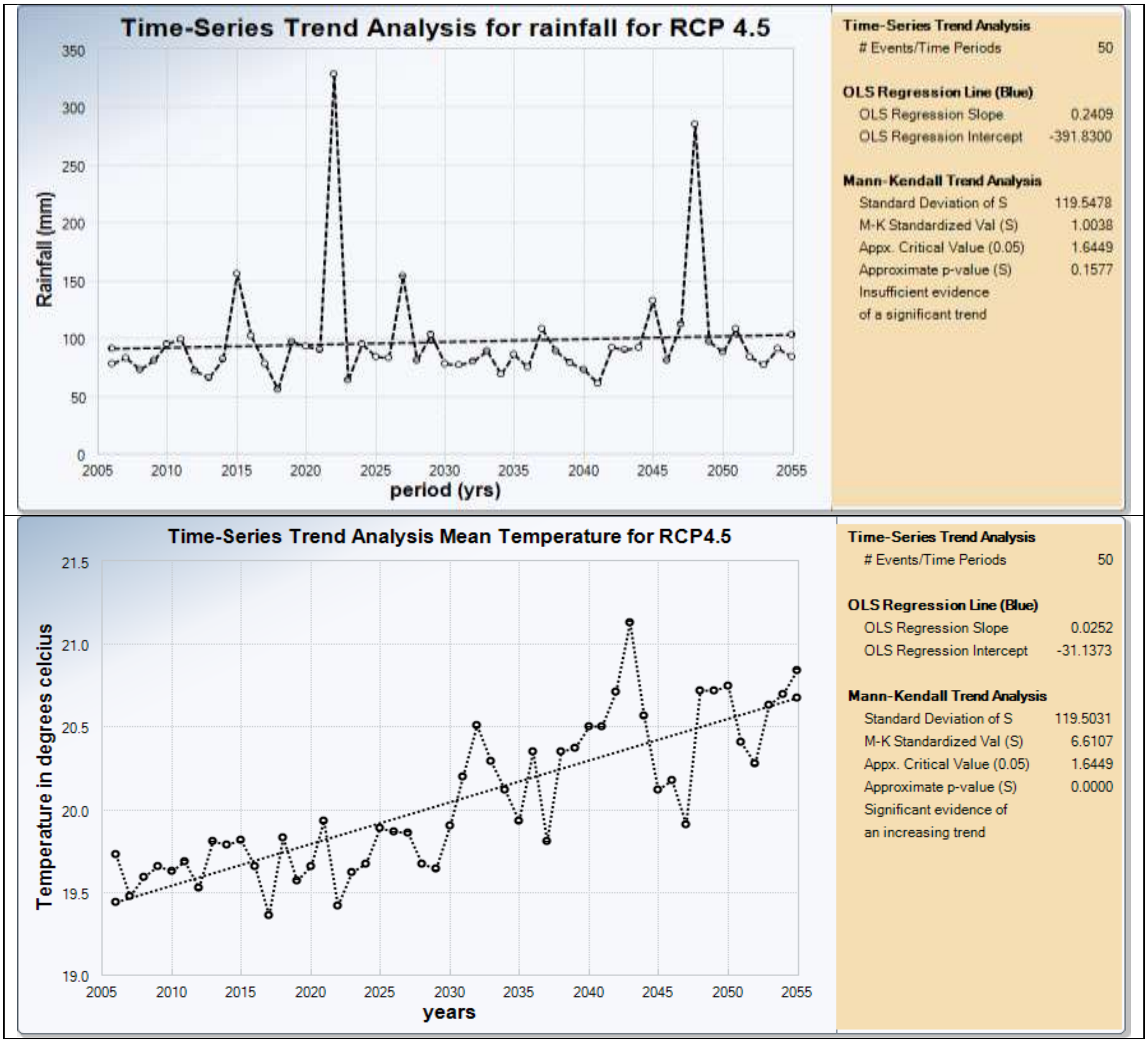

Figure 4.20: Trend analysis for Rainfall and Temperature for RCP4.5 over Narok County

Figure 4.21 presents the trend analysis of the future mean annual precipitation and temperature for Narok County for RCP8.5. Rainfall in this scenario is less than RCP4.5. Only one peak is seen to occur in the year 2045 with 220mm of rainfall. Though there is insufficient evidence of an increasing trend, there is a slow gradual increase with the period 2040-2055 having highly variable rainfall. The slope of temperature in this scenario is steeper than the slope in RCP4.5. Temperatures will be increasing annually and at a higher pace than the latter scenario.

From the analysis of trends of both RCP4.5 and RCP8.5, it is evident that RCP4.5 projects higher amounts of rainfall than RCP8.5 by the year 2055. However, the mean temperature in both scenarios has a significant increasing trend with RCP8.5 projecting a much warmer atmosphere than RCP4.5.

The non-significant increasing trends of increasing rainfall coupled with sharp increasing trends of temperatures have a detrimental effect on the water resources. The elevated high temperatures will have an impact on water resources and the environment in general. Water levels will greatly reduce in streams and rivers including loss of soil moisture and a decrease in water tables due to increased evaporation rates. However, some regions may experience increased amounts of rainfall following an increase in evaporation rates and this may cause flooding in these regions. This calls for proper adaptation measures by water managers and also community resilience.

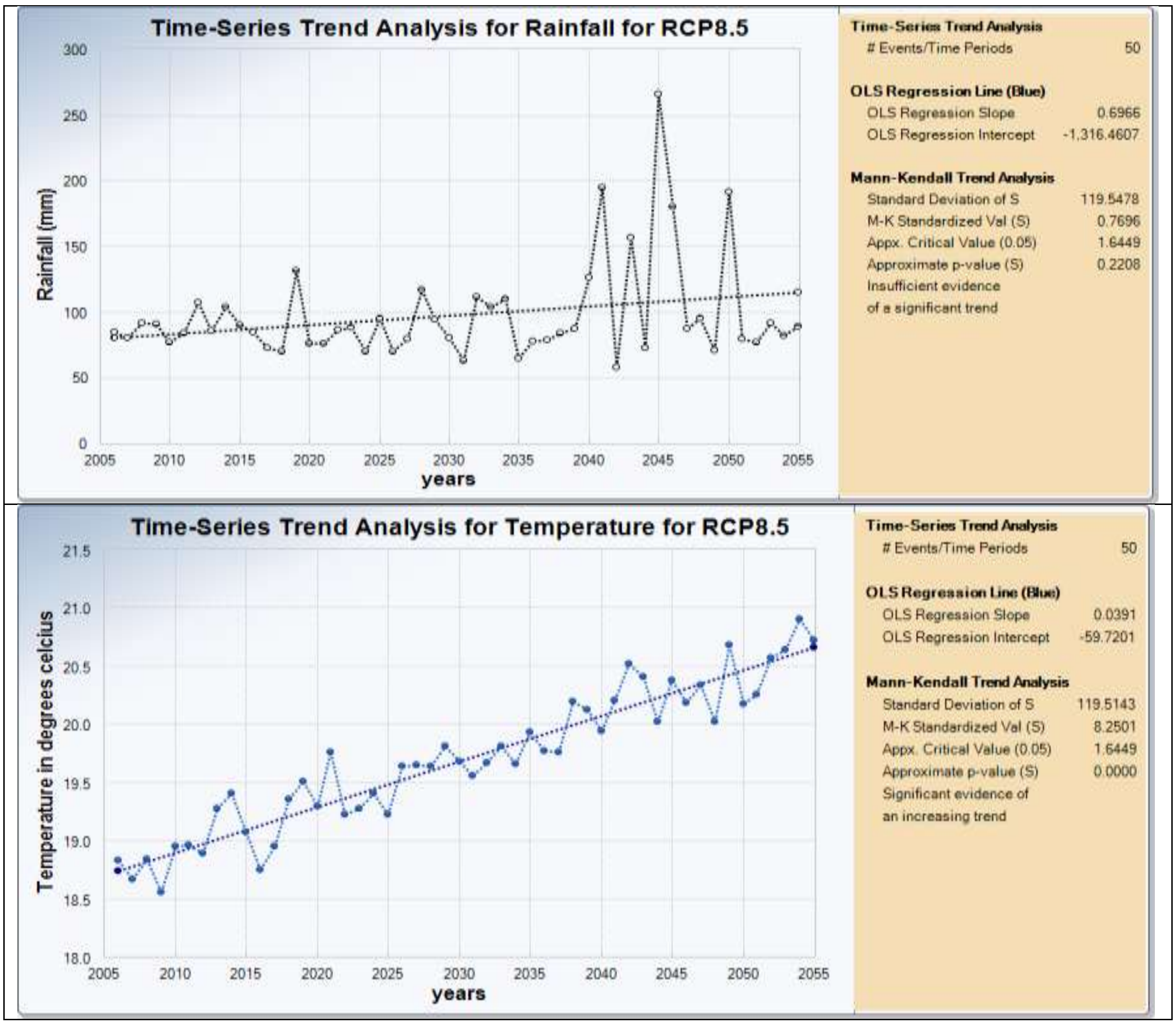

Figure 4.21: Trend analysis for Rainfall and Temperature for RCP8.5 over Narok County

Rainfall distribution was also assessed for both scenarios. To achieve this, data was sectioned into three non-overlapping climate periods; 1981-2005 (baseline), 2006-2030, and 2031-2055. Figure 4.22 shows the distribution of the total annual rainfall and mean temperature over the county for RCP4.5. There is a likelihood of a positive shift in the total annual rainfall in this scenario. It is projected that there will be a positive increasein rainfall from the current period to the year 2030 and then a slight decrease in the period after, to the year 2055. The period 2006-2030 is projected to have an increase in rainfall with a maximum of 2000mm annual mean total rainfall (+25% increase) in comparison with the baseline period. There will be a decrease in the annual mean rainfall in the period 2031-2055 from 2000mm to 1600mm (-20% decrease). The mean temperature under this scenario is projected to increase from about 19°C – 20.5°C by 2030 (1.5°C increase), and a further shift from 19.5°C-21.5°C by the year 2055 (2.5°C increase). This is no good news in the future in the water sector. With the current trends in socioeconomic development in the country, there will be high rates of water demands not only in the region of study but also the country and this will put pressure on the available water resources.

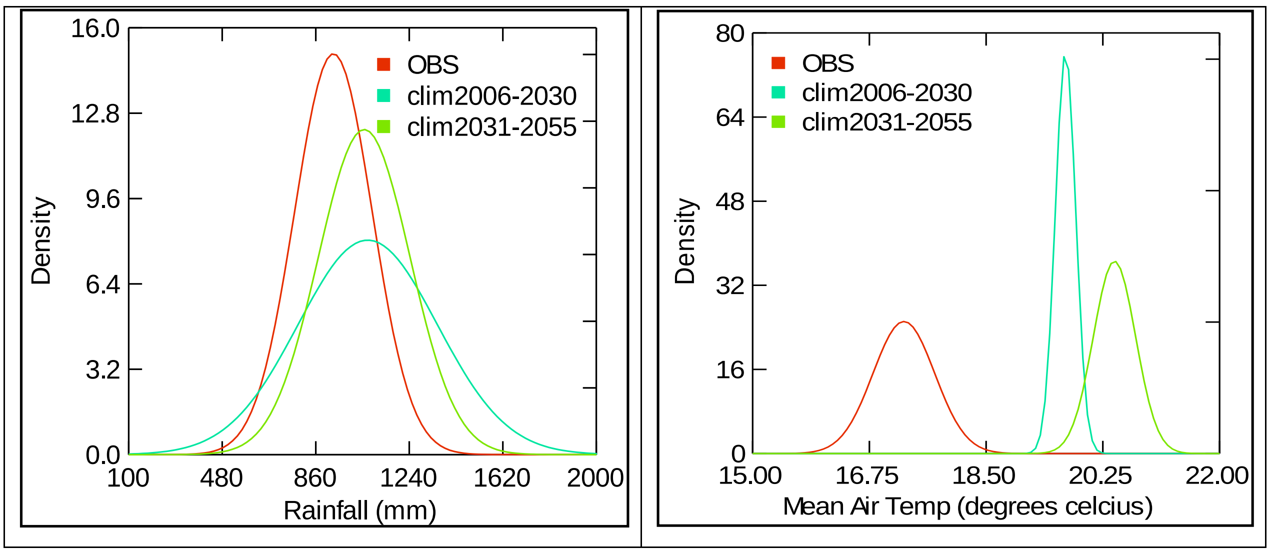

Figure 4.22: Total Annual distribution of Rainfall and Mean Temperature over Narok County for RCP4.5 under different climate periods.

Figure 4.23 shows rainfall and temperature distributions for RCP8.5. this scenario also projects the likelihood of a positive shift in the mean annual total rainfall from 1600mm to about 1700mm (+6% increase) in the period 2006-2030, and a further shift to 1900mm in the period 2031-2055 (+18% increase). The temperature under this scenario is seen to increase progressively until 2055. By the year 2030, temperatures will shift from 18°C-20.5°C (2.5°C), and a further shift from 19-22°C(3°C) by 2055.

From the results in both scenarions, it was seen that, there was a tendency of temperature vlaues shifting towards high values in comparison with the baseline. There was a change in the assymetric distribution of rainfall and tempearure values. Temperature values were skewed towards the hotter and higher values of the distribution for both RCP4.5 and RCP8.5. On the other hand, rainfall was shifting slightly towards the higher values from the mean with minimal skwness. In both scenarios, a slight increase in temperature is likely to cause an increase in rainfall, and in some cases, further warming will lead to a total reduction in rainfall. However, these increased temperature projections are likely to have a negative impact on water resources in the region. The region will suffer from high evaporation rates from surfaces, which might lead to wilting in plants and also decrease in water levels in streams and rivers. This will eventually have an impact on various sectors such as the agricultural and water sectors.

Climate modeling has also been done by several authors including (Mueni, 2016; Ngaina and Mutai, 2013; Ouma, 2015; Rwigi, 2014),and have also found out that, by the year 2050, temperatures are projected to increase up to 2.8°C.They found that changes in mean rainfall are clear evidence of a changing climate. And thus, from the analysis of the temperature and rainfall in the two scenarios, it is clear that climate is changing over the study area.

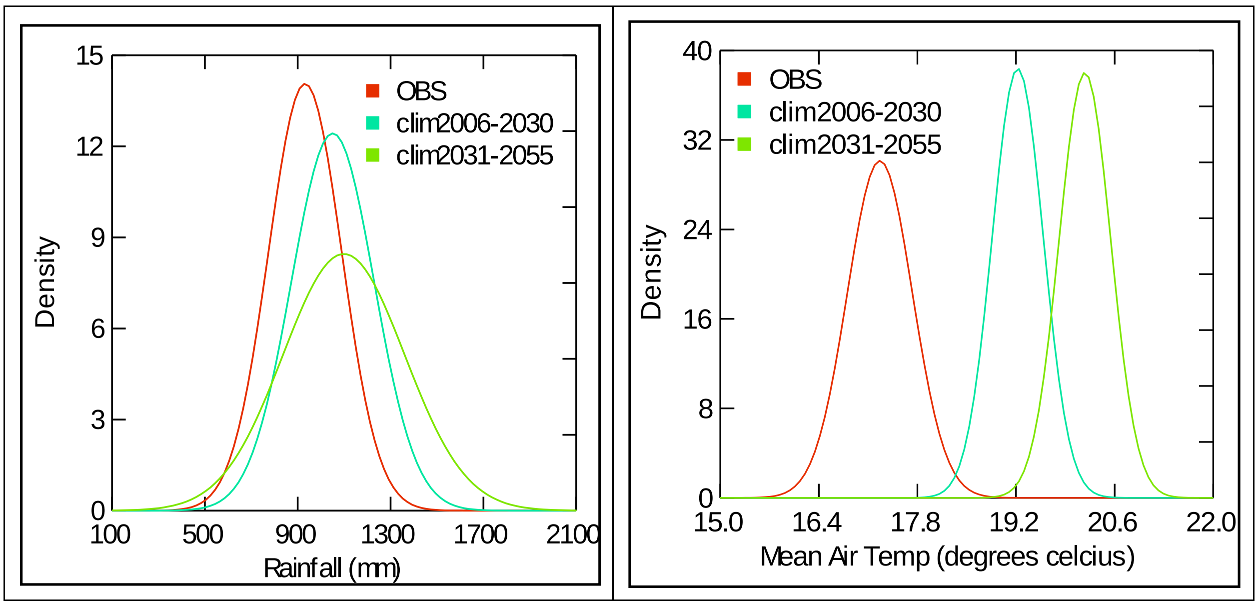

Figure 4.23: Total Annual Rainfall distribution and Mean Temperature over Narok County for RCP8.5 under different climate periods.

4.4 To Assess the Impacts of Climate Change on Surface Water Resources

4.4.1 Hydrological modeling

In this section, WEAP hydrological model is used as the main tool to model the impacts of climate on surface water resources in the county. Included in the results are the model simulations, calibration, and validation, and projection outputs.

4.4.2 Calibration and Validation of the WEAP Model

Before performing any action, a sensitivity analysis was done to establish the most appropriate and sensitive parameters for calibration. This was aided by a manual adjustment of the parameters where six sensitive parameters were adjusted individually at a time and within their allowable ranges (Table 4.5). Sensitivity analysis was done to reduce the gap existing between the observed and the simulated model outputs.

4.4.2.1 Sensitivity Analysis

Sensitivity analysis was done and parameters were ranked according to their sensitivity, starting from the most sensitive to the least, which were also responsible for the Stream flow generation in the basin. Apart from the area and mandatory climate parameters, the most sensitive parameter was crop coefficient *(Kc)* and was ranked 1, followed by the runoff resistance factor *(Rrf)*, while the least were *Z1* and *Z2* as shown in Table 4.5. The runoff Resistance factor*(Rrf)* is an aspect of flow. It controls the rate of surface flow and is dependent on slope and leaf index or the amount of surface land cover. With higher values of Rrf, the quantity and rate of flow is reduced (values close to 1000). Smaller values <5 will correctly simulate runoff with no impediment of the rate of flow.

Table 4.5: Calibration Parameters adopted for modeling the Stream flow

Code	Initials	Parameter	Default value	Values used for Calibration	Range
1	Kc	Crop Coefficient	0	1	0-higher
2	Rrf	Runoff resistance factor	2	default	0-1000
3	Fd	Flow direction	0.15	1	0-1
4	swc	Soil water capacity	1000mm	Default	0-higher
5	Rzc	Root zone conductivity	20mm/month	Default	0-higher
6	Z1	Initial Z1	30%	50%	0-100%
7	Z2	Initial Z2	30%	50%	0-100%
8	-	Area	-	17,944 Km square	-
9	-	Rainfall	-	-	-
10	-	Temperature	-	-	-
11	-	Stream flow	-	-	-

4.4.2.2 Calibration and Validation

This process was done aided by the PEST tool within the WEAP interface. A time series of the monthly Stream flow of observed and WEAP simulated outputs for both calibration and validation periods (1985-1987 and 1988-1990) and together with their regression outputs (Figure 4.24 and figure 4.25), indicated a strong positive correlation between observed and simulated discharge for Ewaso gauge (2K01).

The Stream flow patterns were well captured by the model in almost all the years in all periods (calibration and validation). However, the model slightly overestimates the flows in the year 1987 in the calibration period and underestimated the peak values in April in 1985 and 1988 in all periods. The value of R^2 was 0.83 for the calibration period and R^2=0.97 for the validation period and this indicated that the model was ideal and could be used for further analysis. The improvement of R^2 from 0.83 during the calibration period to 0.97 in validation was due to increased sample size. As the sample size increases, the difference between the expected and observed approaches zero and the value of R^2 becomes less Biased.

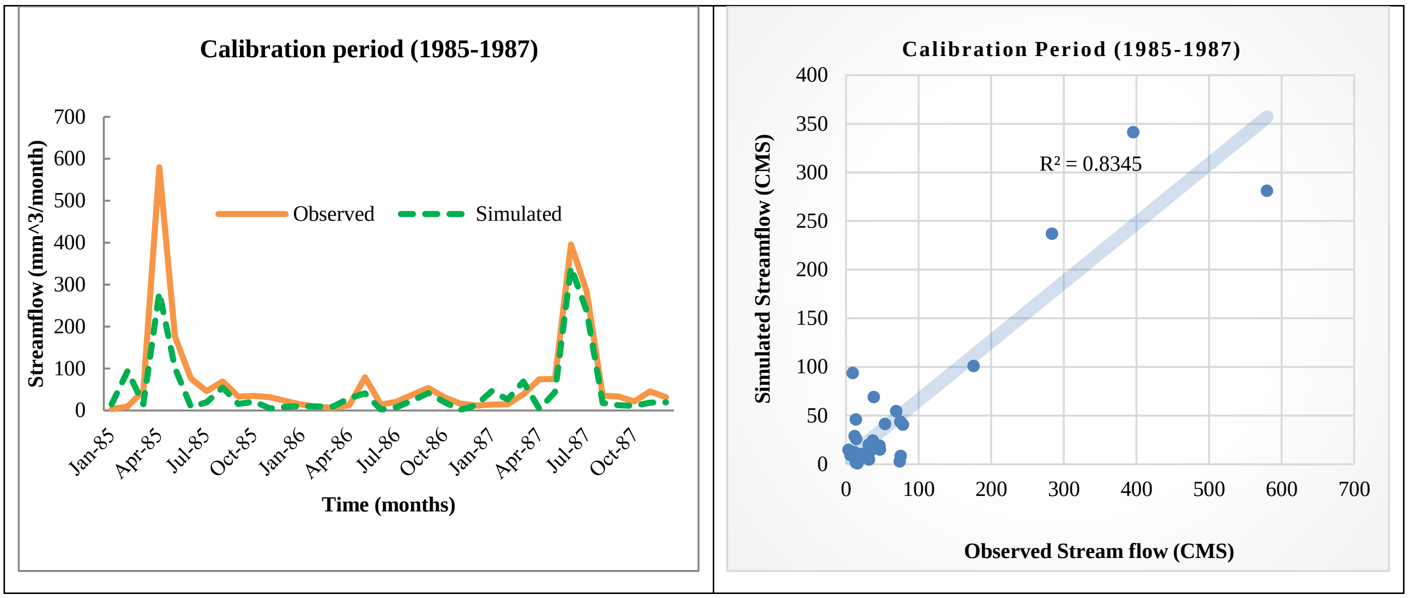

Figure 4.24: Observed and simulated stream flow and a Regression equation during the calibration period for Ewaso RGS.

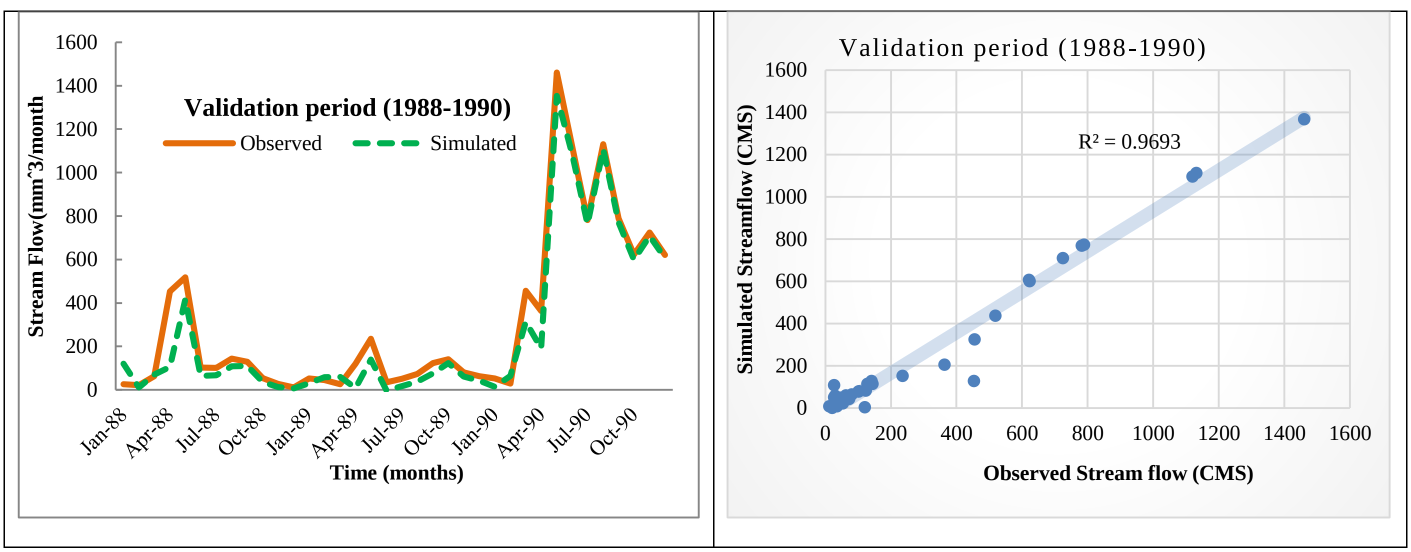

Figure 4.25: Observed and simulated Stream flow and a Regression equation for the validation period at Ewaso RGS.

Three statistics were used to evaluate the performance and accuracy of the model before modeling; Coefficient of Determination (R^2), Nash-Sutcliffe efficiency (NSE), and Percentage Bias (PBIAS), (Table 4.6). From the statistics, it was clear that WEAP performed well in the region in simulating flows. The value of the Coefficient of determination (R^2) was greater than the threshold $R^2 > 0.5$ in both periods, were 0.83 and 0.97 for calibration and validation periods respectively for the monthly flows as shown in Figures 4.24 and 4.25.

The percentage Bias (PBIAS) showed a good performance in simulating the water flows. The calibrated and simulated values fell within the good performance band criteria (±10% ≤ PBIAS ≤ ±25%) as suggested by (Moriasi *et al.*, 2015; Rwigi, 2014). During the calibration period, the PBIAS value was 22.3% while the validation period had a 12.7% PBIAS. The values of NSE in simulating the flows were 0.74 during the calibration period and NSE = 0.96 during the validation period. These fell within the very good performance band (0.75 < NSE ≤ 1.0) according to (Moriasi *et al.*, 2015; Rwigi, 2014), for both periods. Good performance PBIAS, very good performance NSE and a coefficient of determination (R^2) of close to 1.0 ratings by the statistical indices during both periods proves that the model can perform better in simulating hydrological process in a catchment and that the results can be adopted in the planning and management of water sectors.

Table 4.6: Statistics of Observed and Simulated Stream flow for calibration and Validation periods

	Observed Stream flow (CMS)		**Simulated flow (CMS)**		**Model Evaluation Statistics**		
Period	**Mean**	**Standard Dev.**	**Mean**	**Standard Dev.**	**R^2**	**PBIAS**	**NSE**
Calibration(1985-1987)	69.20	117.38	46.83	77.95	0.834	0.223	0.735
Validation (1988-1990)	301.44	375.77	262.90	366.38	0.969	0.127	0.958

4.5 Stream flow Pattern Projection under Climate Change Scenarios

In this section, model simulations and projections under different climate change scenarios, are presented. They are presented in two parts: i. Simulated water yields under RCP4.5 and RCP8.5 and ii. Simulated water yields under Synthetic scenarios. A comparison of water yields under RCP4.5 and RCP8.5 is also presented. The calibration period for the model simulation was the period (1981-2000) as the baseline, while the model simulations were up to the year 2055.

4.5.1 Projection of Stream flow under RCP4.5 and RCP8.5 Scenarios

WEAP model was used to project stream flow patterns under RCP4.5 and RCP8.5 scenarios. A 25-year mean monthly average was chosen with two-time slices (2006-2030and 2031-2055), which were compared against the baseline (1981-2000). An additional time slice (2021-2030) was chosen to present the projections from the current time to the year 2030. Ewaso Nyiro RGS (2K01), was chosen as the representative gauge since the river was flowing through most homogeneous zones, and thus a monthly Stream flow projection under RCP4.5 and RCP8.5 is presented.

Figure 4.26 (a) shows the monthly Stream flow projections under RCP4.5 against the baseline. There is a likelihood of increased water yields from the month on November- March and also July, in all the time slice periods, except for December for the period 2031-2055.Months currently experiencing low water yields (November, December, January, February, March, and July) will experience higher yields mostly by the year 2030, while those with higher yields will experience a fluctuation by 2055 (April-October) except July. This is also in correspondence with the projected rainfall under this scenario (Figure 4.22). The lowest amount of Stream flow projected is 102.4 CMS by the year 2030 and 84.9 CMS by the year 2055. Figure 4.28 (b) shows water yields under RCP8.5. By the year 2030, all the months except January and March are projected to remain dry. January-March and July are projected to have increased yields by 2055. The period 2031-2055 will record the highest amount of discharge in July (306.3 CMS) with a low of 67.9 CMS in September. By 2030, the month of March will have the highest discharge (271 CMS) with the lowest projected to be in September (65 CMS).

From the analysis, both scenarios project a sharp peak in the month of July. This could be due to an increase in rainfall during that month. The period 2021-2030 will have a slight increase in water yields in both scenarios, with RCP4.5 recording a higher yield than RCP8.5. January, February, and March are projected to have increased water yields in both periods. These variations in water yields are however consistent with the rainfall distribution and trends as shown in (figures 4.20 and 4.21) and (figures 4.22 and 4.23) respectively. Rainfall in these scenarios is depicted to have a slow and gradual increase in trends by the year 2055, while temperatures have a significant increasing trend in both scenarios. High temperature is most likely to have an impact on water yields due to high rates of evaporation. An increase in temperature and a decrease in rainfall amount could be the reason behind the decrease in water yields in the region in both scenarios in comparison to observed as shown in Figure 4.14.

Narok County is expected to have a reduction in the amounts of water yields in all seasons in all scenarios. The region is expected to have formidable water reduction in both MAM and OND seasons. This will affect several activities in the region including agriculture, that is more dependent on water for livelihood. Therefore, it would be essential for water managers to take early precautions including sensitizing the communities in this region for proper adaptation and mitigation measure.

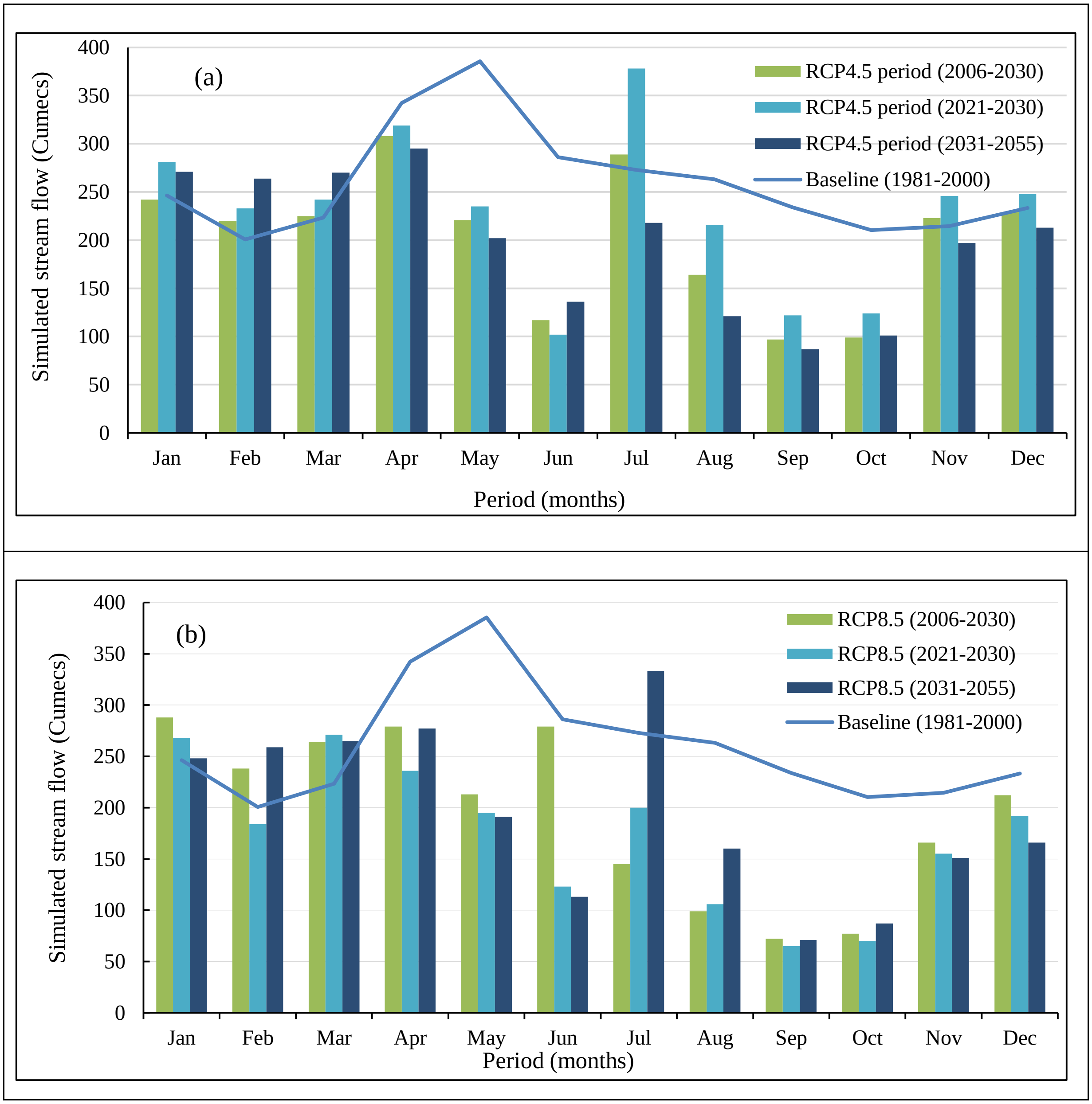

Figure 4.26: Simulated and Baseline mean monthly stream flows for (a) RCP4.5 and (b) RCP8.5 for EWASO Gauge.

Figure 4.27 shows a comparison of Stream flow projections under scenarios RCP4.5 and RCP8.5. The monthly flow in RCP4.5 is projected to have higher yields than in RCP8.5. The months November - April, and July have higher yields of water under RCP4.5. In comparison to the reference account, the annual flow in RCP4.5 Annually, the year 2027 and 2045 will record the highest annual rainfall totals compared to other years in the RCP4.5 scenarios. To the year 2055, RCP8.5 will continue recording below-average rainfall as compared to the RCP4.5 and reference period.

Information obtained from monthly projections will assist the relevant group that can benefit from water, to get an insight on the availability of water during the different seasons such as MAM and OND, with regards to the several activities within these seasons such as planting and harvesting. The annual flows will depict the likelihood of occurrence of a given trend into the future and this is crucial for both short-term and long-term planning especially in the water sector.

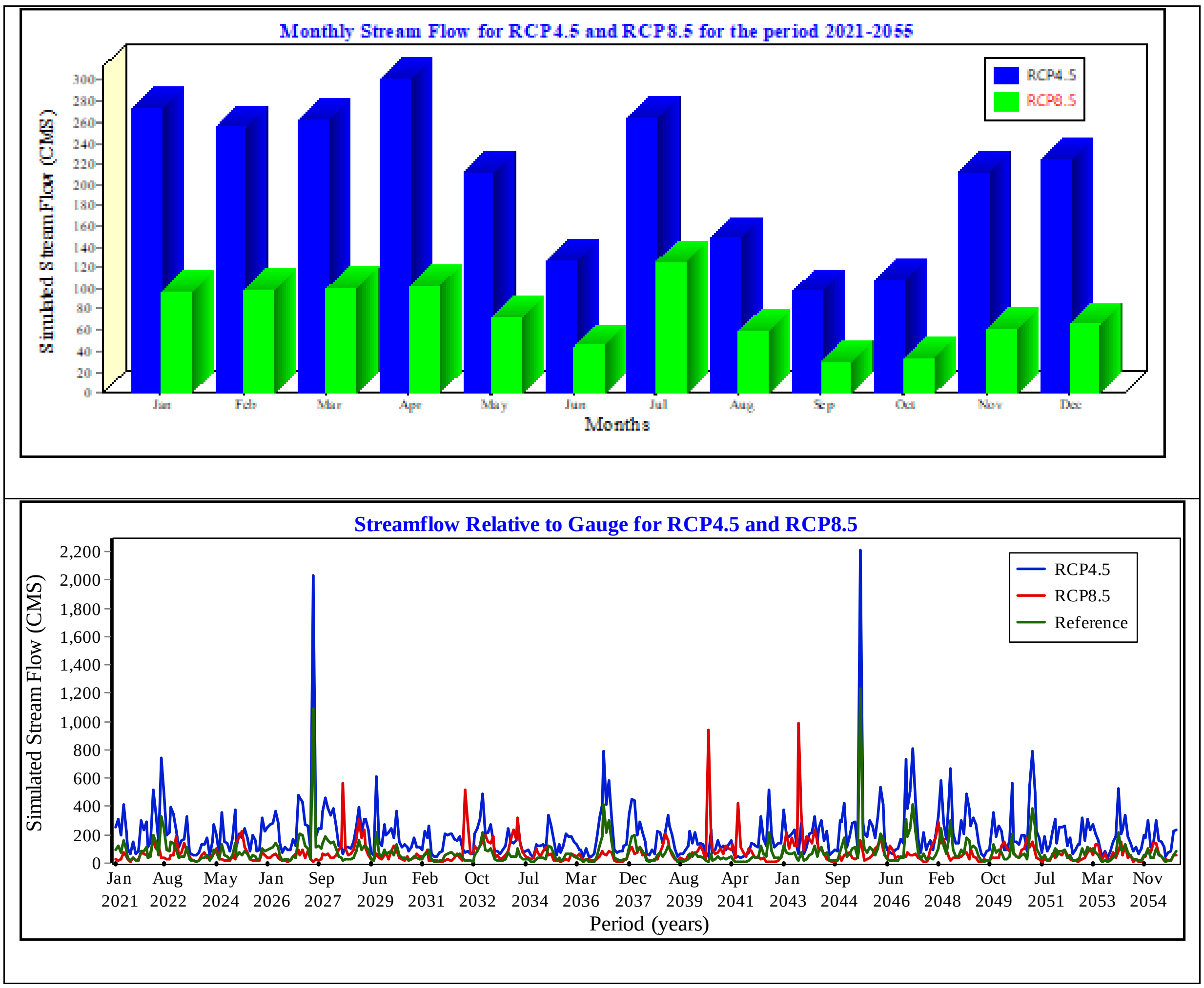

Figure 4.27: Comparison of Monthly and Annual Stream flow projection under RCP4.5 and RCP8.5

4.5.2 Projected stream flow patterns under Synthetic Scenarios

This section presents the results obtained from synthetic scenarios. This are scenarios obtained by changing values in rainfall and temperature or any other climate variable according to preferred thresholds in order to identify the possible outcomes in relation to climate. It is a way of assessing how a region may behave in relation to climate, by altering climate variables such as rainfall and temperature to preferred values. In this study, rainfall and temperature were altered according to needs, to simulate Stream flow. Four scenarios were created (normal temperature and precipitation, increased temperature alone, increase in temperature and precipitation, and an increase in temperature and reduced rainfall). These scenarios are useful in quantifying water yields and availability for the period 2021-2055. Two-time slices were applied; 2021-2030 and 2031-2055 against the baseline 1981-2000.

A change in either precipitation or temperature affects surface runoff directly. Concerning changes in the climate parameters used in each scenario, four different simulations were obtained in regard to the amount of water yields. Figure 4.28 shows projected monthly surface runoff for the period 2021-2030 and 2031-2055. The reference scenario is the current account, with normal rainfall and temperature. Discharge slowly increases from November to April with April recording the highest amount of discharge in both periods, while October the lowest. In comparison with the reference (scenario1), scenario2 records a decrease in discharge in all months and an increase in discharge in Scenario3. Scenario4 is the worst-case scenario with a drastic decrease in the amount of discharge in all months in both periods.

Figure 4.29 presents the projection of annual simulated flows from the four scenarios for the two periods (2021-2030 and 2031-2055). The year 2021 is seen to have no change in all scenarios. There will be an increase in discharge towards the year 2030, with the year 2029 record a higher amount than the previous years and 2024 the lowest. In the second period, the year 2038 is projected to record the highest amounts of discharge than all other years. However, the variation in the amount of discharge is seen to be a cycle of a period of six years, with alternating six dry years and six wet years to the end of 2055. Just like the monthly projections, a slight increment of temperature (2.5°C) in scenario2 could result in a reduced amount of water yields, a 2.5°C increase in temperature with a 10% increase in precipitation (scenario3) will lead to an increase in water yields in all years, while a Scenario 4 is the worst-case scenario, where a combination of temperature increases with a 10% decrease in precipitation would significantly lead to a total reduction of water yields.

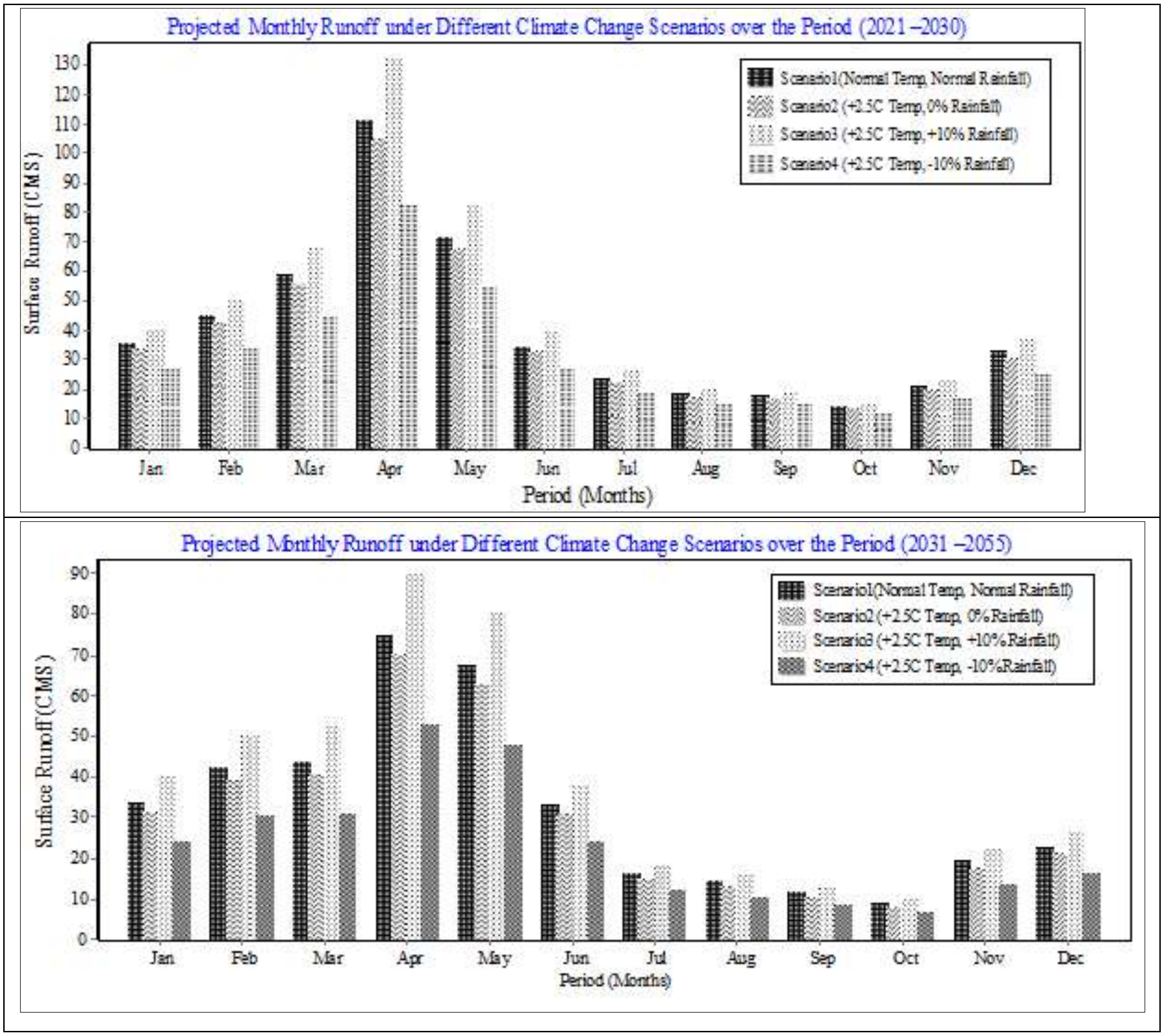

Figure 4.28: Projected monthly Synthetic Scenarios over the period 2021-2055

In both cases, climate change is seen to have an impact on the monthly and annual distribution of water yields. There is a general decrease of runoff in all months in all scenarios subject to the reference period, except for scenario 3 (increased temperature with increased precipitation). However, the magnitude of change in the water yields differs from one month to another, in all scenarios. High temperatures lead to high evaporation rates which eventually lead to a decrease in water yields. An increase in both rainfall and temperature results in high amounts of water yields due to increased intensity and magnitude of rainfall that comes as a result of high temperatures. It could also be because, the increase in temperature leads to Evapotranspiration that is at a lower rate than precipitation rates, and thus an increase in the total amount of water yields. However, a decrease in rainfall with an increase in temperature drastically reduces the amount of discharge due to excessive warming which causes excessive water loss due to excess evaporation rates. This could also be the reason behind the difference between the observed discharge as shown in Figure 4.14 and the simulated discharge under these scenarios.

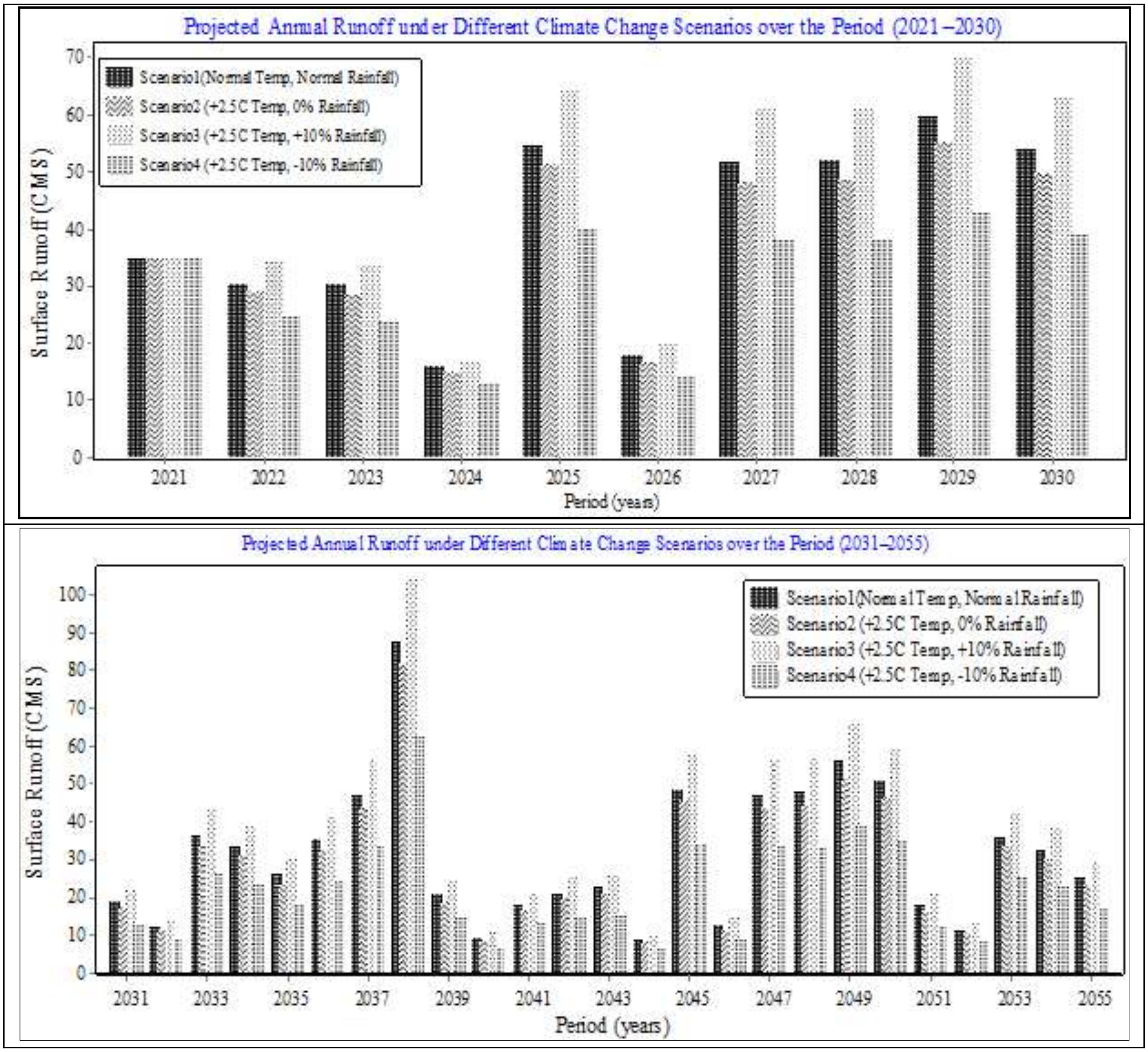

Figure 4.29: Projected Annual Synthetic Scenarios over the period 2021-2055

4.6 Quantifying Water Availability

This section presents results obtained from analysis of water availability due to climate change over the period 2006-2055, for both RCP generate and Synthetic scenario outputs. As stated in section 4.6, changes in water availability are greatly influenced by perturbation in climate such as changes in temperature and precipitation.

Table 4.7 shows the changes in water availability for RCP4.5 and RCP8.5, for the period 2006-2055.It is clearly evident that, the amount of water availability has been decreasing in both scenarios from the period 2006. By the year 2030 since then, RCP4.5 scenario would have had a decrease in the amount of water by a deficit of 19.48% and 25.9% for RCP8.5. In the next decade, RCP4.5 projects a deficit of about 12% and about 34% for RCP8.5. The period 2031-2055 would both have a deficit of at least 25%or more of water availability in both scenarios. These however suggests that, the future state of water availability in the region is on the verge of serious decline and this calls for serious measures and adaptation strategies to be implemented and strictly followed, in order to protect the states of these water resources.

Table 4.7: Changes in water availability for RCP4.5 and RCP8.5

Scenario	Amount of water changes (annual totals (CMCS))			
	Base case	**2006-2030**	**2021-2030**	**2031-2055**
RCP4.5	3,112.17	2,506.58	2,747.19	2,330.95
	-	-605.59	-364.98	-781.22
	-	**-19.48%**	**-11.73%**	**-25.10%**
RCP8.5	3,112.17	2,305.28	2,066.57	2,261.45
	-	-806.89	-1,045.5	-850.72
	-	**-25.93%**	**-33.6%**	**-27.34%**

Table 4.8 shows the changes in water availability over the period 2006-2055 for Synthetic Scenarios. Just like it is depicted in Figures 4.28 and 4.29, a temperature increase of +2.5°C alone (scenario2) would lead to a small decrease in water availability. The amount of water would decrease by 4.93% (25.26CMCS) and 10.9% (43.38CMCS) over the periods 2021-2031 and 2031-2055 respectively. In scenario3, a temperature increase of +2.5°C with a 10% increase in precipitation would result in a small increase in water availability. Water availability would increase by 12.3% (63.08CMCS) over the period 2021-2030 and 18% (71.88CMCS) from 2031-2055. This scenario may be due to a good ratio of moisture present in the atmosphere as a result of Evapotranspiration that is of a lower rate than precipitation rate.

Scenario4 is the worst case scenario for both the periods (2021-2030 and 2031-2055). A +2.5°C increase in temperature coupled with a 10% decrease in rainfall greatly hampers the availability of water in the region. The period 2021-2030 would have a decrease of 30.4% (156CMCS) of water while the period 2031-2055 would be having a 23% (95 CMCS) water deficiency. This may be due to high rates of evaporation and decreased amounts of precipitation. However, a change in water availability in the region is influenced by alteration of various components of the hydrological cycle such as stream flow, Evapotranspiration, and soil moisture. It could also be due to the influence by water demands in the region.

Table 4.8: Changes in water availability for Synthetic Scenarios

Scenario/ Time slice	Amount of water changes (annual totals (CMCS))			
	Scenario1 (Reference)	**Scenario2 (+2.5°C, 0% P)**	**Scenario3 (+2.5°C, +10% P)**	**Scenario4 (+2.5°C, -10% P)**
2021-2030	512.82	487.56	575.90	357.03
	-	-25.26	+63.08	-155.79
	-	**-4.93%**	**+12.30%**	**-30.38%**
2031-2055	399.01	355.63	470.89	305.45
	-	-43.38	+71.88	-93.56
	-	**-10.87%**	**+18.01%**	**-23.45%**

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

In this chapter, the summary and conclusions obtained from this study are presented and recommendations for further research and other applications.

5.1 Conclusions

The main objective of this study was to assess the impacts of climate change on surface water resources in the Rift valley region with the main focus on Narok County, specifically focusing on how climate change has and will affect water yields in the county. To achieve this objective, several methodologies were employed including applying a hydrological model to quantify the availability of water in the region. Principal Component Analysis (PCA) was performed on the observed rainfall and Spatial, temporal, and spectral analysis also performed. CORDEX model projections were used to provide an insight into the future climate scenarios and a hydrological model WEAP applied to project stream flows and assess the impacts of a changing climate on the surface water resources.

From the Principal Component Analysis, five factors were obtained that explained for at least 94.32% of total variance in both unrotated and rotated components. The region was delineated into six homogeneous zones, with each area having a unique and distinct characteristic of climate depending on the location. The region has a bimodal rainfall pattern with two distinct seasons (MAM and OND) in most zones. Zone1, zone5 and zone6 exhibited a tri-modal pattern with an additional JJAS as a wet season. Dry months include DJF and JJA. It was found that rainfall in the region was also highly variable, with the highest variability was observed during the dry seasons; June-August (JJA) and Dec-Feb (DJF). Low variability was observed in wet seasons (MAM and OND). Rainfall in zone4 is highly variable than other zones with Mau recording the highest value of 1.28 in January.

In the long term, rainfall in this region is highly variable. The intensity and magnitude of rains and the frequency cannot explain a significant increase in the trend of rainfall. There was insufficient evidence to explain for increasing trends in all the zones despite the fact that rainfall was gradually increasing and most stations received rains within the normal range (-1, +1). The hydrological regime in this region revealed that, the amount of discharge in rivers is highly dependent on the rainfall distribution in the seasons. High peaks are recorded in MAM and OND for most stations, with DJF and JJA recording low amounts in water yields. The lon-term trends of rivers in this region were significantly increasing. This was consistent with the rate of increase in rainfall over the time scale. However, despite the fact that rainfall was gradually increasing and trends in rivers significantly increasing, this scenario could not cater for the water demands in the region. Rainfall in this region is unevenly distributed. The western region around Kilgoris receives more rains (1400mm) annually compared to the west and central regions, and as a result, rainfall starts from the Western side as it decreases to the East. During MAM and OND seasons, the central region receives the least amount of rains (<300mm). Cyclical variations in rainfall over the region indicated that three dominant and significant spectral peaks occurred between 2-3.2 years, 4-5.5 years, and 6.5- 10 years' cycles were linked to Quassi Biennial Oscillation, ENSO and Solar variability respectively.

Two climate scenarios (RCP4.5 and RCP8.5) provided the future climate projections over the region, with a multimodel Ensemble mean having the best skill in projecting the future climate. It is however more likely that the climate in the future under RCP4.5 will be warmer with an increase in temperature by +1.5°C in temperature by 2030 and further warming by +2.5°C by 2055, and wetter by +25% by 2030, and drier towards 2055 by a reduction in rainfall by -20% by 2055. RCP8.5 projected an even much warmer environment by 2030 with an increase of +2.5°C, and +3.0°C by 2055, with an increase in rainfall in both scenarios of about +6% by 2030 and +18% by 2055. The future pattern of temperature and rainfall was highly skewed in relation to the observed mean. These scenarios are clearly detrimental to the water resources and necessary measure need to be implemented and put in action to conserve the few available resources.

WEAP model was used for assessing the impacts of climate change on surface water resources. Availability of water was done using two approaches; simulation based on GCMs scenarios and simulation under Synthetic scenarios. The GCM generated scenarios under RCP4.5 and RCP8.5 indicated that, the amount of water in streams has been decreasing from the year 2006 and is projected to further decrease in the next decade and until 2055 in both scenarios. There is a general decrease in water yields in all months in all scenarios. However, RCP4.5 when compared to RCP8.5 had higher projections of water yields.

Projections from Synthetic scenarios indicated that the region is highly sensitive to a perturbation in climate. A change in either rainfall or temperature can greatly impact on the amount of water yields. The amounts of water in RCP4.5 are projected to decrease by -11.73% by 2030 and further by -25.10% by 2055, while RCP8.5 critical decrease by -33.6% from the year 2021- 2030 and further by -27.34%. In synthetic scenarios, scenario2 (+2.5°C, +0%P) projects a decrease in water by -4.93% by 2030 and further decrease by -10.87% by 2055. Scenario 3 (+2.5°C, +10%P) projects a +12.30% increased water amounts by 2030 and further +18.01% by 2055. The worst case scenario (+2.5°C, -10%P) projects drastic reductions of water in the region. By 2030, the amount of water will decrease by -30.38% and by 2055 the water availability would have reduced by -23.45%.

The key finding of this study is that, there is clear evidence that Narok County is undergoing a change in climate and that it is highly sensitive to this change. This has affected water resources in the region leading to a decrease in the amount of water yields. It is also evident that the region is highly sensitive to climate change as summarized in table 4.7. Basing on the model output on the future water availability, it is expected that Narok County would face a considerable deficit in water availability. There would be a reduction in streamflow and this may eventually result in environmental and ecosystem degradation, which will influence water tables and watersheds eventually affecting water storage and put pressure on the available water resources. And as such, Narok County will be exposed to vulnerability of drought and also floods.

The findings from this study will therefore greatly contribute to a broad understanding and awareness of the community and also the nation on the ramifications of a change in climate on available water resources in the county. Relevant authorities may also use information from these findings for the management and planning of water resources in different sectors in the county.

In consideration of Kenya's Vision 2030 and African Union Agenda 2063, water security and climate resilience are among the key areas that are being focused on. The major promising option is a low carbon resilient pathway that will ensure a clean and healthy environment. One of the key responses to climate change in Kenya is management of water resources that is directly linked to socio-economic transformation. The ongoing conservation of riparian lands and the reclamation Mau Forest Complex in the study area is one of the biggest steps towards the achievement of the two mentioned agendas. And thus, this study found that RCP4.5 could be the most probable scenario to be adopted which will only be achievable with strict adherence to adaptation and management strategies as a master plan and blue print to reduce GHG emissions by 2050 and before 2100.

5.2 Recommendations

Basing on the findings from this study and the challenges that arose, the following are the general recommendations to the Policymakers, the water sector, and for further research work.

5.2.1 To the policymakers

(i) Basing on the finding from this study, WEAP model has shown that it's potentially suitable in modeling water quantity and availability in Narok County under different climate change scenarios. It is therefore recommended that policy makers can invest in this tool for the implementation and application in the water sector not only in the County but also in the country to plan and manage water resource availability at different scales, towards the Kenya Vision 2030 and Africa Union Agenda 2063 blueprint projects.

5.2.2 To the community

(i) In line with the Kenya vision 2030, findings from this study will assist the relevant authorities and stakeholders to implement effective adaptation measures such as water harvesting and proper storage facilities, especially in areas where there is a likelihood of significant changes, to help protect the lives, communities and livelihood of people, in response to water scarcity.

5.2.3 To Researchers

(i) From the findings obtained in this study, the availability of one synoptic station in the region to establish the spatial distribution of rainfall may not have brought out the spatial rainfall distribution in the region. Some remote and inaccessible areas do not have representative stations, making it a challenge to quantify the rainfall component in hydrological models. It is therefore recommended that, in developing models for both hydrological and meteorological applications, satellite data should be incorporated to improve its accuracy.

(ii) This research was aimed at assessing the impacts of climate change on surface water resources at a county level. The key datasets under investigation were hydrological data of surface water resources within the region. However, due to data unavailability, only one RGS was used for analysis, which was not enough for a full coverage of the whole county. It is therefore recommended that, hydro-meteorological data be readily availed to the public and for research at a lower and reasonable cost for effective research.

(iii) The magnitude, frequency and distribution of precipitation and temperature together with their changes would not have been highlighted without the use of GCMs. It wouldn't have been possible to also assess and quantify the future water availability in the study area. And in this regard, a coupled integration of GCMs and WEAP hydrological model is strongly recommended for precise evaluation of climate change and its impact on the water sector, including future changes within the study area.

(iv) Individual climate models have also shown weaknesses in simulating climate on a local scale. It would be necessary to assess individual models on their sensitivity in the region together with correction of biases before any analysis is done.

(v) This study has only used one capability; simulating surface water hydrology. It would be ideal to incorporate other factors such as demographic changes, water demands, land cover/use changes, Water quality, Groundwater, and Economics would provide a whole picture of water resources

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