ASSESSING THE IMPACTS OF CLIMATE CHANGE ON STREAMFLOW IN MALABA RIVER CATCHMENT, UGANDA

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By

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Integrated Water Resources Management of the University of Dar es Salaam

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CERTIFICATION

The undersigned certify that she has read and hereby recommended for acceptance by the University of Dar es Salaam as dissertation entitled: ***Assessing the impacts of climate change on streamflow in Malaba River Catchment, Uganda***, in Partial fulfillment of the requirements for the degree of Master of Integrated Water Resources Management of the University of Dar es Salaam.

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Dr. D. M. M. Mulungu

(Supervisor)

Date ……………………………………………...

DECLARATION

AND

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I, **Kangume Charity**, declare that this dissertation is my own original work and that it has not been presented and will not be presented to any other University for a similar or any other degree award.

Signature ………………………………………………….

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DEDICATION

This dissertation is dedicated to my parents – Mr and Mrs. Barabanawe Francis and siblings – Samantha, Sydney, Cydrone and Celia.

LIST OF ABBREVIATIONS

AOGCMs	Atmosphere Ocean General Circulation Models
AR	Annual Report
CMI	Climatic Moisture Index
DWRM	Directorate of Water Resources Management
DEM	Digital Elevation Model
ENSO	El Nino Southern Oscillation
FDC	Flow Duration Curve
FMI	Finnish Meteorological Institute
GCM	Global Circulation Model
GHG	Green House Gases
GLUE	Generalized Likelihood Uncertainty Estimation
HADCM3	Hadley Centre Coupled Model, version 3
HADGEM	Hadley Centre Global Environmental Model, version 1
HRU	Hydrological Response Unit
IPCC	Intergovernmental Panel on Climate Change
IS	Importance Sampling
ISRIC	International Soils Reference and Information Centre
LAM	Limited Area Models
LARS-WG	Long Ashton Research Stochastic Weather generator
LH-OAT	Latin Hypercube One-factor-At-a-Time
MAKESENS	Mann-Kendall Test and Sen’s Slope Estimate
MCMC	Markov chain Monte Carlo
MNPD	Ministry of National Planning and Devolution

MWE	Ministry of Water and Environment
NBI	Nile basin Initiative
NSE	Nash-Sutcliffe Efficiency
NWP	Numerical Weather Prediction
ParaSol	Parameter Solution
PBias	Percentage Bias
PSO	Particle Swarm Optimization
R^2	Coefficient of Determination
RCPs	Representative Concentration Pathways
RCM	Regional Circulation model
RMSE	Root Mean Square Error
SRES	Special Report on Emissions Scenarios
SUFI	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Programs
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational Scientific and Cultural
WMO	World Meteorological Organization
WWAP	World Water Assessment Report

ABSTRACT

Malaba River is very vulnerable to climate change because it relies heavily on rainfall as its main flow contributor. This study's main objective was to assess the impacts of climate change on streamflow in Malaba River Catchment, Uganda and it was achieved by downscaling the future (2020-2050) precipitation and temperature variables for A1B and A2 scenarios and simulating the projected climate with calibrated SWAT model for the two scenarios. The trend analysis was done by Mann-Kendall test and its magnitude was estimated using the Theil-Sen approach. Change analysis of the projected climate and simulated flow was determined against a baseline period of 1980-2004 (for climate) and 1986-2015 (for flow) respectively.

The projected areal rainfall will increase by 0.34 mm per year for A1B which is averagely 1% less than the annual baseline period. Areal rainfall for A2 scenario will increase by 0.41 mm per year which is averagely 9% more than the baseline period. SWAT model was successfully calibrated and validated with NSE of 0.55 and 0.35 respectively.

From the developed Flow Duration Curve, A2 scenario displayed higher flows for all the percentiles as compared to the baseline flows while A1B scenario has lower flows for percentiles less than 50, and equal or slightly higher flows for percentiles greater than 50 as compared to the baseline flows. Therefore the Ministry of Water and Environment Uganda will be empowered with these results to carry out water resources management plan to prevent the effects that might rise from the high and low flows.

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CHAPTER ONE

INTRODUCTION

1.1 General Introduction

Our water resources, the only essential part of life are endangered by climate change and increasing population. The oceans, atmosphere, ice and land characteristics describe the climate system. The climate system remains in balance when the sun energy is balanced by the Earth's surface radiation. An increase in concentration of greenhouse gases 'flips' this balance, redirecting larger amounts of radiated energy back to surface of the earth. According to the IPCC AR5 in 2013, climate change may be manifested through the changes in the climate mean properties such as the Global Mean Surface Temperature and in a report released in 2007 it had risen by more than $0.76^{0}C$ over the last century. The past three decades have been warmer than the previous decades and this is attributed to natural and anthropogenic causes. Climate change has a huge impact on weather patterns, rainfall and the hydrological cycle thus impacting streamflow which in turn affects soil moisture and groundwater recharge (UNESCO, 2007).

Roughly 25% of the population in Africa is at present experiencing water shortages (Bates *et al*., 2008). This is confirmed by the Climate Moisture Index (CMI) for Africa which is a measure of possible water availability affected by the climate is below -0.75 (whereas the global range is -0.10 to -0.25). This is indicative of the drier conditions across the continent (Vorosmarty *et al*., 2005). About 65% of the African population will be at risk of water stress by 2025 (Gunasekara *et al*., 2014). Climate change is most likely to have an effect on developing countries like Uganda whose major economy relies heavily on water. Variability in water supply has a big effect on health and welfare in poor areas. In the past, climate variability has had considerable effects in Uganda with floods in 1961, 1962, 1997, 1998 and in 2007 which destroyed a lot of infrastructure and commercial activities, displaced many people (Hepworth *et al.*, 2008). In the 1993/94 event, droughts affected a significant number of people which led to increased destruction of property, poverty, migration and disease outbreak. The above factors bear witness that the current and future situation regarding water availability is dire.

Malaba River is of importance as it drains its waters into Lake Kyoga which contributes flow to the Upper Nile. In 2005/06, there were registered low flows in Malaba River in January and February which led to a substantial water deficit to the surrounding irrigation and town water supply schemes. Climate change has led to a decline in the terrestrial and freshwater biodiversity in Busia County (more than half the length of Malaba River is located in Busia County). Varying rainfall patterns due to climate change have affected both land preparation and food production leading to lower yields. The occasional rise in temperature affects moisture retention by soil which leads to wilting of plants, thus lower yields due to stress. Subsequently, this has led to increased food insecurity (MNPD, 2013). This specific research of assessing the impacts of climate change on streamflow in this catchment has never been carried out on Malaba River. Climate change is an additional source of uncertainty, thus necessitating a paradigm shift from conventional approaches to water resource planning and management in the catchment, which normally assume a static climate.

1.2 Statement of the Problem

Climate change is one of the biggest problems affecting the world's water. The United Nations has acknowledged that climate change is caused by human activities. Uganda is one of the countries that are greatly prone to the impacts of climate change. Her economy and the well being of her citizens are tightly bound to climate through water resources.

Over the past years, Uganda has experienced frequency of droughts, increase in the intensity and occurrence of heavy rains which have led to floods and landslides. These have in turn had an effect on surface water quantity. According to MWE (2012), the water levels in Lake Victoria have greatly reduced over the years and this is attributed to both climatic and anthropogenic factors.

Malaba River is an important focal area to the Lake Kyoga basin and the Nile basin at large. Malaba River which is located in eastern Uganda is used for many human activities such as cultivation and domestic users. It is prone to climate change because of its heavy reliance on rainfall as its major flow contribution. There are uncertainties over the exact nature of impacts of future climate change in the Malaba River catchment but what can-not be denied is that climate variability will impact on the hydrological cycle which will change the distribution of surface flow. Therefore, there is a great need for successful water resources planning by assessing the impacts of future climate change on water availability and not just responding to emergency situations to ensure life and sustainable development.

1.3 Research Objectives

1.3.1 General Objective

To assess the impacts of future climate change (2020-2050) on streamflow in Malaba River

1.3.2 Specific Objectives

1. To project the climate change variables during 2020-2050 period for the Malaba River catchment based on the selected climate scenarios.
2. To simulate streamflow of the catchment using SWAT model.
3. To assess the impact of climate change on streamflow.

1.4 Research Questions

1. What is the regime of projected climate change variables for the selected climate scenarios?
2. How suitable is SWAT model for simulating streamflow in catchment?
3. What is the extent of impacts of climate change on streamflow?

1.5 Significance of the Study

The stakeholders in Kyoga Water Management Zone will be empowered with the findings which will enable them to plan ahead interms of water availability for the different water users. The Ministry of water and environment in Uganda will be in position to strengthen the catchment planning process and this will be a platform for further studies to be carried out on the other catchments and the Government of

Uganda will also benefit by having more publications on climate change at the end of this research.

1.6 Scope of the Study

This study concentrated on how Malaba River catchment responds to major stresses of climate change interms of water quantity. The study indirectly took into account the other non-climatic impacts for example demographic trends, technological and socio-economic development depending on the selected climate scenarios. It did not consider the impact of climate change on water quality and socio economic activities. Changes in land use were not considered in simulation of future stream flow under changing climate. However, the method used in this study separated the impacts of changes in land use on streamflow. Therefore, the impacts were explicitly from climate change.

This study only deals with streamflow only in Malaba River and not other surface streams in the catchment.

CHAPTER TWO

LITERATURE REVIEW

2.1 Uganda's Climate

Uganda's tropical climate is described by seasonal rainfall due to the movement of latitudes along the low-pressure channel of the equator and convergence zone of the inter-tropics. In the tropics, the most significant climate element is rainfall that plays a significant part in the economies of the majority tropical countries (Nsubuga *et al.*, 2014). Uganda's rainfall displays a huge variance in time (temporal) and space (spatial). The spatial variation is credited to large and local scale systems such as inland water bodies which include Lake Victoria, Lake Kyoga, among others and the difficult topography. The two main rainfall regimes experienced in Uganda are bimodal and unimodal. March to June is the first rainy season, while August to November is the second one. Uganda's mean annual rainfall is roughly about 1300 mm and this shows great spatial variability, ranging from 100 mm in the dry areas and over 3000 mm on the slopes of Mountain Elgon (MWE, 2012). The country has a moderate climate with a long-term mean temperature of 21^0C. Mean annual temperatures range from 15^0C to 30^0C in July and February respectively.

2.2 General Overview of Water Resources in Uganda

Uganda's total area covers 241,038 km^2, of which 18% is open water and wetlands. The area is spread across the equator between latitude 10^0 30' South and 10^0 40' North, and longitude 29^0 30' West and 29^0 35' East. Most areas in the country lie at an average altitude of 1,200 m above sea level with the Albert Nile area having an altitude of 620 m atleast and an altitude of 5,110 m above sea level at most at the Mt.

Rwenzori peak (NBI, 2014). Uganda possesses plentiful water resources and one of them is the second largest freshwater lake in the world (Lake Victoria) among others. Major rivers such as the Nile is the longest river in the world, Rwizi, Katonga, Kafu, Mpologoma, Malaba and Aswa (MWE, 2015). Most parts of Uganda lie within the upper river basin of the White Nile except a small part located in the northeast which drains into Kenya's Lake Turkana basin. The country is partitioned into eight major sub-basins that drain into the Nile and these are: L. Victoria, L. Kyoga, R. Kafu, L. George and Edward, L. Albert, R. Aswa, Albert Nile and Kidepo Valley.

2.3 Overview of Malaba River catchment

The sub-catchment receives an annual rainfall of between 760 mm and 2000 mm. About 50 per cent of the rainfall falls in the long rainy season, which is at its peak between late March and late May, while 25 per cent falls during the short rains between August and October. The dry season with scattered rains falls from December to February. The annual mean maximum temperatures for the sub-catchment range between 23.0°C and 25.5°C while the mean minimum temperature range between 19.0°C and 22.0°C. Middle of Malaba Sub-catchment is in a sub-humid type of climate with an average relative humidity of 52% to 89%. The flow series of the river is low during the dry months of December to the end of January after which the flows increases to maximum in July and August. There are other streams in both Kenya and Uganda that drains into Malaba River and contribute to the annual flow volume of the river. The sub-catchment is endowed with various types of wetland that are precious resources to the communities of the sub-catchment. Biodiversity in the sub-catchment consists of numerous plant species and avifauna that best indicates its rich endowment of natural resources.

The population of the sub-catchment is currently 189,235 persons (NBI, 2014). With the growth rate for Busia County, Kenya as 3.1% whilst that of Tororo District, Uganda as 2.4% (Moses, 2009) per annum, the sub-catchment's population is expected to increase at a faster rate which will put pressure on the available natural resources. This necessitates the development of a plan that shall ensure that the communities in the sub-catchment attain maximum benefits from utilizing the available natural resources in a more sustainable manner.

2.4 Climate Change

Our water resources are experiencing great pressure due to global climate change and its awareness is being raised. Long-term climate change has been experienced at global, regional, and ocean basin scales, due to increasing concentration of greenhouse gases most especially carbon dioxide. These include changes in precipitation amounts and timings, arctic temperatures and different types of extreme weather like heavy rainfall, drought, and heat waves (IPCC, 2007).

The pattern of rainfall is unevenly distributed across the world and is governed by atmospheric circulation patterns and moisture availability. These two factors are affected by temperature so the pattern of rainfall is expected to change due to changing temperature. The changes include the type of precipitation, the amount, the intensity and the frequency. Rainfall has increased by 0.2 to 0.3% for every decade in the African tropics (10°N to 10°S) with a decrease in the Northern Hemisphere sub-tropics (10°N to 30°N) throughout the 20th century by approximately 0.3% per decade (Trenberth and Josey, 2007). Rise in temperatures has caused the melting of ice and glaciers on mountain tops. Mountain Rwenzori is one of a few mountains in Africa with a permanent ice-cap. Current studies have exposed that the ice cap on this mountain has decreased significantly. About 82% of the Mt Kilimanjaro 1912 ice cap in Kenya has melted and by 1990, 40% of Mt Rwenzori had receded compared to 1955 recorded cover (UNESCO, 2007). These changes have been attributed to global warming (IPCC, 2007). Increasing global average air and ocean temperature can change the type of rainfall during winter season (IPCC, 2007)

Several climate change standards and classifications have been developed to evaluate and quantify these issues over the past two decades. The Intergovernmental Panel on Climate Change (IPCC) which was set up by the World Meteorological Organization (WMO) and the United Nations Environment Program (UNEP) was created in 1988. Its main responsibility is to put in order, based on available scientific information, evaluation on all angels of climate change and its effects, with a purpose of creating rational strategic responses. Currently the IPCC's responsibility is stated in Principles Governing IPCC Work as, "...to evaluate on a broad, aim, open and see-through foundation of the scientific, technical, social and economic data applicable to knowing the scientific base of anthropogenic climate change, it’s possible effects and alternatives for adaptation and improvement”.

IPCC reports ought to be unbiased in relevance to policy, even though they might be required to deal purposely with scientific, technical, social and economic factors related to the application of specific policies. Through the IPCC, the world's climate experts make the most current scientific results in relation to climate each five to seven years. These reports are presented to the political leaders of the world. The IPCC Fourth Assessment Report (AR4) was issued in 2007 and comprehensive assessments were released in 1990, 1996, 2002 (IPCC, 2007)

The changing climate in Uganda presents very serious national challenges and risks across various sectors such as agriculture, water resources and energy, which support the economy and the wellbeing of its people (Nsubuga *et al.*, 2014). For example DWRM (2011) identified 8 seasonal droughts within the Lake Victoria basin in the period between 1990 and 1999. 2004/5 was the prominent drought period when the water level in Lake Victoria dropped by a meter below the 10 year average. From a hydrological perspective, Lake Victoria, the largest water resource exerts a big influence in Uganda's climate. The main source of water for the water body is rain, but due to rainfall anomalies, the lake has consequently displayed large and rapid changes. Hastenrath (2001) demonstrated that there is a significant correlation between rainfall series and water levels in lake or river.

2.4.1 The Climatological Baseline

It has been recommended to achieve a numerical explanation of the expected climatic changes in order to have a basis for assessing impacts of climate change in the future. It is very essential to describe the current-day or historical climate of an area or region-this is commonly known as the climatological baseline before considering future climate. This baseline period is important because it describes the observed climate and this climate is usually combined with information from climate change to create climate scenarios. The baseline period serves as a point of reference to determine the modelled climate change of the future based on the results from climate scenarios (Houghton, 2001). The baseline period is selected depending on the availability of the observed climate data and the following criteria is usually followed (IPCC-TGICA, 2007):

- Replica of the day-to-day or current mean climate in the study area
- Adequate period to include climatic variations of wide range, including several considerable weather periods (e.g. severe drought or cool seasons)
- Availability, abundance and spatially distributed data of all major climatic variables.
- High quality data sufficient enough to be used in assessing impacts

According to WMO, the “normal” period of 30 years which doesn’t overlap is known as climatological baseline. 1961-1990 is the current WMO normal. Several substitute sources of climatic baseline data that may be useful in impact assessment are: (IPCC-TGICA, 2007)

i. National Metereological agencies
ii. Global data sets and supranational
iii. Outputs from climate models
iv. Weather generator

I National Metereological agencies

National meteorological agencies are the most popular sources of observed climate data that is used in impact studies or assessments. Among other public services, the agencies main responsibilities are the everyday operation and maintenance of the equipment and weather prediction.

II Global data sets and supranational

A side's from fulfilling a country's needs, climatic data from several countries has been joined into several global datasets and supranational. These datasets consist of observations over land and ocean variables at a monthly time step, atmospheric and surface observations are at a daily time step from areas all over the globe, for current decades, observations from the satellite.

III Climate model outputs

Data from continental climate models that might be helpful in explaining the climatological baselines is of two types and these are: reanalysis data and GCM and RCM output.

Reanalysis data; this is data that is gridded at a fine resolution which combines observed data with simulated data from numerical models. During the assimilation of data, the observed data which is sparsely accessible and unevenly throughout the globe, together with data from the former model predictions and satellites, are put into weather predicting model with a short-range. This results into a broad and dynamically reliable gridded dataset with three dimensions (the “analysis”). At that specific time, it signifies the finest estimate of the atmosphere.

Fine resolution datasets have been generated by reanalyzing the historical observational data that were operationally used as inputs into former versions of weather predicting models using the present generation of numerical models. Climatic scientists have mainly used these datasets for model improvement and testing. On the other hand, scenario developers and impact analysts always find uses for such data, for example, by investigating relationships between reanalyzed atmosphere and surface variables to create climate scenarios for regions that are downscaled from GCM.

GCM and RCM output simulations: An additional source of data on the observed climate is from AOGCMs simulated every century which try to characterize the dynamics of the climate system from the globe done willingly by human changes in an atmospheric composition.

IV Weather generators

Baseline climate can also be characterized by using the stochastic weather generator. Daily or sub-daily synthetic weather is generated at a particular site based on the numerical features of the previously observed climate using computer models.

2.5 Global Circulation Models (GCMs)

Climate models apply basic principles of the physical laws controlling mass and energy interactions in the global system which enables us to obtain knowledge and forecast the outcomes of greenhouse gas emissions. Models known as Global Circulation Model (GCM) that use mathematics generally estimate the current climate and project future climate by taking into consideration greenhouse gases and aerosols. Generally, several GCMs simulate continental and regional scale processes and offer a realistically precise depiction of the mean climate of the earth. Nevertheless, while GCMs established major skills at the global and spherical scales and they include a huge percentage of the difficulty of the system globally, they are naturally not capable of predicting sub-grid scale features and dynamics locally (Dibike *et al.*, 2008).

Predicting the weather in the short (1-3 days) and medium (4-10 days) range is done using Numerical weather prediction (NWP) models. GCM's run for a longer duration i.e. years and hence one is able to learn about the climate in a statistical sense with the help of the means and standard deviations. A good example of an excellent NWP model is one that is able to precisely forecast the movement and development of turbulences such as frontal systems and tropical cyclones. After some time (e.g. 2 weeks) all GCMs get it wrong and turn out to be ineffective from a standpoint of weather foresight (Barker *et al.*, 2007). Depending on the quality of the turbulent statistics, the GCM quality is judged too. A precise combination of the rapid atmosphere to the long memory of the sluggish ocean is very important to simulate the El Nino Southern Oscillation (ENSO). GCM's can additionally be combined to dynamic models of sea, ice and land conditions. Dynamic ocean models are often not combined with short to medium range NWP models (Cayan *et al*., 2007). Table 2.1 contains the summarized comparison between GCMs and NWP models.

Table 2.1: Comparison between NWP models and GCMs

Source: http://www-das.uwyo.edu

Differences	**GCM**	**NWP**
Purpose	Climate forecasting	Weather forecasting
Spatial variability	Continental	Continental or regional
Temporal range	Annually	Daily
Spatial resolution	Mostly coarse	variable (20-100 km)
Initial conditions significance	Low	High
Cloud and radiation significance	High	Low
Significance of Surface	High	Low
Ocean dynamics significance	High	Low
Model stability significance	High	Low
Time dimensions	Vital	Neglected
Similarities		
Physics	Motion equations not forgetting radiative transfer and water conservation equations	
Technique	Limited expression of nonstop equations, or spectral depiction)	
Productivity	3 dimensional movement of the atmosphere and variability of state	
Greatest time step	restricted by spatial resolution	

The scale disparity between GCM resolution and the progressively more small scales necessary by impact analysts can be eliminated by downscaling (Wilby *et al*., 1998). Model simulations in to the future “predictions” are based on assumptions concerning future emissions of greenhouse gases caused by anthropogenic factors, which later are based on assumptions about numerous factors relating to human activities. Therefore it is unsuitable and perhaps deceptive to identify future climate simulations as ‘predictions’. These are rather identified as ‘projections’ to emphasize the likely exploration of future climate may arise from a range of assumptions regarding human activities (Cayan *et al.*, 2007)

2.6 Climate Change Scenarios

Representative Concentration Pathways (RCPs) are four greenhouse gas concentration trajectories adopted by the IPCC for its fifth Assessment Report (AR5) in 2014. They describe four possible climate futures, all of which are considered possible depending on how much greenhouse gases are emitted in the years to come. The four RCPs, RCP2.6, RCP4.5, RCP6, and RCP8.5, are named after a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2 respectively). RCP 2.6 assumes that global annual GHG emissions (measured in CO_2-equivalents) peak from 2010-2020 with considerable reduction thereafter. Emissions in RCP 4.5 peak around 2040, and then decline. In RCP 6, emissions peak around 2080, then declines. In RCP 8.5, emissions continue to rise throughout the 21st century (IPCC, 2014). These scenarios were not used because they are not present in LARS-WG model.

The IPCC (2007) developed four climate scenarios to project emission gases and temperatures for the future. These scenarios are used by researchers and policy makers to assess potential future conditions and compare them to baseline conditions in lack of climate change. These scenarios can also be used to evaluate adaptation scenarios to mitigate the harmful impacts of climate change.

According to the Special Report on Emissions Scenarios (SRES) (IPCC, 2007), climate change scenarios are not forecasts of the future but instead they are potential future scenarios where every scenario represents a way the future might open out. Scenarios describe potential demographic conditions, environmental conditions, social conditions, policies, economic conditions and technologies. According to the IPCC (2007), the scenarios are described as follows:

- A1 Scenario: "Describes a potential world of extremely fast growth in the economy, worldwide population that reaches the peak in mid-century and reduces after that, and the fast introduction of latest and additional competent technologies. The main fundamental themes are unity among regions, ability to build capacity and greater than before traditional and societal interactions, with a significant decrease in per capita income in differences regions. Three A1 groups are well-known by their emphasis on technology: fossil-intensive (A1FI), sources without fossil energy (A1T) or equilibrium of all sources (A1B)."
- A2 Scenario: "Describes a very diverse continent. The fundamental theme is independence and protection of local identities. Very slow combination of fertility patterns across regions resulting into ever growing population. Development of the economy is mostly regional and uneven slow changing of per capita economic growth and technology as compared to other scenarios."
- B1 Scenario: "Describes a unified globe whose population growth is as low as in the A1 scenario but with fast change in structures in the economy in the direction of economical service and information, among decrease in intensity of material and the clean and resource-efficient introduction of technologies.

The importance is on world wide solutions to financial, societal and environmental sustainability, not forgetting enhanced fairness, but with no extra initiatives in climate."

- B2 Scenario: "Describes a globe whose importance is on economic, social and environmental sustainability local solutions. At a lower rate than A2, its global population is ever growing, median levels of development in the economy, and lower and extra wide-ranging change in technology compared to B1 and A1 storylines. Even though the scenario is also oriented towards protection of the environment and societal fairness, it concentrates on local and regional scales.

Some climate change lessening scenarios demonstrate possible futures of global warming can be reduced by planned actions for example using green energies. For example, one easing scenario of climate change can define a desired long-term aim of carbon dioxide concentration and selected the required actions to obtain the aim such as putting a limit to national and international greenhouse gas emissions. Preventive scenarios can be compared to other scenarios like A2 and B2 inorder to have an overview on their effects when it comes to reducing the global warming (Socolow and Pacalat *et al.*, 2006). The concentration of carbon dioxide has reached about 375 ppm Limitation of emission of carbon dioxide has a lot of issues such as cost which can make it hard to reach an agreement between governments and agencies. So the 550 ppm policy is one of the feasible policies that can be considered by policy makers and scientists to project temperature.

2.7 Assessing Water Resources Impacts of Climate Change

Several types of models that simulate the hydrological processes in a catchment are required for the assessment of water resources. Many modelling approaches have been developed and previous models have been modified. Nevertheless, it should be taken into consideration that each model has its own advantages and disadvantages. Purpose, data availability, spatial and temporal scales are some of the factors that are considered when choosing an appropriate model.

In providing detailed information on how estimating how climate variability/change is affecting our water resources, climate models are seen as the very helpful. Elshamy *et al. (2008)* and Nawaz *et al. (2010)* used temporal-spatio statistical downscaling technique for the various GCMs to assess climate change impacts on Nile River at Dongola and at Diem (Blue Nile), and varying trends depending on the GCM used were displayed.

2.8 Hydroclimatic Models

2.8.1 Rainfall Runoff Modelling

A rainfall-runoff model is, by definition, a simplification of a complex, non-linear, time and space varying hydrological process reality (Shrestha, 2009). Several attempts have been conducted to categorize rainfall-runoff models. The categories are in general based on the subsequent criteria: (i) the application of physical principles and their extent in the structure of the model; (ii) the handling of parameters and model inputs in relation to space and time. From the physical process description (first criterion), stochastic and deterministic are the two categories to which a rainfall-runoff model can be attributed. Randomness is not considered in a deterministic model therefore for a given input the same output is always produced. Outputs that are to some extent random are produced by a stochastic model (Hayhoe, 2000).

On this basis deterministic rainfall-runoff models are classified as: (i) data-driven models, (ii) conceptual models; and (iii) physically based models. A physically distributed model was used in this study. This is because of the extensiveness of the sub-basin as well as the requirement of factoring in most of the sub-basin features in the modelling activity.

Several of the physically distributed models are MIKE SHE, SWAT etc. SWAT is a recurring-temporal distributed model that is used both at basin or sub-basin level model (Arnold *et al*., 2012). SWAT model was developed to forecast the effects of different water management decisions, chemical and sediment loading with logical precision. SWAT inputs are readily available, thus the least data is required to make a run and also it is efficient computationally. One of the merits of using SWAT model is that little time or time is needed to execute the simulation of large watersheds. Long-term effects can be studied with SWAT, also it has the powers of modelling watersheds without monitoring station and its data. Water balance equation is used by SWAT model (Equation 2.1) behind which all processes occur in the watershed (Neitsch *et al*., 2005).

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{perc} - Q_{gw}) \qquad (2.1)$$

Where:

SW_t and SW_o are final and initial soil water content respectively (mm/d)

t is the time (day)

R_{day} is the rainfall (mm/d)

Q_{surf} is the runoff (mm/d)

E_a is the evapo-transpiration (mm/d)

W_{perc} is the percolation (mm/d)

Q_{gw} is the return flow (mm/d).

SCS curve (Chai *et al.*, 2011) and the Green and Ampt infiltration method (1911) are used in SWAT for surface runoff estimation. The SCS curve number is a function of the permeability of the soil, landuse and water conditions of the soil. Mein and Larson (1973) modified the Green and Ampt infiltration method to determine the permeability of the ponding time. Surface runoff can also be determined by using the Green- Ampt Mein-Larson excess rainfall method. However, this method needs rainfall data at sub-daily time step.

Penman-Monteith, Priestley-Taylor and Hargreaves method are three methods that are incorporated into SWAT for computing potential evapo-transpiration. Penman-Monteith equation includes mechanisms that explain energy required to maintain evaporation and the required parameters are wind speed, relative humidity, air temperature and solar radiation. Priestley - Taylor method requires relative humidity, temperature and solar radiation, whereas temperature only is needed for Hargreaves method.

2.8.1.1 Hydrological Model Selection

The choice of model starts with the model being able to solve the problem in question. The three types of model structures; lumped, semi-distributed and fully-distributed. The first task is to choose the type which can give the best solution objectives without compromising the accuracy of the results. Semi-distributed models structures are more based physically than lumped and also they demand less data than fully-distributed models (Cunderlik and Simonovic, 2007). The selected model has to be reasonably cheap, its ability to simulate most if not all hydrological processes (inception and infiltration, evapotranspiration), and technical support (experts) should be available to minimize delays. Three models were compared to find the best semi-distributed model to be applied (see Table 2.2)

Table 2.2: Comparison of three selected semi-distributed models

Source: Cunderlik and Simonovic, 2007

Model and its criteria		**HBV**	**HEC-HMS**	**SWAT**
Temporal scale		Daily	Adjustable	Daily
Spatial scale		Adjustable	Adjustable	Average
Processes modelled	Occasional-simulation	Present	Present	Absent
	Recurring simulation	Present	Present	Present
	Ice melting	Present	Absent	Present
	Interception and permeability	Present	Present	Present
	Evapotranspiration	Present	Present	Present
	Routing of reservoir	Present	Uncontrollable	Present
Cost		Unknown	Free	Free
Duration of set-up		Average	Average	Long
Expertise		Average	Average	High
Technical support		Available	Available	Available

From the above, SWAT model became more suitable because of its ability to capture hydrological conditions in a catchment and also the availability of skilled people that have used it before. However, model limitations which could make modelling impossible such as poor calibration and validation have been reported from SWAT studies but these are said to be slightly influenced by inadequate rainfall distribution of the rain gauges in the catchment (Arnold *et al*., 2012). Therefore, it was decided that SWAT can be used for this research.

2.8.1.2 SWAT Model Parameter Sensitivity Analysis

Sensitivity analysis of SWAT model parameters is a mechanism used to evaluate the input parameters to determine how they impact the model output; not only is it helpful for the development of the model but also for the validation of the model thus helpful in the reduction of uncertainty (Hamby, 1995). The sensitivity analysis minimizes on the parameters to be used in calibration by considering the parameters that are most sensitive thus fundamentally affecting the simulation process behavior.

SWAT embeds a sensitivity analysis procedure called Latin Hypercube One-factor-At-a-Time (LH-OAT). This statistical method of sensitivity analysis is used for analyzing the sensitivity of SWAT model parameters. Ndomba *et al.* (2007) recommended that parameter sensitivity analysis can be done before and after calibration and with or without observed flow data. Rainfall runoff models have parameters that are not directly measured often, but are only estimated by calibration against a historical record of measured output data.

The Latin Hypercube simulation is based on the principles of Monte Carlo with a stratified sampling. After the subdivision of each parameter into ‘N’ ranges, an occurrence probability of 1/N is obtained. The One-factor –At-a-Time design uses the Latin Hypercube samples as starting points and one parameter is changed at a time. For N intervals with 'm' parameters, a total of N(m+1) runs are done. The objective functions are the change of the mean value of the output variables (e.g. mean flow) for the case of non observed data, and the sum of the squared of errors (SSQ) between the observations and the simulations when there is an observed data for the required output variables (Van Griensven, 2009).

The final sensitivity analysis results are ranked parameters, where the parameter with the highest impact gets rank 1, and the one with the least impact gets a lower rank. Rank 1 is the most important parameter, and as the ranking increases the importance of the parameter reduces (Van Griensven *et al*, 2006)

2.8.1.3 Calibration of SWAT Model

Calibration minimizes the error between the output simulated by the model and the data collected in the field (Das and Perera, 2013). Wagener *et al.* (2001) suggested that about 8 years of data are sufficient to obtain calibrations that are fairly insensitive to the selected period. Further, the reduction in parameter uncertainty is maxima when the wettest data periods on record are used. It has been also shown that there is no need for the data to consist of consecutive water-years.

Even though physically based models do not in principle need extensive hydro-meteorological data for their calibration, they do need the assessment of many parameters describing the physical characteristics of the watershed on a spatially distributed basis and large amounts of data about the model initially (e.g. soil moisture content, initial water depth). Most of the time, however, such data are not available (Shrestha, 2009). Hence an automatic means of calibration fits for this difficult resulting from large number of parameters. There several procedures for calibration of SWAT model, some of the common ones are Parameter Solution (ParaSol), Generalized Likelihood Uncertainty Estimation (GLUE), Particle Swarm Optimization (PSO), Importance Sampling (IS), Markov chain Monte Carlo (MCMC), and Sequential Uncertainty Fitting (SUFI). Yang *et al.* (2008) reported that SUFI procedure is efficient in optimization, because it takes few runs in comparison to other calibration procedures mentioned earlier. Thus SUFI procedure was preferred over others for calibration of parameters in this study.

SUFI procedure has a different approach which optimizes the use of the Latin Hypercube Sampling (LHS) procedure together with an algorithm that is global in order to observe the behaviour of functions objectively. SUFI procedure is sequential in nature which means that before choosing the final estimates, iteration can always be made. It has a Bayesian framework, signifying that domains which are uncertainty (prior, posterior) are related to each parameter and operated in the method. It is a fitting procedure which conditions unidentified parameter estimates on a range of observed values. Lastly, it is an iterative procedure, needing a stopping rule that is provided by a vital value of a goal function (Nasr *et al.*, 2007). SUFI procedure has been integrated into the SWAT Calibration and Uncertainty Programs (SWAT-CUP) software, and it has been enhanced with capability of skipping missing observed flow data in calibration. SWATCUP is available online for free such as the EAWAG website (Abbaspour, 2015)

2.8.1.4 Climate Customization in SWAT

SWAT can be used to simulate several climate customization options. By adjusting the climatic variables such as rainfall, temperature etc that are fed into the SWAT model, climate change can be simulated. An easier way is to have factors to be adjustment set for the different climatic variables. The adjustment factors in SWAT are allowed to vary monthly in order to enable the user in simulating seasonal changes in climatic conditions. The alteration of temperature and precipitation are straightforward (Neitsch *et al.*, 2005) as below:

$$T_{mx} = T_{mx} + adj_{tmp} \tag{2.2}$$

$$T_{mn} = T_{mn} + adj_{tmp} \tag{2.3}$$

Where, T_{mx} and T_{mn} are maximum and minimum daily temperature (^{0}C) respectively and adj_{tmp} is the change in temperature (^{0}C).

$$R_{day} = R_{day} x(1 + \frac{adjpcp}{100}) \tag{2.4}$$

Rday is the rainfall received in the sub-catchment on a particular day (mm H_2O), and adj_{pcp} is the change in rainfall in percentage

2.8.2 Downscaling Models

Climate change information is essential for lots of impact studies at much finer spatial scale yet GCMs have hundreds of kilometers resolutions (Dibike *et al.*, 2008). Therefore downscaling methods have come up as a way of linking atmospheric variables to a scale of grid and sub-grid. Numerical and statistical are the two major methods for obtaining data on regional or local scales from the GCMs generated scenarios of global climate (Wilby *et al.*, 1998). Numerical downscaling (referred to as dynamic downscaling) involves a regional climate model (RCM) and statistical downscaling includes statistical relationship between the large-scale climatic state and local variations derived from historical data records. These two approaches are discussed below.

2.8.2.1 Dynamic Downscaling

It involves climate model of finer-scale regionally, and is also called limited area models (LAMs) within the climate model of coarser scale globally. Outputs from the conditions of a GCM boundary for the interested region are used in a dynamic method. Future climate at a scale of a region is calculated using a climate model fully physical in nature. The major benefit of dynamical models is that conditions at local scale are taken into account, which may include surface vegetation or chemistry changes in atmosphere in physically regular ways. However Regional climate models (RCMs) require as much processing time as the GCM to calculate the same scenarios and they cannot be transferred to new regions easily. At the start of the RCM results are also sensitive to choice of the initial conditions (especially soil moisture and soil temperature) (Nasr *et al.*, 2007)

Pisinaras *et al.* (2016) also noted the ability of RCMs to practically simulate climate features such as orographic rainfall, regional scale climate anomalies and extreme climate events. Model skills are based so much on biases carried on from the used GCM and also the existence and strength of regional scale forcings such as vegetation cover, land-sea contrast and orography.

2.8.2.2 Statistical Downscaling

Statistical downscaling includes numerical development of relationships between predictors (atmospheric variables at large scale) and predictand (surface variables at local scale) (Wilby *et al.*, 1998). A good number of common forms have predictand as a function of the predictors. It seeks to obtain information locally from scales that are larger. Mostly, the climate at regional scale is seen as random process accustomed upon a fundamental climate regime at large-scale. Hence, the assurance in data that is downscaled is primarily reliant on the soundness of GCM field's at large scale. For example, derivative variables such as rainfall are regularly not strong information at both the regional and local scale whereas tropospheric quantities such as temperature are fundamental physical GCM parameters and are competently represented by GCMs (Van Griensven *et al.*, 2006)

According to Wilby *et al.* (1998), the following assumptions are involved in statistical downscaling: (i) predictor variables large and small scale suitable relationships can be derived (ii) based on conditions of future climate, observed relationships are applicable (iii) GCMs are good at characterizing the changes of predictor variables.

Over the past few years, the development of varied statistical downscaling techniques has come up and each method normally one of the three categories i.e. regression method, stochastic weather generators and weather typing schemes (Wilby *et al.*, 2004). A comparison between statistical and dynamical downscaling models was carried out as shown in Table 2.3.

Table 2.3: Comparison of statistical and dynamical downscaling methods

	Statistical downscaling	Dynamical downscaling
Advantages	➢ Cheap and user efficient ➢ Provision of climatic variables at point-scale ➢ Unavailable RCM variables can be derived ➢ Other regions can apply it easily ➢ Has acknowledged statistical measures and standards ➢ Includes observations into method directly	➢ Responses are based on processes that are consistent physically ➢ GCM scale output data has finer resolutions
Disadvantages	➢ Needs long and reliable observed historical data series for calibration ➢ Depends on choice of predictors ➢ Non-stationarity in the predictor-predictand relationship ➢ Does not include climate system feedbacks ➢ Affected by biases in underlying GCM's ➢ Domain size, climate region and season affects downscaling skill	➢ Intensive computationally ➢ Limited number of scenario ensembles available ➢ Depends on GCM boundary forcing

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter outlines and shows the materials and methods used in this study. This includes the means by which the researcher was able to assess the study area and compile data for analysis. This study is based on secondary data.

3.1.1 Description of Study Area

Malaba River catchment is part of the Lake Kyoga basin which is one of the eight major surface water basin delineations for Uganda. The area considered for the study as the Malaba River catchment covers about 1604.4 km^2 with approximately an altitude of 1077 meters above the sea level and the centre at 34.2^o East and 0.62^o North. The river has its origins on the slopes of Mount Elgon on the border between Uganda and Kenya and flows through the districts of Mbale, Tororo and Pallisa before finally discharging into Lake Kyoga. The study area has one weather station (Tororo) within its boundary with Mbale and Bungoma outside its boundaries as shown in Figure 3.1.

Due to insufficient rainfall stations with sufficient data, rainfall data from Mbale station was replaced with SWAT station whose data was downloaded from *globalweather.tamu* website.

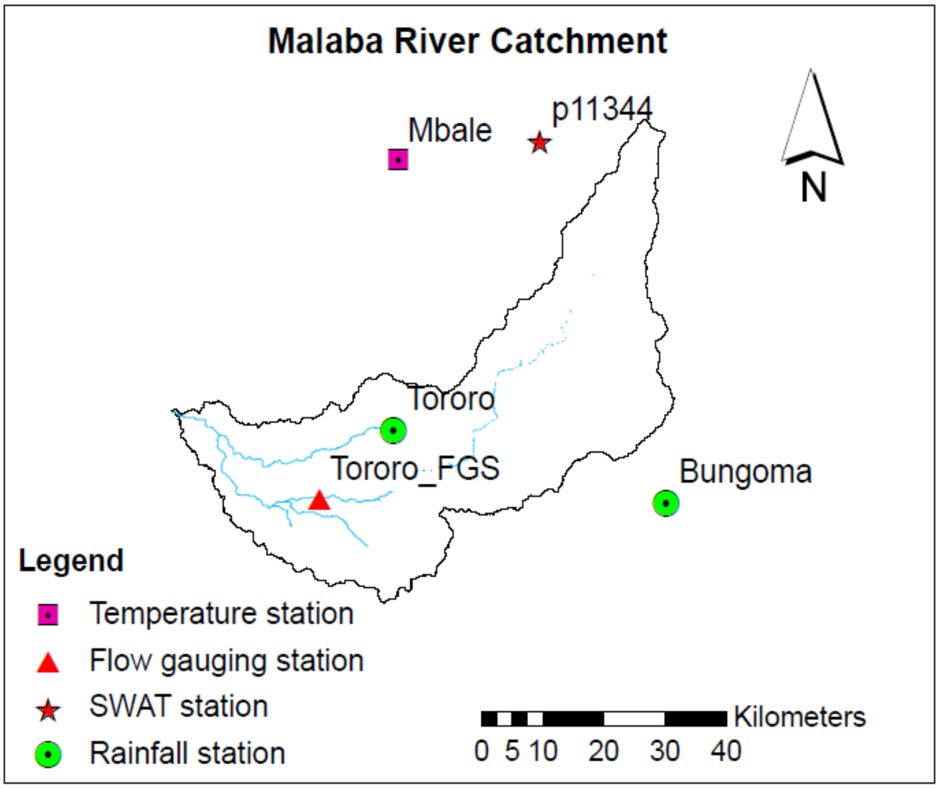


Figure 3.1: Location map of Malaba River catchment

3.2 Data Collection

Some of the data were collected from responsible ministry's in Uganda and websites as presented in the Table 3.1.

Table 3.1: Data acquired from the respective ministry's and websites

Sn	Data type	Stations/Locations	Source, (Period/Age)	Resolution		Data Format
				Spatial	Temporal	
1	Rainfall	3 stations	MWE (1980-2014)	Point	Daily (mm)	Text file
2	Temperature	1 station	MWE (1980-2014)	Point	Daily (^{0}C)	Spreadsheet
3	Flow	1 station	MWE (1980-2014)	Point	Daily (^{0}C)	Spreadsheet
4	DEM	Malaba river sub-basin	USGS STRM-DEM (2009)	90 x 90 m	N/A	Geotiff tiles
5	Landuse	Africa	Africover Land cover Classification and Natural Resources services, FAO (2009)	1:250,000	N/A	Raster
6	Soil data	Uganda	Southern Africa database for soil and terrain developed by International Soils Reference and Information Centre, ISRIC (2005)	1:2,000,000	N/A	Raster
7	HADCM3, HADGM & EMPH5 models (A1B & A2)	World	IPCC4 (CMIP3) from (2020-2050)	25 km	Daily Time series	Text file

Note; MWE-Ministry of Water and Environment, IPCC-Intergovernmental Panel on Climate Change

3.3 Modelling Framework for the Study

Methods used in this study involved the following procedures: data analysis, downscaling of future climate variables for selected scenarios, rainfall-runoff modelling and analysis of simulated stream flow (2020-2050) as shown in Figure 3.2 below.

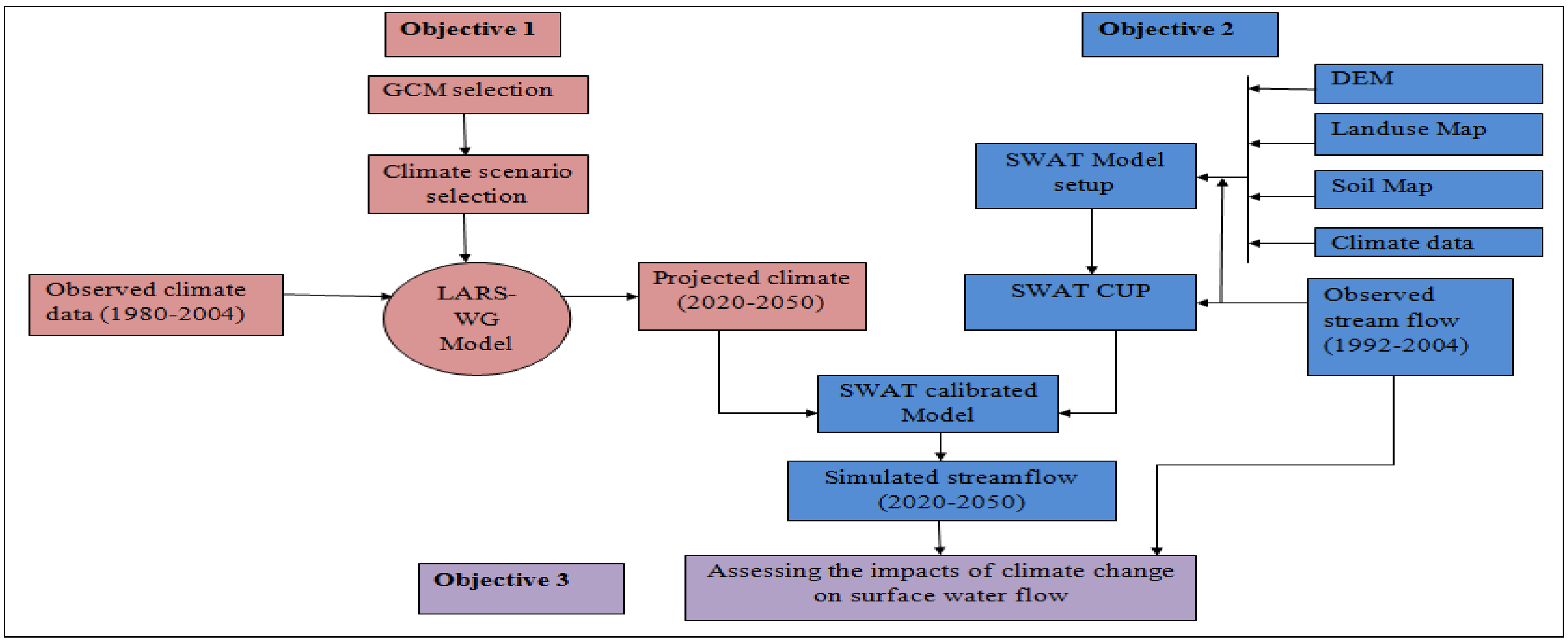


Figure 3.2: Modelling framework of study

3.4 Data Preparation and Processing

3.4.1 Rainfall Time Series

Rainfall daily time series for Tororo (1980-2010), Mbale (2002-2014) and Bungoma (1980-2004) stations were collected from the Uganda National Metereological Authority. These data were used for understanding the rainfall patterns and trends within the catchment. Mbale data was not used during the preliminary analysis because it has a significant 85% data gaps.

Table 3.2: Available rainfall stations in Malaba River catchment

Name	Longitude	Latitude	Elevation	Period	% missing
Mbale	34.167	1.067	1127	2002-2014	85
Tororo	34.160	0.683	1170	1980-2010	9
Bungoma	34.560	0.580	1400	1980-2004	0
ID11344	34.375	1.093	2150	1980-2004	0

It is common to find gaps in metereological data and these are caused by vandalism and malfunctioning of equipment and several other factors. Table 3.2 shows that Mbale, Tororo and Bungoma have missing data with 85% (2002-2014), 9% (1980-2010) and 0% (1980-2004) respectively.

A timeline in Figure 3.3 was created to display the missing gaps of the rainfall stations in and outside the catchment.

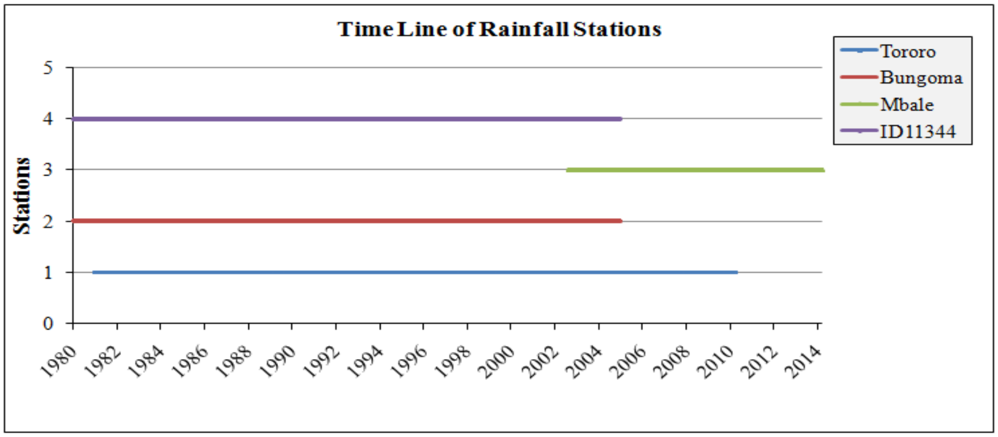


Figure 3.3: Timeline of available rainfall stations in Malaba River catchment

A common study period of 1980-2004 was chosen for the stations i.e. Tororo, Bungoma and SWAT station for calculating the mean areal rainfall of the catchment. Therefore, a preliminary rainfall data analysis was carried out based on these three stations only i.e. Tororo, Bungoma and ID11344.

3.4.2 Stream Flow Time Series Data

This data is from the Tororo flow gauging station and the recorded data is from mid 1992 to mid 2015. From the below flow diagram, it is shown that there is missing data in 1992, 1996, 2006 and 2015. The high peaks are in 1998 and 2010 with a flow of 49 m^3/s and 50.4 m^3/s respectively.

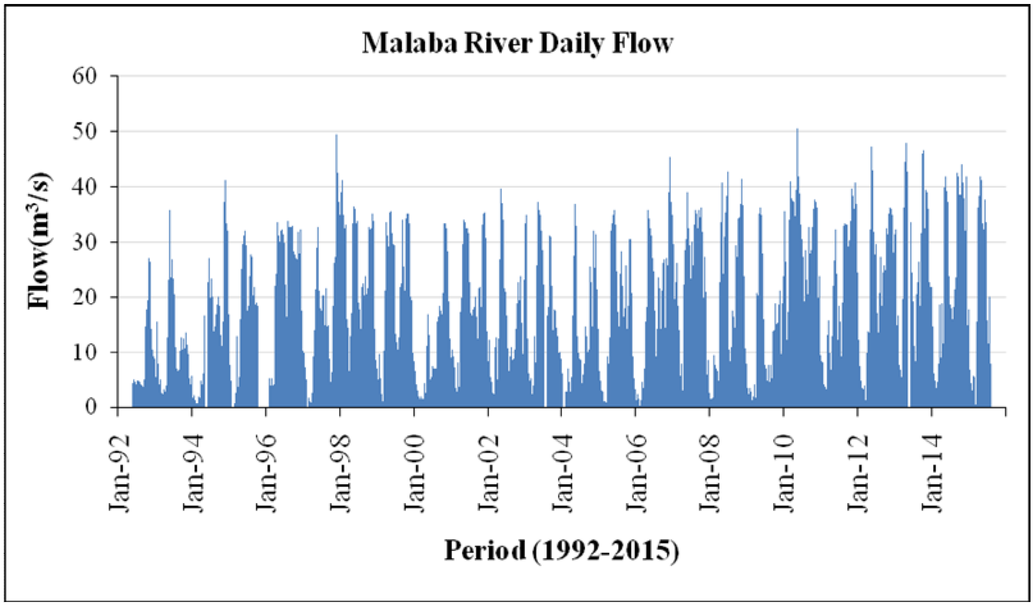


Figure 3.4: Stream flow time series of Malaba River

3.5 Data Analysis

3.5.1 Baseline Rainfall Seasonality

It is known that rainfall as a climatic parameter has temporal and spatial variations and therefore it is important to be informed on the rainfall seasonality in the catchment. This is basically carried out to investigate the variations in rainfall regimes over the years. To illustrate the mean monthly variations of the rainfall, the data was first pre-processed to monthly time series and means were calculated over each stations time period. Histogram plots were then produced in Microsoft Excel to display the patterns of the rainfall for the respective stations.

$$\overline{X}_{ij} = \frac{\Sigma_{i=1}^{N} x_{ij}}{N} \qquad (3.1)$$

Where:

i is number of years

j is the respective month (j=1, 2, …., 12)

3.5.2 Areal Rainfall

This was computed to determine the average precipitation received by the entire catchment. The best method used depended on the type of data. Thiessen Polygon method was chosen because the rainfall stations are few. It is also known as weighted mean method. Rainfall varies in both intensity and duration and is not uniform over the entire basin or catchment. Therefore recorded rainfall of each rain gauge is weighted in relation to the polygon area, it represents using the following equation;

$$\overline{P} = \sum_i^n P_i\left(\frac{A_i}{A_T}\right) \tag{3.2}$$

Where:

P stands for areal rainfall (mm),

P for rainfall gauging station data (mm),

A for area corresponding to the particular rainfall gauging station (Km^2),

A for total area covering all rainfall gauging stations (Km^2),

n is the number of Thiessen polygons.

3.5.3 Trend Analysis

Trend analysis is basically done to determine whether the change in the annual rainfall throughout the last years is significant or not and to ensure that the selected period represents the historic rainfall regime in the country. Time series of each rainfall station were analysed for trend using two tests i.e. Mann Kendall and Sen’s slope. To illustrate annual climatological and hydrological variables, the data was first pre-processed to annual time series. Plots were then produced as a simple approach to trend detection and in each plot, a trend line was fitted. The study used trend analysis software for Mann-Kendall test (Chiew and Siriwardena, 2002) and MAKESENS 1.0 (Salmi *et al.*, 2002) for the Sen's slope estimator for linear regression analysis. In producing visualizations of the data, Microsoft Excel software was used.

3.5.3.1 Mann-Kendall Test

Mann-Kendall test was used to analyze the trend in the time series data. This non-parametric rank based method is mostly used to evaluate the significance of monotonic trends in hydroclimatic time series (Salmi *et al.*, 2002). It does not assume data to have any form of distribution form hence is as influential as other counterparts.

The test is as follows; Assuming X_1, X_2, . . ., X_n be a series of data over a time period, Mann proposed that $H_{0,}$ the null hypothesis be tested and the data comes from a series with identically distributed and independent variables. Over time, the data of the H_1, the alternative hypothesis, follows a monotonic trend over time. Under H_0, the Mann–Kendall test statistic is,

$$S = \sum_{i=j}^{n-1} \sum_{j=i+1}^{n} sgn(X_j - X_i) \tag{3.3}$$

Where;

$$sgn(\theta) = \begin{cases} +1 \dots \dots \theta > 0 \\ 0 \dots \dots \theta = 0 \\ -1 \dots \dots \theta < 0 \end{cases} \tag{3.4}$$

Under H_o, statistic is roughly distributed normally when $n \geq 8$, then both the mean and variance are zero as shown below:

$$\sigma^2 = \frac{n(n-1)(2n+5)}{18} \tag{3.5}$$

As a result, *Z* statistics that are standardized go after a normal distribution:

$$z = \begin{cases} \frac{S-1}{\sigma} \; if \; S > 0 \\ 0 \quad if \; S = 0 \\ \frac{S+1}{\sigma} \; if \; S < 0 \end{cases} \tag{3.6}$$

When the computed *Z* value is greater than the critical then there is a trend (Arnold *et al.*, 2012).

A positive value of Zs means an increasing trend while a negative value means a decreasing trend. Statistical trends are commonly assessed at the 5% significance level (Salmi *et al.*, 2002).

3.5.3.2 Sen's Slope Estimator

Trend magnitudes were determined using the Theil-Sen Approach (TSA) (Salmi *et al.*, 2002) so as to confirm and map trends detected by the Mann-Kendall method. The TSA is recommended because it is more robust to outliers as opposed to other parametric tests such as linear regression. The slope estimator (β) is the median over all pairs of points in the time series (Salmi *et al.*, 2002)

$$\beta = \text{Median}\left(\frac{y_j - y_i}{X_j - x_i}\right) \tag{3.7}$$

$$for \; all \; i < j \; and \; i = 1, 2, \ldots..(n-1);$$

j = 2, 3… n

3.5.4 Stream Flow Response to Rainfall

Hydrological processes are a sign of collective effects of climate, vegetation and soil, resulting in changes of streamflow at the basin scale. Changes in the amount of water flow from Malaba River have been attributed to climate change among other factors. To understand the influence of climate change on streamflow, an investigation of the stream flow response to historic climate needs to be carried out. A common time period for the streamflow and climate data was chosen i.e. 1992-2004. To illustrate this response, rainfall and stream flow data was pre-processed to mean monthly time series. In producing visualizations of the data, Microsoft Excel was used.

3.6 Projection of Climate Change Variables from 2020-2050

3.6.1 Downscaling of Future Climate

There are two downscaling methods namely dynamic and statistical. At small and large scales, the links between the climates of dynamic techniques are based while statistical downscaling methods use relationships between locally observed weather variables and atmospheric variables at large scale. Statistical method was used for this research because it derives local scale data from larger scale using random and or deterministic functions (Salathe *et al.*, 2008)

The LARS-WG model was used for predicting the future climate in this study (Semenov and Barrow, 2002). It has been applied successfully in several similar case studies (Mwiturubani *et al*., 2010).

3.6.2 LARS-WG Model Description

LARS-WG uses semi-empirical distributions for both wet and dry lengths day series, daily rainfall and solar radiations as described in (Semenov and Barrow, 2002).

The simulation of rainfall event is modeled as varied wet and dry series, where a wet day is a day with rainfall > 0 mm. The duration of each series is randomly chosen from the wet month taking into consideration when the series starts. When the distributions are being determined, the month in which observed series start is also allocated. The rainfall value generated for a wet day for a particular month is not related or linked to the duration of the wet period or the amount of rainfall on past days.

Temperature at daily time step is considered a random process (evolving with time) with averages and variances of a wet or dry day. It is used in simulating the same process is as presented in Hayhoe, (2000). Order 3 of the Fourier series models the seasonal averages and variances and their residuals are rounded off by a distribution that is normal. The average Fourier series is adjusted to the observed average values monthly but before adjusting the variance of the Fourier series, the observed monthly variances are adjusted first to offer a likely daily mean variance by eliminating the likely effects of a month's mean changes. Using the already obtained mean for the fitted Fourier series, the adjustment is calculated. Analysis of the time autocorrelation for temperature requires the observed residual which is obtained by eliminating the average observed data. For simplicity an assumption of both of these being constant annually is made and the average observed data is used. Residuals from temperature have cross correlation pre-set at 0.6. Incase simulated minimum temperature is higher than simulated maximum temperature, the minimum temperature is replaced by the maximum less than 0.1.

Many locations have showed that the solar radiation that is distributed normally at daily time step, is unsuitable for certain climates (Semenov and Barrow, 2002). Different distributions were used to describe solar radiation because it varies extensively on wet and dry days. Solar radiation is modeled differently from temperature and a calculated autocorrelation for solar radiation was concluded to be the same annually. LARS-WG uses sunshine hours as an option to solar radiation data. Sunshine hours may be used instead of solar radiation because LARS-WG has the ability to convert these automatically to solar radiation using the approach described in Taylor *et al.* (1986).

3.6.3 Selection of Global Circulation Models

There are many climate models that are free to the public for providing future climate change projections. All these models are mathematical ones hence they simulate global climate varying in sizes and scales. Using twenty-four global climate models under three major greenhouse gas emission scenarios (A1B, A2, B1), the forth assessment of the Intergovernmental Panel on Climate Change (IPCC) provides future climate change projections (Barker, 2007). Therefore the GCMs used in this study were selected randomly in LARS-WG model based on their inclusion in the IPCC's Fourth Assessment Report (AR4) and also the availability of three emission scenarios.

Three GCMs were compared with observed data for rainfall and temperature to determine their accuracy in simulating the climate of the area. The GCM with the highest correlation efficiency with observed data was used for projecting climate for the respective variable i.e. precipitation and temperature from 2020-2050.

3.6.4 Selection of Climate Scenario

The Intergovernmental Panel on Climate Change (IPCC) defines a scenario as 'an often basic depiction of how the future may develop based on a rational and inside consistent set of assumptions of driving forces and key relationships. The Special Report on Emissions Scenarios (SRES) has been widely used in climate change research and assessments in the past and was based on descriptive storylines that conveyed the general logic primarily the related quantitative descriptions of future economic, demographic, technology, and emissions trends.

Based on economic and population growth the climate scenarios were selected. A1B predicts a future of very fast economic growth and a combination of technological developments, A2 predicts a future world of fair economic growth and a higher population growth and B1 predicts a convergent world with the same global population that peaks in mid-century and declines thereafter and B2 predicts a world in which the stress is on local solutions to economic, social, and environmental sustainability.

For this study only A1B and A2 scenarios were considered because they explain the most "likely to happen" development paths i.e. medium and high development path respectively. These scenarios have also already been used in Uganda for climate change studies (Jassogne *et al*., 2013).

3.6.5 Generation of Projected Climate Variables

Semenov and Barrow, (2002) developed the Long Ashton Research Station Weather Generator (LARS-WG) in 1997. This stochastic model is able to simulate future climate variation locally in response to climate change by outputs downscaled from AOGCMs outputs. Historical datasets are used as inputs into the model and data at daily time step of infinite lengths are produced. Three steps were carried out in the LARS-WG model to simulate the synthetic weather. These are site analysis (model calibration), Q-test (model validation) and Generator.

3.6.6 Weather Generation

The usual way of filling missing data is to use the data of a nearby station either using regression analysis or spatial interpolation. In some cases, the nearby stations have missing data hence their data cannot be used. This is one of the main constraints that led to the use of LARS weather generator model to fill in the missing data for better projection of future climate.

Observed rainfall data for Tororo, Mbale and Bungoma stations were collected while maximum and minimum temperature was collected for only Mbale station. The temperature data for one station was used as a representation for the whole catchment since temperature does not vary much.

In this study, LARS-WG model ability to generate rainfall time series under limited data was analysed. The daily rainfall for Tororo, Mbale, Bungoma stations and temperature for Mbale station (1980-2010) were used for the model input and 30 years of synthetic data were generated. Comparisons between the observed and simulated data were based on the monthly statistics such as mean difference and variance.

3.6.7 LARS-WG Model Calibration

LARS-WG model calibration is also known as site analysis. It was calibrated using the historical observed data i.e. precipitation, maximum and minimum temperature of Tororo station for 1980-2010 time period. To determine the statistical characteristics of the results, they were analysed. The results are stored in two files. The parameter file (*.wg) contains the parameters required by LARS-WG to generate the synthetic weather time series and the statistic file contains the seasonal frequency distributions, which is used in the Q-test process also known as model validation.

3.6.8 LARS-WG Model Validation

Once calibrated was done using the observed data for a station, Q-test (validation) was carried out to confirm the performance of the model. Synthetic weather data is generated with the same statistical characteristics as observed data based on the parameter files that were derived during calibration. Model validation helps to verify the capability of the model to generate synthetic data.

3.6.8.1 Analysis of the LARS-WG Calibration and Validation Results

When the site parameters are calculated, LARS-WG automatically creates a tst-file which contains results of statistical tests. The Kolmogorov-Smirnov (K-S) test is performed for testing equality of the seasonal distributions for daily rainfall and temperature data determined from observed and downscaled data. The test calculates a p-value, based on which the modeler uses to accept or reject the hypothesis. Therefore the modeler is able to determine the difference between the observed and simulated variable if any.

3.6.9 Analysis of Future Climate Scenarios

3.6.9.1 Analysis by Trend

The time series of projected climate for each scenario was analysed for trend using Mann-Kendall method and Theil Sen's slope was used to determine the magnitude of the trend. The data was pre-processed to annual time series and Microsoft excel was used for visualization purposes. The results of this analysis were based on the 5% significant level.

3.6.9.2 Analysis by Changes

The time series of projected climate for each scenario was analysed for changes against a baseline period of (1980-2004) for both areal rainfall and temperature. The areal rainfall change was expressed in percentage while the temperature change was expressed as a difference. The changes were done on a monthly basis using Microsoft excel.

3.7 SWAT Model Setup

ArcSWAT was used in the study through ArcGIS 9.3 user interface. The first step was to delineate the watershed using the DEM. The sub basins (15) were created as well as the drainage system of the study area. From the soil, slope and soil maps, the hydrologic response units (HRUs) were generated (85 HRUs). The SWAT model was selected to simulate rainfall runoff of Malaba river sub basin from 1992 to 2004. The meteorological input data was; maximum temperature, minimum temperature, and precipitation. The meteorological and stream flow data sets were prepared as dbf files and uploaded into SWAT. The available data for both meteorological and stream flow data allows analysis period of 1992 to 2004. Then the DEM, land use, soil, rainfall, temperature data and water use data were also inserted in the model. Due to availability of only rainfall and temperature data, the SWAT model was set to compute potential evapotranspiration using Hargreaves method.

Figure 3.5 provides a schematic view of SWAT setup as well as data inputs.

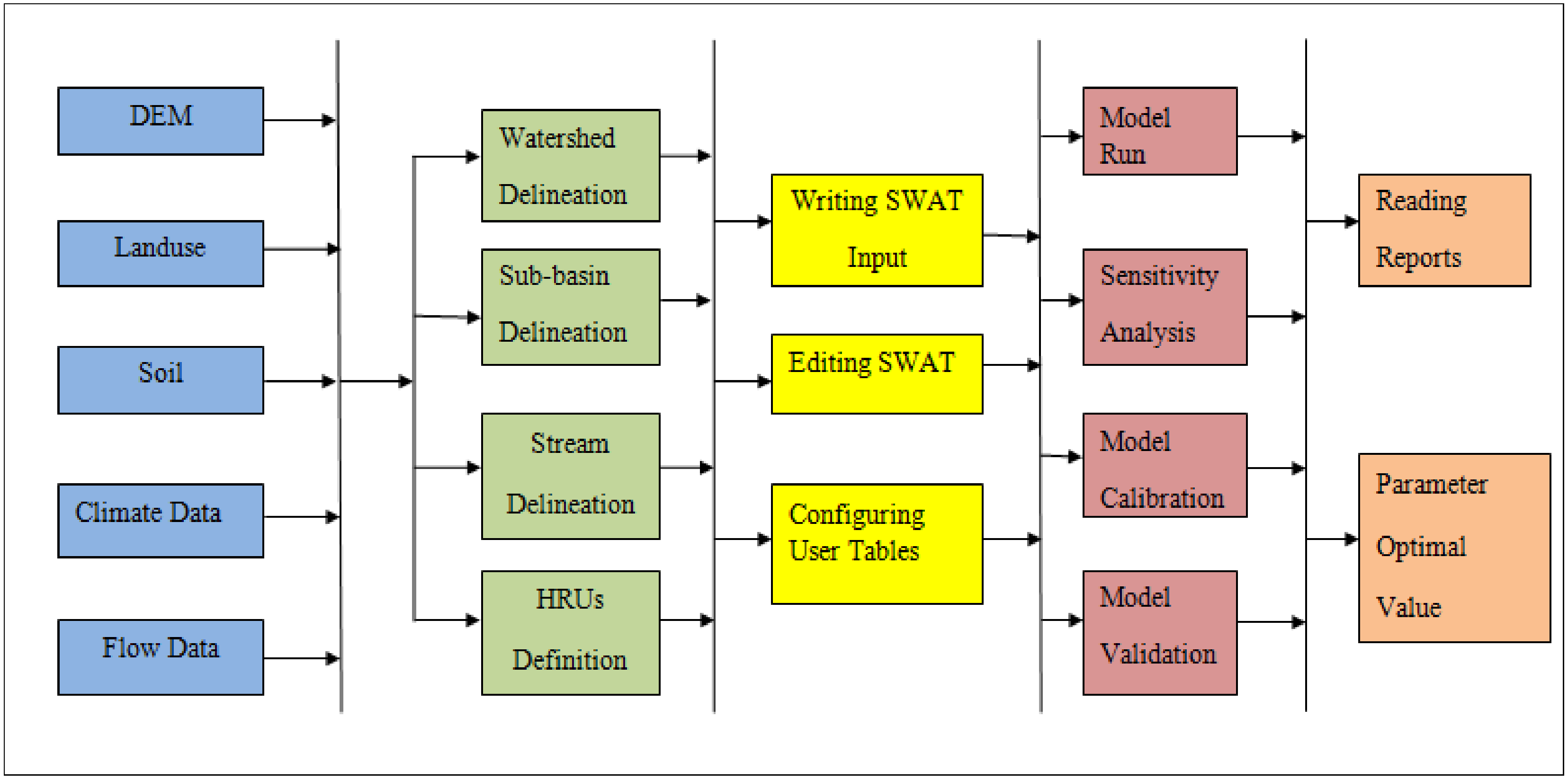


Figure 3.5: Schematic view of SWAT model

i. Digital Elevation Model (DEM)

The DEM was used for; delineating the watershed, creating the sub-basins, stream network and longest reaches generation, calculating terrain slope and channel slope. The DEM used was a 90 X 90 m ASTERGDEM raster. Figure 3.6 of the DEM shows that, the Northern (upper) side of the catchment has an elevation of 4298 and the southern has 1086 masl.

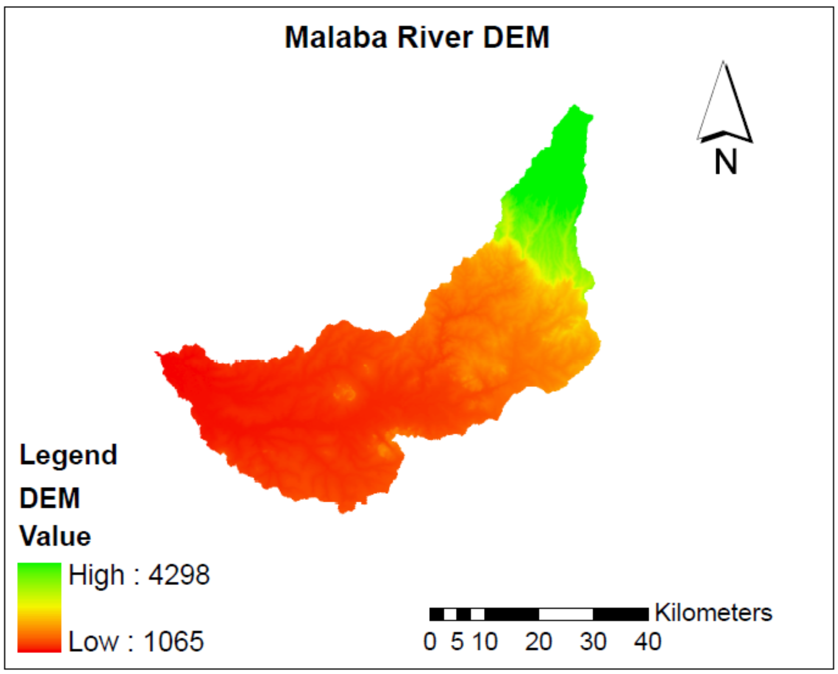


Figure 3.6: DEM of Malaba River catchment

ii. Landuse Map

Land use map of 1998 was used in this study. SWAT uses the land use map as either a shape file or a raster file. When it is a shape file, the SWAT model converts it to raster file. Land use data was classified so as to determine the extent of the different classes during the simulations of hydrological modelling. Land use change was not considered in simulation of future stream flow under changing climate, this set-up will give separate impact of climate change on hydrology (setting constant land use as for the baseline period). However, this classification is coded in SWAT during Land use/soil/slope definition. For example, urban categories were given Residential-URBN, Savannah-SAVA, Farmland-Agricultural Land Generic (AGRL), Forests-Broadleaved Trees Forest (FOEB), Bushes-Range Bush (RNGB), Grassland-GRAS, and Plantations-Agricultural Land Row Crops (AGRR). The map was projected to Arc_1960_UTM_Zone_36N.

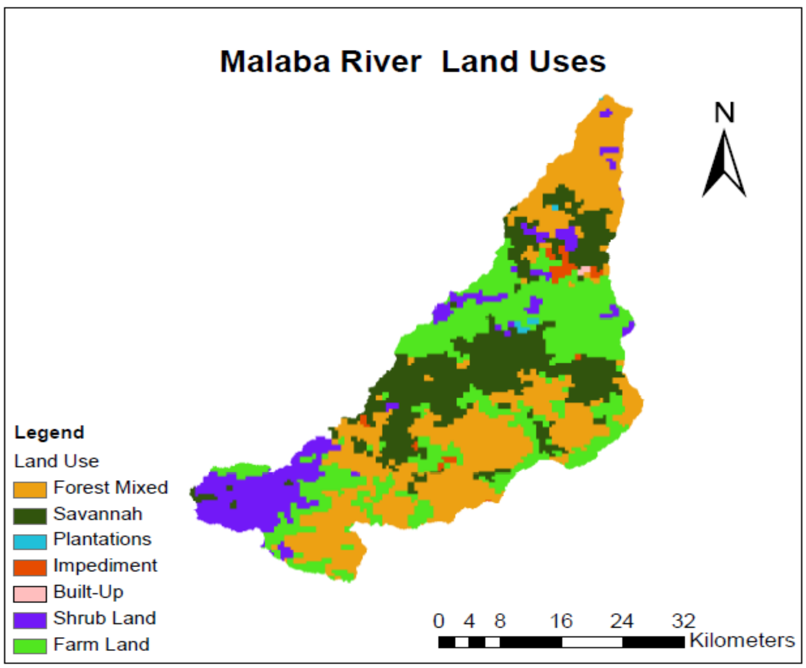


Figure 3. 7: Spatial distribution of land use in the sub-basin

Table 3. 3: Percentage coverage of Land uses in Malaba River catchment

Sn	Land use	Area (km^2)	Percentage (%)
1	Farmland	36.256	36%
2	Built-up area	6.802	7%
3	Impediment	2.133	2%
4	Forests mixed	17.314	17%
5	Plantations	33.342	33%
6	Shrub land	1.574	2%
7	Savannah	2.85	3%
	Total	100.271	100%

Majority of the landuse in the catchment are Farmland, Banana Plantations, and Forests with 36%, 33% and 17% land use as shown in the above table. This therefore is an indication that the catchment lies in rural area.

iii. Soil Map

Soil was classified into texture form from generic names using the Africa User - Soil Definitions provided for Southern Africa but developed by International Soils Reference and Information Centre, ISRIC in 2003. Most of the soil in the sub-basin is sandy-clay-loam and loam (Table 3.5 and Fig. 3.8). Loam soil is found at top of the catchment, whereas sandy-clay-loam is found downstream of the catchment. This therefore means that there might be a higher retention of water downstream of the sub-basin rather than at the centre.

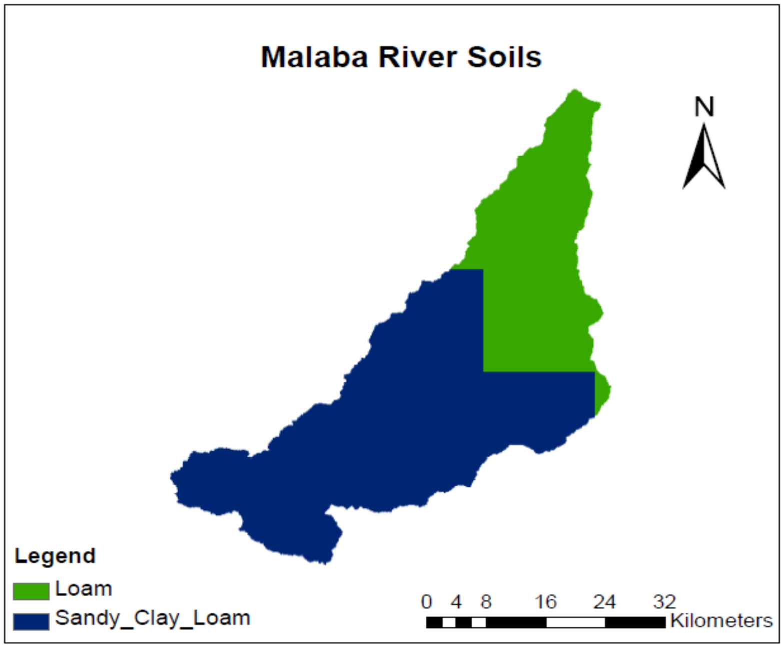


Figure 3. 8: Soil map of Malaba River catchment

Another observation from soil texture is that there is no pure sand in the sub-basin; therefore this suggests that possibilities of high level of channel erosion that is likely to change the channel dimensions are minimal.

iv. Slopes Map

The slopes were classified into four categories- 0 – 5, 5 - 15, 15 – 25 and 25 – 9999.

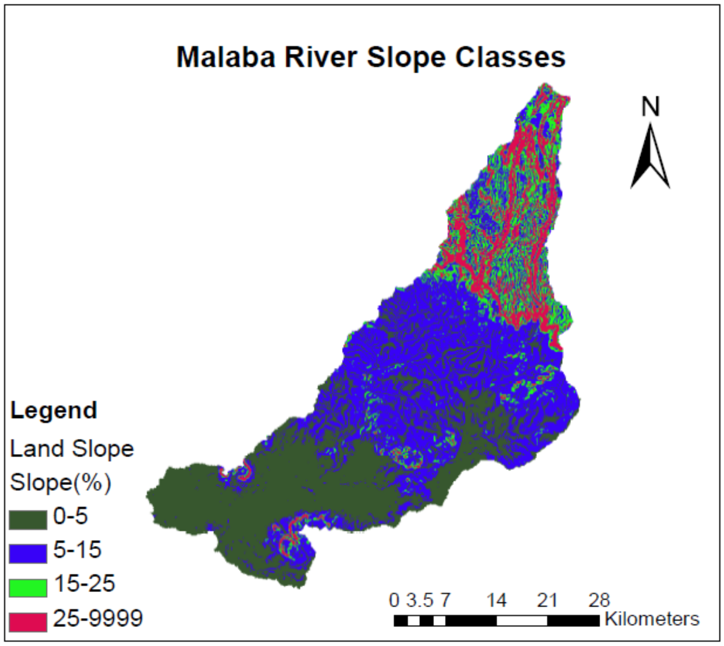


Figure 3. 9: Classes of slopes in Malaba River Catchment

It can be seen that the slopes are mostly within the 0 to 30 range.

Table 3. 4: Percentage (%) of the different slope ranges

Sn	Slope Range	Area (Km^2)	Percentage (%)
1	0-5	613.22	40%
2	5-15	638.24	42%
3	15-25	144.80	10%
4	25-99	123.51	8%
	Total	1519.77	100%

v. HRU definition

The threshold percentages for the HRU definition were set as 20% land use, 10% soil and 20% slope. These are default thresholds suggested by SWAT manual. The threshold percentages are areas which SWAT considers (exceeding or equal) in order to form a HRU over the total area of the sub-basin. They are derived by looking at the distribution of land use, slope and soil within the sub basins.

3.8 SWAT Parameter Sensitivity Analysis and Calibration

The first step of calibration is to determine the parameters related to the process to be modelled. The second step is to determine how these parameters affect the processes being modelled. This is termed sensitivity analysis. Sensitivity analysis can either be local or global. Local sensitivity is when one parameter is changed at a time and global is when all values are changed at once. Between the two, global is better as one parameter depends on the other however; it needs a large simulation (Arnold *et al.*, 2012). Sensitivity analyses help to avoid over parameterization (Muys *et al.*, 2004)

The Malaba River Catchment's SWAT model was then executed to analyze the sensitivity of model parameters so that calibration could concentrate to the ones which affect the model flow behaviour. This sensitivity analysis used observed flow data in ArcSWAT.

Model calibration is a procedure of changing the parameters in the model in order to represent the characteristics of the catchment in the model. Calibration is either manual, automatic or semi-automatic. Manual calibration is laborious when there are many parameters (Arnold *et al*., 2012). However it can be used to refine calibration.

Auto calibration depends on the upper and lower limits parameters and it is powerful in SWAT when combined with manual calibration.

3.8.1 Model Calibration

Calibration and validation for SWAT 2009 was done outside the ArcSWAT model. SWAT Calibration Uncertainty Procedure (SWAT-CUP) was therefore used. SWAT-CUP links SWAT to the following procedures; Sequential Uncertainty Fitting (SUFI-2), Parameter Solution (ParaSol), Generalized Likelihood Uncertainty Estimation (GLUE), Markov chain Monte Carlo (MCMC) and Particle Swarm Optimization (PSO). SUFI-2 and GLUE account for uncertainties in driving variables (rainfall), conceptual model parameters and measured data and ParaSol and MCMC account for model parameter uncertainty (Arnold *et al.*, 2012). MCMC is the most complicated procedure of them all and requires a lot of simulations (Abbaspour, 2015). In Parasol, Shuffle Complex (SCEUA) algorithm is used to minimize the difference between observed flow and simulated flow (Lo and Koralegedara, 2015).

In the current study, the model warm up period is 4 years (1988-1991) and the calibration period is from 1992 to 1999 and the validation period is from 2000 to 2004. The commonly used optimization objective functions are Nash-Sutcliffe Efficiency (NSE), Root Means Square Error (RMSE) and Percentage bias (PBias) and coefficient of determination (R^2). However, Moriasi *et al.* (2007) recommend three statistics coefficients; NSE, PBias and RMSE. These are statistical tests to check the relationship between the observed and the simulated stream flows. Moriasi *et al.* (2007) propose NSE be above 0.5 for hydrologic and pollutant evaluations on both daily and monthly time step.

3.8.2 Validation

Validation is a process of checking whether the calibrated model can reproduce sufficient simulations. Similar statistical functions used in calibration to determine model efficiency were also used for validation. It was done by time series dataset which were not used in calibration. Arnold *et al.* (2012) suggests that both datasets used for calibration and validation should include wet and dry years but this is not possible to achieve. However, Santhi *et al.* (2008) recommends the wet period used for calibration to have high runoff events. Currently, there are no guiding principles for separating data for calibration and validation but guidelines should take into account the minimum length of period required for calibration and validation. The validation was done from 2000 to 2004 using same parameters obtained from calibration step.

3.8.3 Uncertainties

There are three sources of uncertainties associated with hydrologic modelling and these are; uncertainties in the observed data, data used in calibration and finally data used in the conceptual model and model parameters.

In SUFI-2 the uncertainties are quantified by the *p-factor* which is the percentage of data bracketed by the 95% prediction uncertainty (95 PPU). The 95 PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable, disallowing 5% of the very bad simulations (Abbaspour *et al.*, 2015).

Another factor used to quantify the uncertainty is the *r-factor*, which is the average thickness of 95% probability band. SUFI-2 attempts to bracket most of the measured data with the smallest *r-factor* variable (Abbaspour *et al.*, 2015). When the *r-factor* and *p-factor* are within required limits, other statistical analysis can be used to further check the consistency between the measured and observed reading.

3.8.4 SWAT Model Key Equations

a) Potential Evapotranspiration (PET)

The potential evapotranspiration (PET) was calculated using the Hargreaves method because data is readily available. The equation used was;

$$\lambda E_0 = 0.0023 \text{ x } H_0 \text{ x } (T_{mx} - T_{mn})^{0.5} \text{ x } (T_{av} + 17.8) \quad (3.8)$$

Where: λ is the Latent heat of vaporization (MJ Kg^{-1})

E_0 is the Potential Evapotranspiration (mmd^{-1})

H_0 is extraterrestrial radiation (MJ m^{-2} d^{-1})

T_{mx} is maximum temperature for a given day (^0C)

T_{mm} is minimum temperature for a given day (^0C)

T_{av} is mean air temperature (^0C)

b) Surface runoff generation

The SCS curve number equation was used to estimate the amount of runoff under the varying landuse and soil types. The SCS equation is;

$$Q_{surf} = \left(\frac{Rday - 0.25}{Rday + 0.85}\right)^2 \quad (3.9)$$

Where: Q_{surf} is accumulated runoff (mm)

R_{day} is rainfall depth for the day (mm)

c) Water balance

This equation is behind all the processes that occur in the watershed (refer to page 21).

d) Surface runoff routing

This equation was used to calculate the amount of surface runoff that is discharged into the main channel.

$$Q_{surf} = (Q^1_{surf} + Q_{stor}) \times (1 - \exp(\frac{-surlag}{Tconc})) \qquad (3.10)$$

Where: Qsurf is the amount of surface runoff discharged to the main channel (mm)

Q^1_{surf} is the amount of surface runoff generated in the subbasin (mm)

Q_{store} is surface runoff stored or lagged from the previous day (mm)

Surlag is the surface runoff lag coefficient

T_{conc} is time of concentration for the subbasin

e) Water Balance of the reach

This equation was used for the water storage in the reach at the end of the time step.

$$V_{stored2} = V_{stored1} + V_{in} - V_{out} - t_{loss} - E_{ch} + div + V_{bnk} \qquad (3.11)$$

Where; $V_{stored2}$ is volume of water in the reach at the end of time step (m^3)

$V_{stored1}$ is volume of water in the reach at the beginning of time step (m^3)

V_{in} is volume of water flowing into the reach during the time step (m^3)

V_{out} is volume flowing out of the reach during the time step (m^3)

E_{ch} is evaporation from the reach for the day (m^3)

d_{iv} is volume of water added or removed from the reach for the day through diversion (m^3)

V_{bnk} is volume of water added to the reach via return from the bank storage (m^3)

t_{loss} is the volume water lost through transmission (m^3)

3.9 Analysis of Simulated Surface Flow for Climate Scenarios

This was achieved by comparing the simulated surface flow of the A1B and A2 scenarios for period of 2020-2050 with the baseline period.

3.9.1 Selection of Baseline Period

According to the World Meteorological Organization, a baseline period for any climate change studies should be of atleast 30 year period. Unfortunately observed data for both flow and climate is not sufficient for all the stations in the Malaba river catchment for conducting climate change studies. Therefore observed climate data was used to create synthesized data using LARS-WG which was used to simulate surface flow for 1986-2015 period.

The 30 year period used in this analysis will be fitting to signify the impact of climate change because the variability of water availability within a decade is not only impacted by climate change within that decade, but also the decade before.

3.9.2 Analysis by Changes

The time series of projected climate for each scenario was analysed for changes against a baseline period of (1986-2015). The changes were done on a monthly basis using Microsoft excel. This was mainly to determine whether there is a shift in the hydrological season.

3.9.3 Simulated Flow Variation Assessment

The simulated flow was analysed using Flow Duration Curve. Flow Duration Curve is a cumulative frequency curve that shows the percent of time during which specified discharges were equaled or exceeded in a given period. Therefore it was developed for flow variation assessment with daily flows for simulated flow (2020-2050) which was compared to the baseline flow period (1980-2015). To prepare the FDC, the daily flows for the respective period were ranked from the highest to the lowest flows during which the flow equaled or exceeded the specified percentiles was computed.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This section summarizes the results of this study and provides explanatory analysis to highlight key findings. These results were generated following the methods highlighted in Chapter Three. The results are first presented on a preliminary analysis of the metereological and hydrological nature of the study area. This was mainly to have a full understanding of the hydroclimatic trends for the period of 1992-2004 in Malaba river catchment.

The future climate variables (rainfall and temperature) of the study area were projected for the period 2020-2050 for A1B and A2 climate scenarios using the three randomly selected GCMs from LARS-WG model i.e. HADCM3, HADGM and EMPH5. SWAT model was used to simulate streamflow of the projected climate in the respective climate scenarios.

For investigating hydroclimatic trends for both baseline analysis and projected period, the non-parametric Mann-Kendall method was used to test the existence of a trend in the annual time series. Sen's slope estimator was also applied to estimate the magnitude of the trend. This was attained by the application of trend analysis software and statistical template, Makessens 1.0 developed by the Finnish Metereological Institute (FMI).

4.2 Baseline Analysis

4.2.1 Rainfall Seasonality Analysis

Figure 4.1 shows bimodal rainfall patterns for both Tororo and Bungoma stations. Tororo station registers April and May as the wettest months with mean monthly rainfall of approximately 200 mm followed by October and November. The long rains are received between March and May while the short rains are received between October and November.

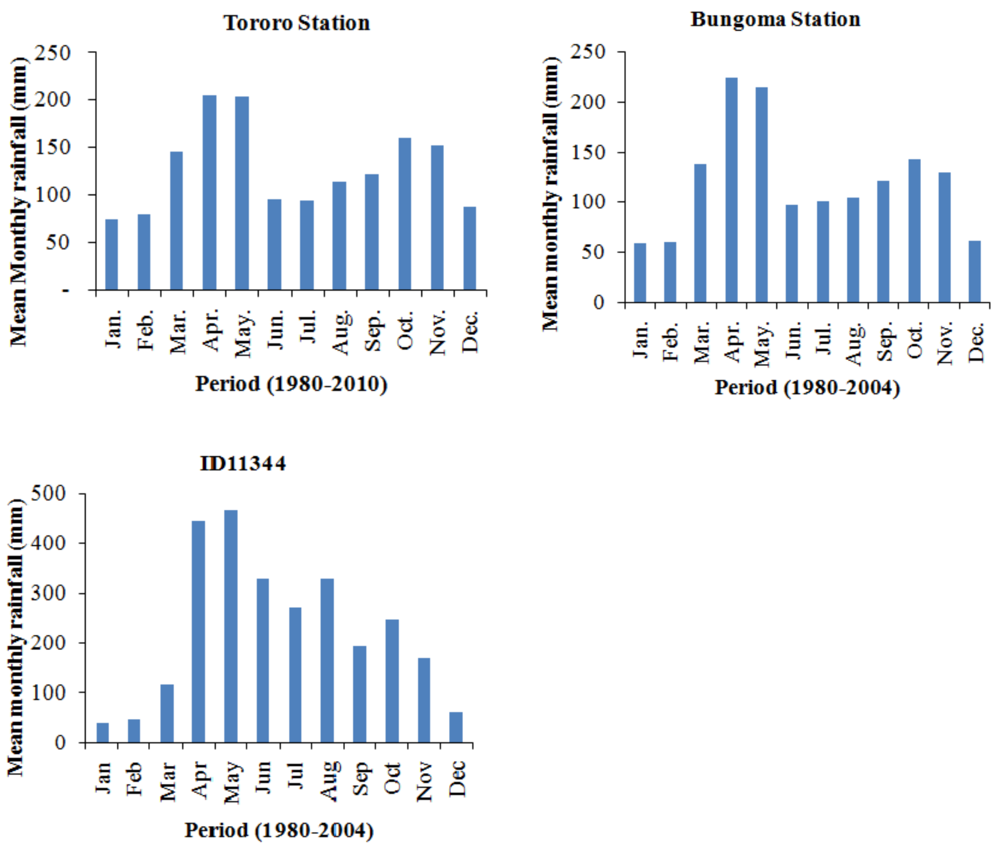


Figure 4.1: Mean Monthly Rainfall for stations in Malaba River catchment

ID11344 station displays a bimodal rainfall patterns with the wettest month being registered in May and April and the short rains being registered in January and February.

Bungoma station is located on the Kenyan side of the study area. It displays a mean monthly rainfall of approximately 84 mm. It has an annual rainfall of approximately 1440 mm which is 84 mm less than what Tororo contributes. April and May are the wettest months with a mean monthly rainfall of approximately 225 mm. The long rains are received between March and May while the short rains are received between October and November. Therefore the rainfall registered at the Tororo and Bungoma stations displays an almost similar pattern with a difference in received rainfall.

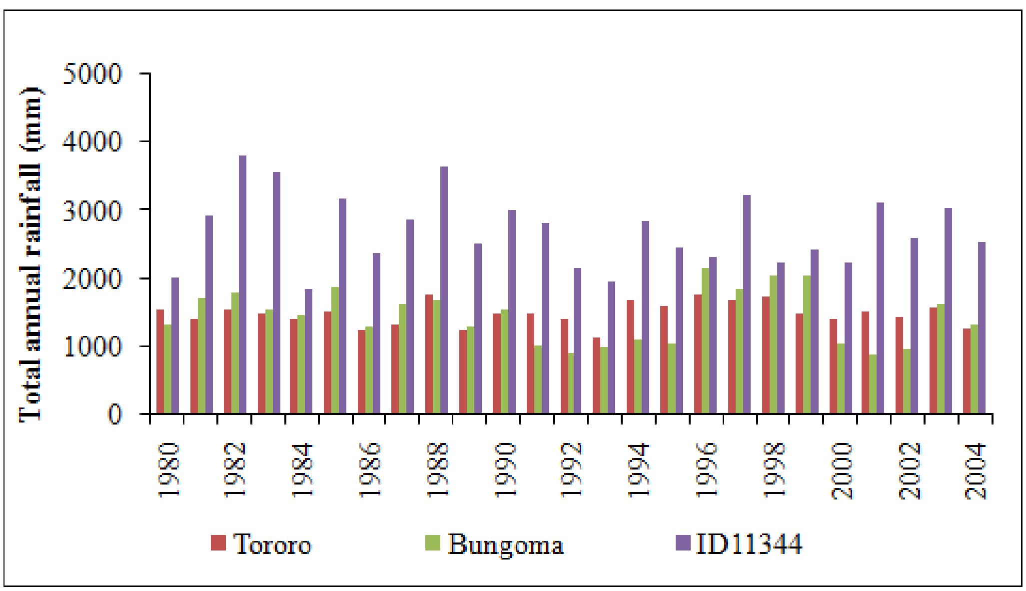


Figure 4.2: Total annual rainfall for stations

Figure 4.2, displays that ID11344 station has a higher total annual rainfall as compared to Bungoma and Tororo station. This is attributed to the fact that it is satellite data and not observed rainfall data. Bungoma station displays a higher annual rainfall in 1981-82, 1985, 1996-1999 as compared to Tororo station and Tororo station displays a higher annual rainfall in 1991-1995 and 2000-2002.

4.2.2 Areal Rainfall

Table 4.1, displays the weighted area of each rainfall station in Malaba River catchment. Mbale station was not included in the calculation of the areal rainfall because it had 85% of missing data and also because it didn't share the same common period (1980-2004) as the other two stations. It was however replaced with SWAT station (ID11344) whose study period is from 1980-2004

Table 4. 1: Rainfall contribution area of the stations

No.	Stations	% of Rainfall area contribution
1	Tororo	56
2	Bungoma	17
3	ID11344	27

Therefore the calculated annual mean areal rainfall (1980-2004) is 1,751.69 mm for the three stations.

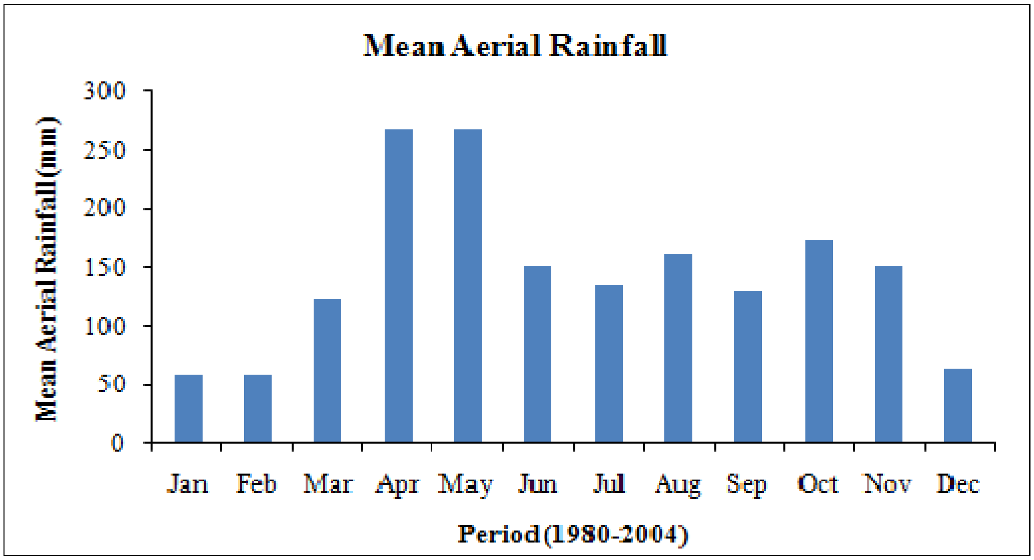


Figure 4.3: Mean areal rainfall of Malaba River Catchment

Figure 4.3, displays that the catchment has a bimodal rainfall pattern with a mean monthly rainfall of approximately 110 mm. The long rains are received between April and May while the short rains are received between December and February.

4.2.2 Data Trend Analysis

Annual rainfall data for Tororo station (1980-2010), Bungoma station (1980-2004), ID11344 (1980-2004), Mean Areal rainfall (MAR) (1980-2004) and flow data (1992-2004) was tested for trend to investigate the existence of a long term trend in the basin and the magnitude through Mann-Kendall and Sen's slope estimator respectively. The tests were done at 5% level of significance and the results are presented in Table 4.2.

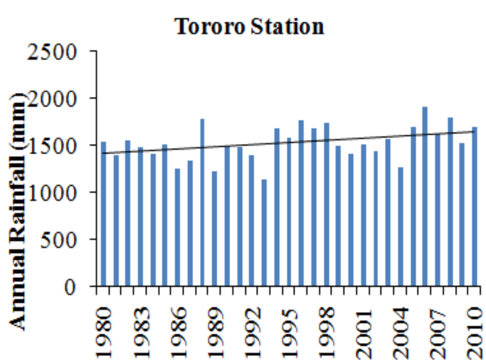
Table 4.2: Trend results for annual rainfall and flow for Malaba River catchment

Station	N (years)	Mann-Kendall	Sen's slope	Trend
Tororo	30	+	0.470	1
Bungoma	24	-	0.489	0
ID11344	24	-	0.087	0
MAR	24	+	1.632	0
Flow gauge	22	+	1.523	1

Note; (+) Mann-Kendall - Increasing trend, (-) Mann-Kendall – Decreasing trend, 1 – Significant trend, 0 – Non significant trend

The above results were illustrated in Figures 4.4-4.7, fitted with trendlines.

a) Rainfall



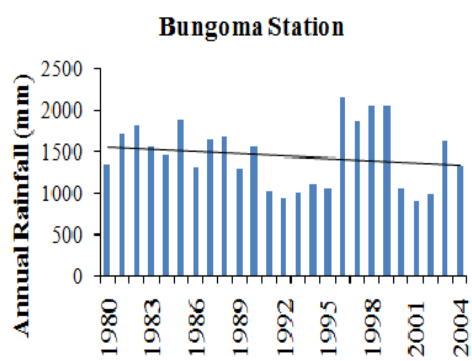


Figure 4.4: Annual rainfall variations of Tororo and Bungoma stations

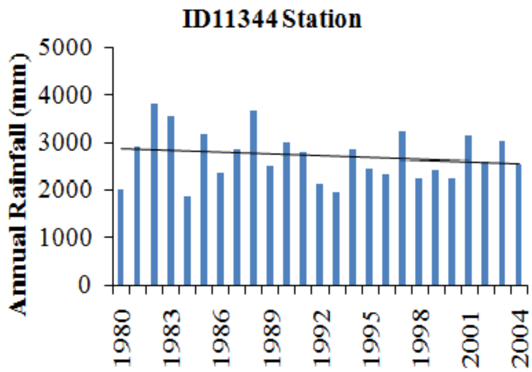


Figure 4.5: Annual rainfall variation for ID11344 stations

From Figure 4.4 and 4.5, the annual rainfall has a significant increasing trend at a rate of 0.47 mm per year for Tororo station. Bungoma and ID11344 stations have no significant decreasing trends at a rate of 0.489 mm per year and 0.087 mm per year respectively.

b) Areal rainfall

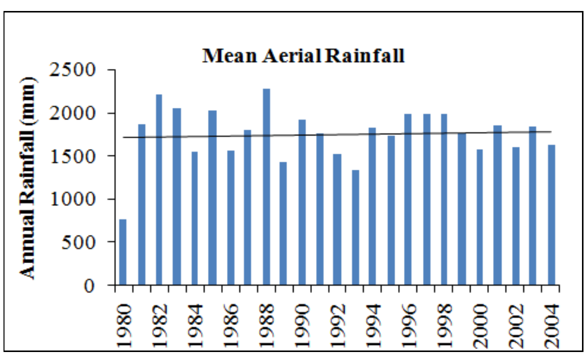


Figure 4.6: Annual areal rainfall trend for Malaba River catchment

Figure 4.6, displays that the lowest annual areal rainfall was received in 1980 and the highest in 1988 with 769 mm and 2269 mm respectively. The annual rainfall has a non significant increasing trend at a rate of 1.632 mm per year.

c) Stream flow

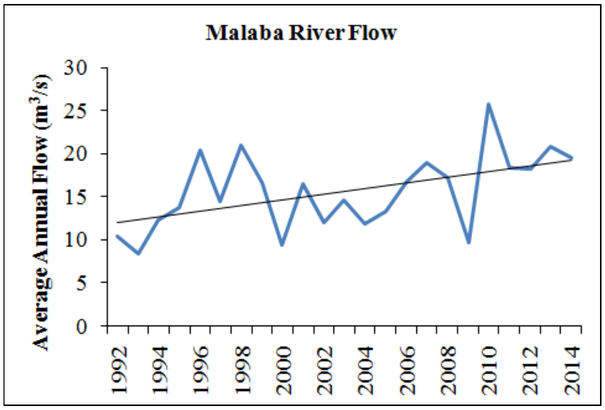


Figure 4.7: Annual stream flow for Malaba River

Figure 4.7, displays that the lowest flow was registered in 1993 and highest in 2010 with 8.4 m^3/s and 25.7 m^3/s respectively. Malaba River has a significant increasing trend magnitude of 1.523 m^3 annually. This therefore suggests that the increasing mean areal precipitation explains the increasing trend of the streamflow.

4.2.3 Stream Flow Response to Rainfall

To understand the influence of climate change on streamflow, an investigation of the stream flow response to historic climate was carried out. A common time period for the streamflow and climate data was chosen i.e. 1992-2004. To illustrate this response, rainfall and stream flow data was pre-processed to mean monthly time series. In producing visualizations of the data, Microsoft Excel was used.

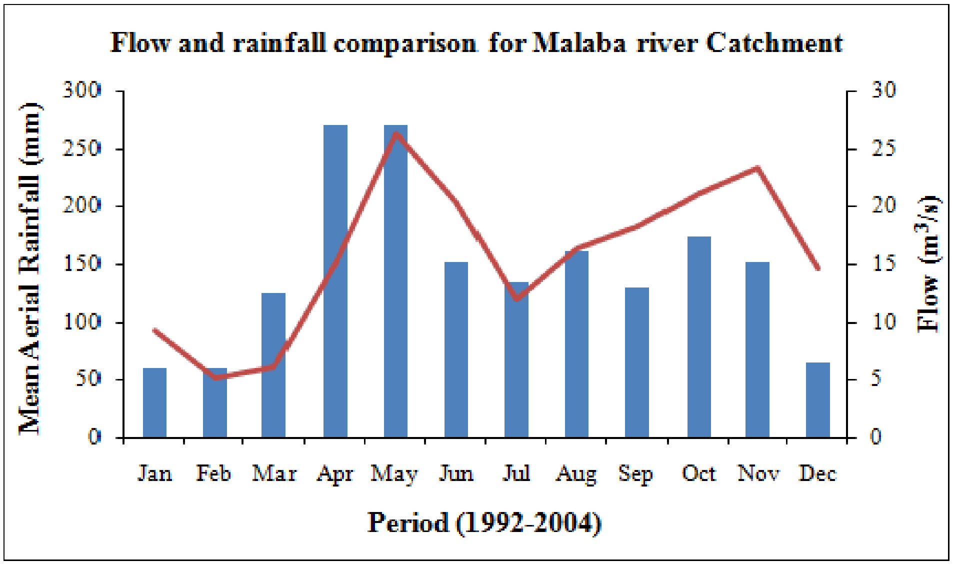


Figure 4.8: Stream flow response to mean areal rainfall from 1992-2004

From Figure 4.8, it is displayed that when there is an increase in rainfall, the stream increases too. However, it can be seen that there is slight lag time in streamflow response to rainfall and this can be attributed to other factors such as land use. It can be concluded that indeed fluctuations in rainfall have an impact on streamflow therefore the historic climate change has contributed to fluctuations in stream flow.

4.3 Projection of Climate Change Variables for Malaba River catchment (2020-2050)

4.3.1 Weather Generation

It is common to find gaps in weather data and this arises from many causes. LARS weather generator was used to fill gaps for Tororo (rainfall) and Mbale (temperature) stations data before any projection could be done. The daily rainfall data for Tororo (1980-2004) was used for the model input and 30 years of synthetic data were generated. The daily maximum and minimum temperature for Mbale station only was generated for 30 years and taken as a representation for the whole catchment. Comparisons between the observed and simulated data were based on the monthly statistics such as mean difference and variance. The ability of LARS-WG model to generate rainfall and temperature time series under limited data is discussed below. Table 4.3 and 4.4 show output data from the statistical tests, showing the comparison of the observed & simulated data and variances with those of 30 years of synthetic data generated by LARS-WG for Tororo, Mbale and Bungoma stations.

Table 4. 3: Rainfall for Tororo, Mbale and Bungoma stations

Months	J	F	M	A	M	J	J	A	S	O	N	D
Tororo												
Obs.mean	90	79	142	219	193	78	76	126	113	160	164	86
Obs.var	58	71	52	81	65	44	44	5	48	66	72	71
Sim.mean	93	73	152	249	162	82	76	122	131	172	180	75
Sim.var	59	48	54	79	60	39	34	68	44	76	87	52

Note; Obs-Observed data, Sim-Simulated data, var-variance

Table 4. 4: Temperature for Mbale station

Maximum temperature for Mbale station												
Months	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Obs.mean	31	32	31	29	29	29	28	28	29	29	29	30
Obs.var	0.5	0.6	0.4	0.5	0.2	0.2	0.2	0.3	0.2	0.3	0.3	0.5
Sim.mean	31	32	31	29	29	28	28	28	29	29	29	30
Sim.var	0.4	0.5	0.4	0.4	0.2	0.2	0.2	0.2	0.2	0.2	0.4	0.5
Minimum Temperature												
Months	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Obs.mean	17	17	17	18	18	17	17	17	17	17	17	17
Obs.var	0.2	0.3	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
Sim.mean	17	17	17	18	18	17	17	17	17	17	17	17
Sim.var	0.2	0.2	0.1	0.2	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3

Note; Obs-Observed data, Sim-Simulated data, var-variance

It can be seen from the above table that both the mean and variance of the daily observed and simulated data are in close range hence LARS-WG generated good time series data. Therefore LARS-WG was used to fill the daily data gaps observed at Tororo and Mbale stations in (1980-2004) time period. The variance which indicates the deviation and the mean for the central value of the monthly data was obtained for both the observed and simulated data. The above data was further summarized in graphs for proper visualization and analysis. The Figures 4.8-4.9 display the comparisons of observed and simulated mean and variance for rainfall, maximum and minimum temperature for the three stations.

a) Rainfall

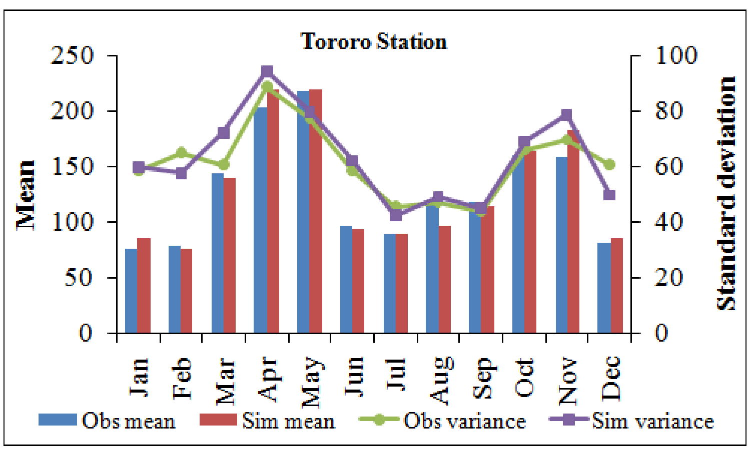


Figure 4.9: Comparison of the mean monthly rainfall at Tororo station

b) Temperature

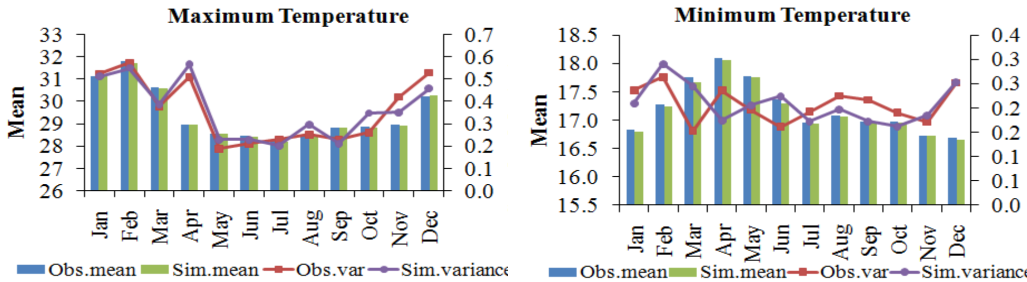


Figure 4.10: Comparison of the mean monthly temperature at Mbale station

4.3.2 LARS-WG Model Calibration and Validation

Statistical tests were created after the site parameters were calculated. The statistical tests which are K-S test and p- test assess the ability of LARS-WG to generate variety of weather statistics accurately. If p-value is very low and below the significance level of 0.05, then the generated simulated climate is unlikely to be the same as the 'true' climate (Semenov, 2010). Table 4.5 presents the (K-S) and p-test results indicating the accuracy of LARS-WG model.

Table 4.5: Results from comparing observed and downscaled data

Type of data	Station	Parameters	K-S test	p-value	Accuracy
Observed (1980-2004)	Tororo	Rainfall	0.59	0.99	Good
	ID11344		0.05	1.00	Very good
	Bungoma		0.13	0.94	Good
	Mbale	Maximum Temperature	0.08	0.99	Good
		Minimum Temperature	0.08	0.99	Good
Downscaled (2020-2050)	Tororo	Rainfall	0.07	1.00	Very good
	ID11344		0.06	1.00	Very good
	Bungoma		0.11	0.92	Good
	Mbale	Maximum Temperature	0.07	1.00	Very good
		Minimum Temperature	0.06	1.00	Very good

Note; Fair-(0.05-0.1), Good-(0.1-0.8), Very good-(0.8 and above), for K-S and p-values

The above results from statistical tests were for a significant level of 5%. It can be seen from the above table that LARS-WG generated climate that is most likely to be the same as the 'true' climate. This is an indication of the suitability of LARS-WG for the climate downscaling in Malaba River catchment.

4.4 Generation of Future Climate Scenarios

From the above analysis, it can be concluded that LARS-WG model shows good performance in generating projected daily rainfall, maximum and minimum temperature.

In this study, the local-scale climate scenarios based on SRES A1B and A2 were simulated by the randomly selected three GCMs which are HADCM3, HADGEM and EMPH5 using LARS-WG (5.5) for the time period 2020-2050.

4.4.1 Selection of GCM

The gap filled data was compared with the downscaled data for each GCM and climate variable. R^2 (Coefficient of determination) was used to determine the accuracy of the GCMs in projecting the climate for period of 1980-2004.

Table 4.6: R^2 of the GCMs between observed and downscaled data

AIB Scenario			
Parameter	**HADCM3**	**HADGEM**	**EMPH5**
Rainfall	0.37	0.66	0.56
Maximum	0.39	0.46	0.53
Minimum	0.49	0.25	0.62
A2 Scenario			
Parameter	**HADCM3**	**HADGEM**	**EMPH5**
Rainfall	0.3	0.54	0.5
Maximum	0.45	0.55	0.56
Minimum	0.3	0.34	0.44

From Table 4.6, HADGEM has a higher correlation which is an indication that it has a good accuracy compared to the other GCMs in projecting rainfall while EMPH5 has good projection accuracy for temperature. Therefore HADGEM was used for projecting rainfall at all the stations and EMPH5 was used for projecting temperature.

4.4.1 Trend Analysis of Future Climate Scenarios

The trend of the projected climate variables of all the selected GCMs was determined using Mann-Kendall method and the Theil Sen's slope was used to determine the magnitude of the trend. The results of this analysis are based on the 5% significant level. The results of the trend analysis for the scenarios are summarized in Table 4.7 and Table 4.8.

a) Areal Rainfall

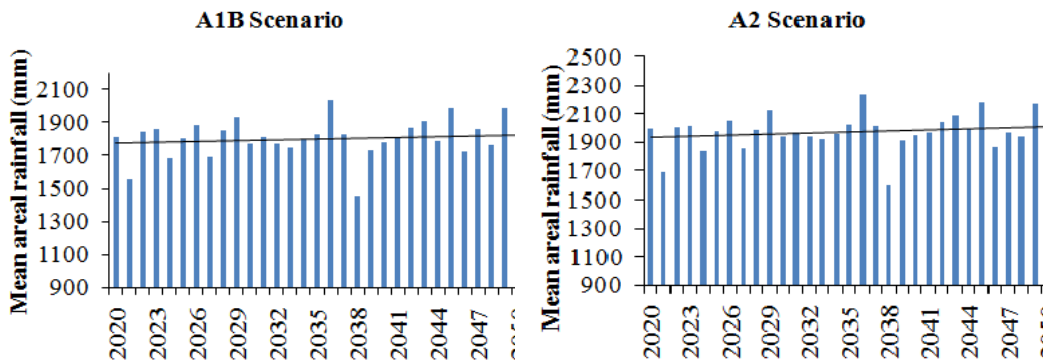


Figure 4.11: Trend in mean areal rainfall

From Figure 4.11, A1B scenario displays an increasing trend with magnitude of 0.34 mm per year and A2 scenario displays an increasing trend with magnitude of 0.408 mm per year.

b) Maximum Temperature

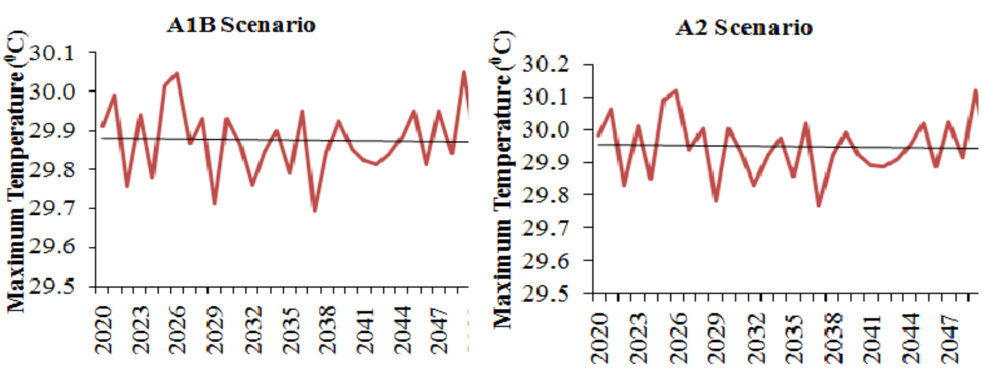


Figure 4.12: Projected annual maximum temperature of the Malaba River catchment

Figure 4.12 displays that both A1B and A2 scenarios display a non significant decreasing trend with magnitude of 0.004^{0}C.

c) Minimum Temperature

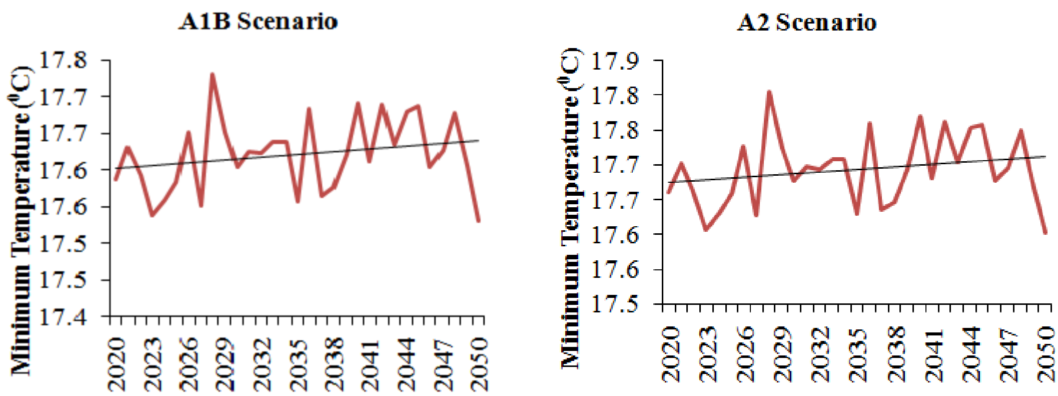


Figure 4.13: Projected annual minimum temperature of Malaba River catchment

Figure 4.13 displays that A1B scenario displays a non significant increasing trend with magnitude of 0.001^{0}C per year and A2 scenario displays a non significant increasing trend with a magnitude of 0.002^{0}C per year

Table 4.7: Trend analysis results for A1B climate scenario (2020-2050)

Climate variable	GCM	Mann-Kendall	Sen's slope	Trend
Aerial Rainfall	HADGEM	+	0.340	0
Maximum Temperature	EMPH5	-	0.004	0
Minimum Temperature	EMPH5	+	0.001	0

Note; (+) Mann-Kendall - Increasing trend, (-) Mann-Kendall – Decreasing trend, 1 – Significant trend, 0 – Non significant trend

Table 4. 8: Trend analysis results for A2 climate scenario (2020-2050)

Climate variable	GCM	Mann-Kendall	Sen's slope	Trend
Rainfall	HADGEM	+	0.408	0
Maximum Temperature	EMPH5	-	0.004	0
Minimum Temperature	EMPH5	+	0.002	0

Note; (+) Mann-Kendall - Increasing trend, (-) Mann-Kendall – Decreasing trend, 1 – Significant trend, 0 – Non significant trend

From the above results, rainfall for both scenarios displays an increasing trend. Rainfall has a significant increasing trend of at least a magnitude of 0.419 mm annually and temperature has an increasing non-significant trend of at least 0.001^{0}C annually.

4.4.2 Change Analysis of Future Climate Scenarios

The change in projected climate was determined by using the observed (1980-2004) as base period for both rainfall and temperature. Rainfall change was calculated in terms of percentage while temperature change was calculated in terms of absolute (^{0}c). The results which were calculated in Microsoft excel are displayed and explained below.

a) Rainfall

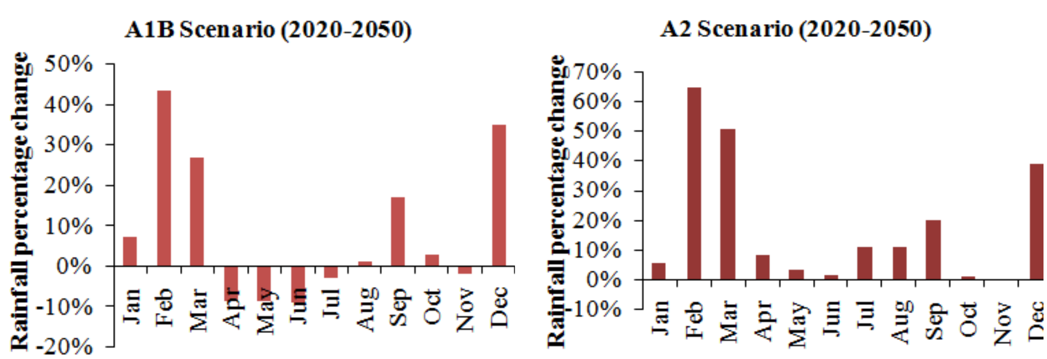


Figure 4.14: Average monthly changes in areal rainfall for Malaba River catchment

For A1B scenario, areal rainfall will increase by an average of 8% of the baseline monthly rainfall. For A2 scenario, areal rainfall will increase by an average of 18% of the baseline monthly rainfall (Figure 4.13).

a) Maximum Temperature

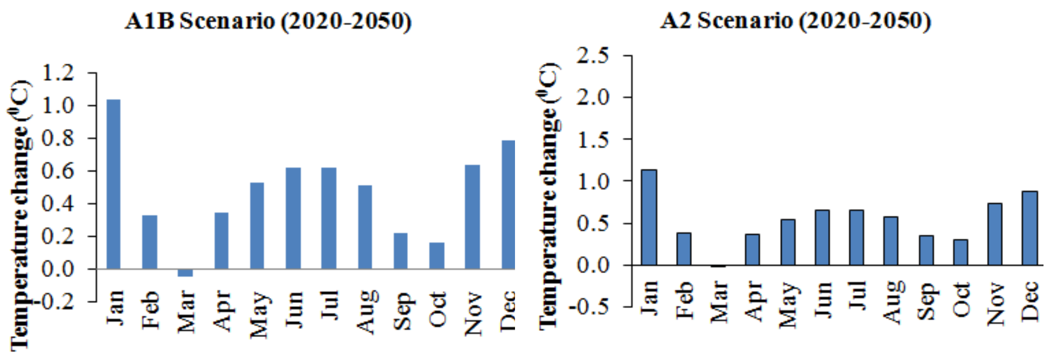


Figure 4.15: Monthly changes in maximum temperature for Malaba River catchment

For A1B scenario, maximum temperature will increase by atleast 0.2^{0}C monthly and for A2 scenario, maximum temperature will increase by atleast 0.3^{0}C monthly (Figure 4.15).

b) Minimum Temperature

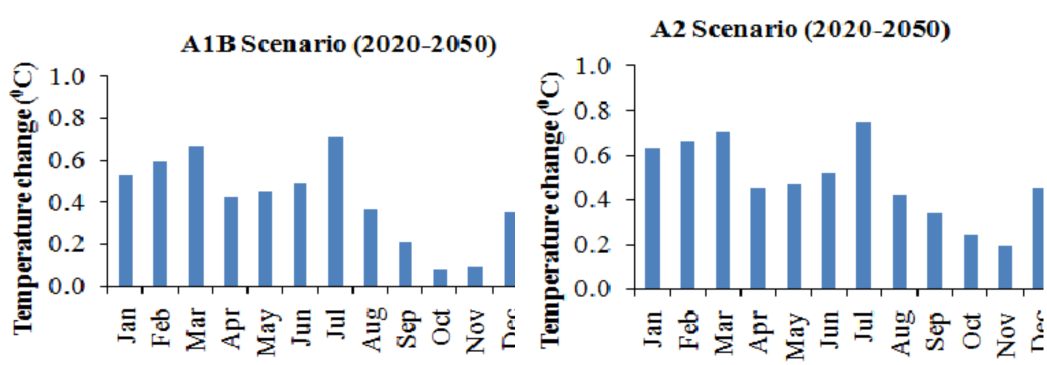


Figure 4.16: Monthly changes in minimum temperature for Malaba River catchment

For A1B scenario, minimum temperature will increase by 0.1^{0}C monthly and for A2 scenario, minimum temperature will increase by atleast 0.2^{0}C monthly (Figure 4.16)

Therefore areal rainfall in the catchment will increase significantly by approximately 2% per month and maximum and minimum temperature will not increase significantly.

These results are supported by Niang *et al.* (2014) which shows that precipitation in Uganda will decrease in the months of June and July by the end of the 21st century, this is as a result of weakening Somali jet and Indian monsoon. Jassogne et al. (2013) also stated an increasing trend in maximum and minimum temperature over the next 50 years starting from 2015.

4.5 SWAT Modelling

The SWAT model for Malaba River Catchment was built with a 90 m x 90 m DEM. The automatic delineation was carried out with an area of 6475.83 Ha and 15 sub basins and 83 HRU's were generated.

4.5.1 Sensitivity Analysis

For this study, a sensitivity analysis was done in SWAT using observed data for 1000 simulations. The 10 most sensitive parameters were used for calibration. The parameters are ranked from most to least sensitive

Table 4.9 displays that the most sensitive parameter is CN2 which is the initial SCS runoff curve number for moisture condition. It is responsible for runoff generation and depends on factors such as; soil type, soil texture, soil permeability, land use properties etc. The second most sensitive parameter is SURLAG which is the surface runoff lag time. It controls the fraction of the total water to get to the reach at any given day. The third sensitive parameter is ESCO which is the soil evaporation compensation factor. It allows for modifying the depth distribution used to meet the soil evaporation demand to account for the effect of capillary action. The forth sensitive parameter is Alpha_Bf which is the base flow alpha factor in days. The fifth most sensitive parameter is Ch_K2 which is the effective hydraulic conductivity in the main channel alluvium.

Table 4.9: Results of sensitivity analysis with observed flow

Sn	Parameter	Description	Rank
1	Cn2	SCS runoff curve number factor	1
2	Surlag	Surface runoff lag time (days)	2
3	Esco	Soil evaporation compensation factor	3
4	Alpha_Bf	Base flow alpha factor (days)	4
5	Ch_K2	Effective hydraulic conductivity in main channel alluvium	5
6	Ch_N2	Manning's value for the main channel	6
7	Sol_Awc	Available water capacity (mm H20/mm soil)	7
8	Blai	Max leaf area index	8
9	Gwqmn	Threshold water depth in the shallow aquifer for flow occur (mm)	9
10	GW_Revap	Groundwater "revap" coefficient	10
11	Canmx	Maximum canopy storage	11
12	Sol_Z	Depth from soil surface to bottom of layer	12
13	GW_Delay	Groundwater delay (days)	13
14	Slope	Average slope steepness	14
15	Sol_K	Saturated hydraulic conductivity (mm/hr)	15
16	Slsubbsn	Average slope length	16
17	Revapmn	Threshold water depth in the shallow aquifer for "revap" to occur (mm)	17
18	Biomix	Biological mixing efficiency	18
19	Epco	Plant uptake compensation factor	19
20	Sol_Alb	Moist soil albedo	20
21	Sftmp	Snowfall temperature	27
22	Smfmn	Minimum melt rate for snow during the year	27
23	Smfmx	Maximum melt rate for snow during the year	27
24	Smtmp	Snow melt base temperature	27
25	Timp	Snow pack temperature lag factor	27
26	Tlaps	Temperature lapse rate	27

4.5.2 Model calibration and Validation

The outlet station in sub basin 14, was calibrated using data from 1988-1999 (4 years for warm up). A given set of calibration parameter values were found to give a good simulated stream flow. The optimum calibration parameters are presented in Table 4.10

Table 4.10: Calibration Parameters

No	Parameter name	Fitted value	Min value	Max value
1	r_CN2	-0.247	-0.25	-0.17
2	v_SURLAG	30.75	30.30	38.20
3	v_ESCO	1.28	1.10	1.30
4	v_APLHA_BF	0.22	0.18	0.24
5	v_CH_K2	191.43	138.50	219.40
6	v_CH_N2	0.95	0.88	0.97
7	r_SOL_AWC	1.39	1.29	1.46
8	r_BLAI	0.277	0.27	0.36
9	v_GWQMN	3253.02	2771.20	3845.90
10	r_GW_REVAP	0.073	0.06	0.09
"v" means Replacement of the default parameter "r" means multiplication to default parameter				

The optimum value of the most sensitive parameter CN2 is small and this shows that the soils have high infiltration capacity and streamflow generation occurs only when the soils are saturated. The Nash Sutcliffe Efficiency (NSE) function was used as the optimization function during calibration with a minimum threshold for the behavioural solution at 0.5.

The calibration hydrograph presented in Figure 4.17, shows that the NSE is 55%, R^2 is 0.59, p-factor is 44% and r-factor is 0.57. The validation period was from 2000-2004. Figure 4.18 shows that the NSE is 35%, p-factor is 40% and r-factor is 59%.

The NS of the calibration is better than that one of validation and this could be attributed to some factors such as the spatial distribution of the rainfall stations and also the change in rainfall for the two data sets. LARS-WG was used for extension of the records and gap filling for the missing climate data hence this could have contributed to the low efficiency of the validation results.

The p-factor of validation is better than that of calibration but the band width is not very large. This could be attributed to uncertainities in input data or some processes which were not captured by the model. However the model captures the trend of the observed flow.

4.6 Projected Streamflow

The calibrated model was then used to simulate the stream flow in the catchment for 2020-2050 periods for both the A1B and B2 climate change scenarios. Figure 4.17 and Figure 4.18 show the relationship between the observed and simulated streamflow during the calibration and validation periods.

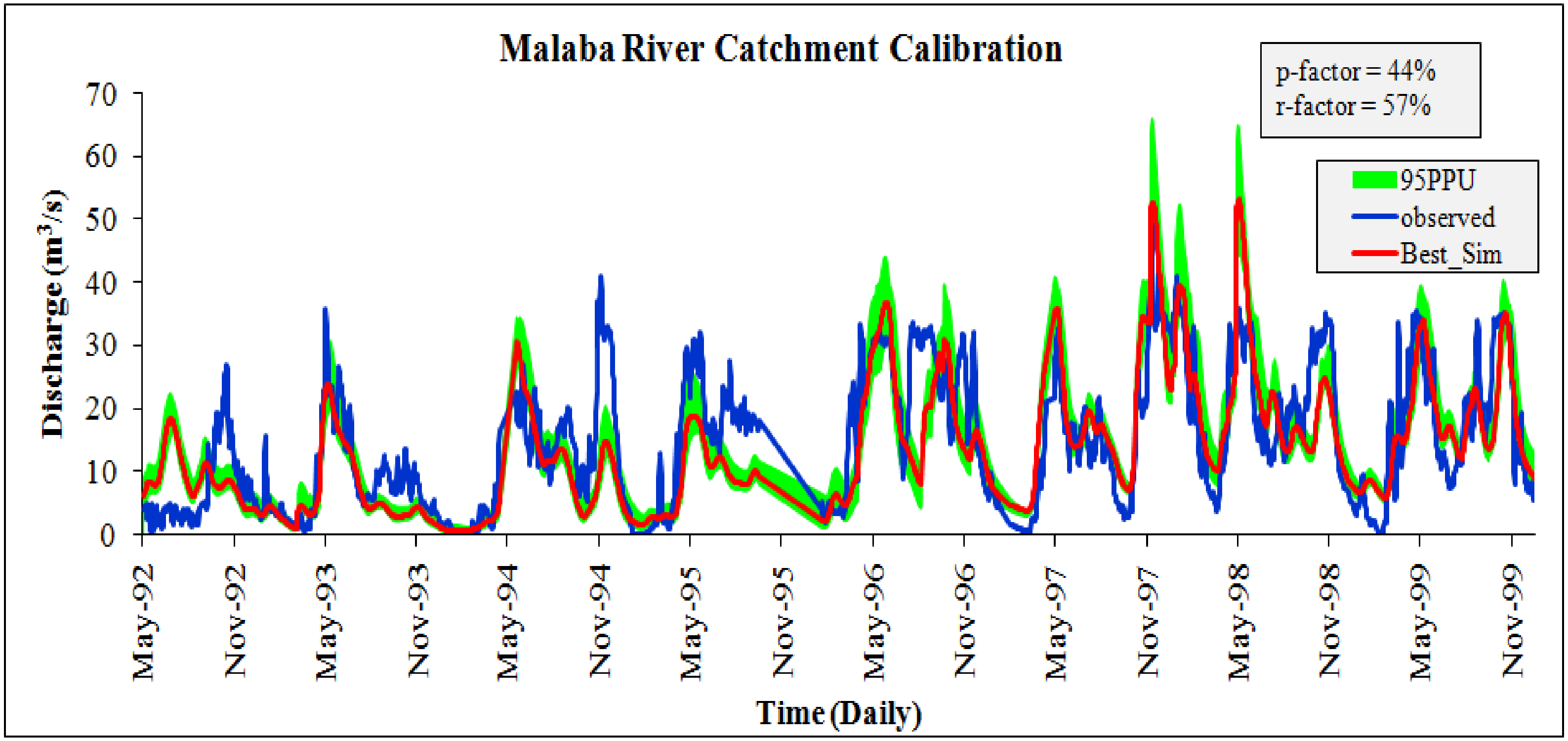


Figure 4.17: Streamflow of Malaba River during SWAT calibration period

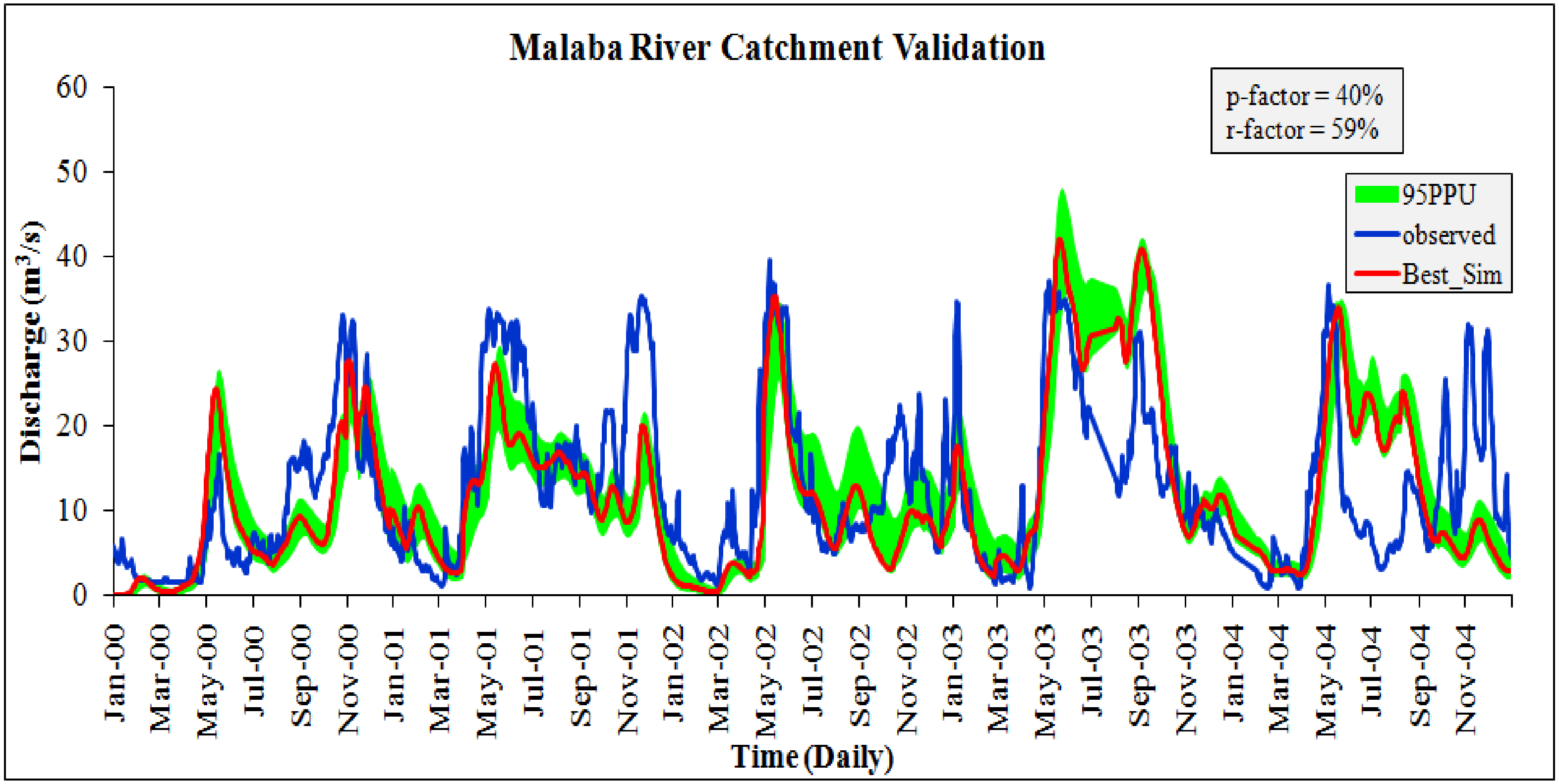


Figure 4.18: Streamflow of Malaba River during SWAT validation period

4.6.1 Analysis of Simulated Streamflow for Climate Scenarios

4.6.1.1 Selection of Flow Baseline Period

LARS weather generator was used to extend the observed weather data for the three stations i.e. Bungoma and Tororo. Daily rainfall data for Tororo and Bungoma stations (1980-2004) were used for the model input and 35 years of synthetic data were generated. The representative generated 35 years of daily temperature for Mbale station were taken as a representative for the whole catchment. Comparisons between the observed and simulated data are based on the monthly statistics such as mean difference and variance (Table 4.11).

Table 4.11: Rainfall for Bungoma and Tororo stations

	Bungoma Station											
	J	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Obs mean	60	58	136	225	216	96	96	99	116	147	126	59
Sim mean	70	51	119	232	203	110	105	106	120	152	124	46
Obs var	52	46	89	76	93	48	49	45	61	80	65	45
Sim var	54	40	84	65	87	47	50	43	68	77	66	42
	Tororo Station											
	J	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Obs mean	76	79	143	203	217	97	89	115	118	159	159	81
Sim mean	85	76	139	219	219	93	89	96	113	163	183	85
Obs var	58	65	61	89	78	58	46	47	44	66	70	61
Sim var	60	58	72	95	80	62	42	49	45	69	79	50

Note; obs-observed data, Sim-simulated data, var-variance

From Table 4.11, both the mean and variance of the observed and simulated data are in close range hence LARS-WG generated times series data that is similar to observed data. Therefore, LARS-WG was used to extend the rainfall time series data for both Bungoma and Tororo stations. The results were further summarized in graphs for proper visualization. The Figure 4.19 displays the comparisons of observed and simulated mean and variance for rainfall.

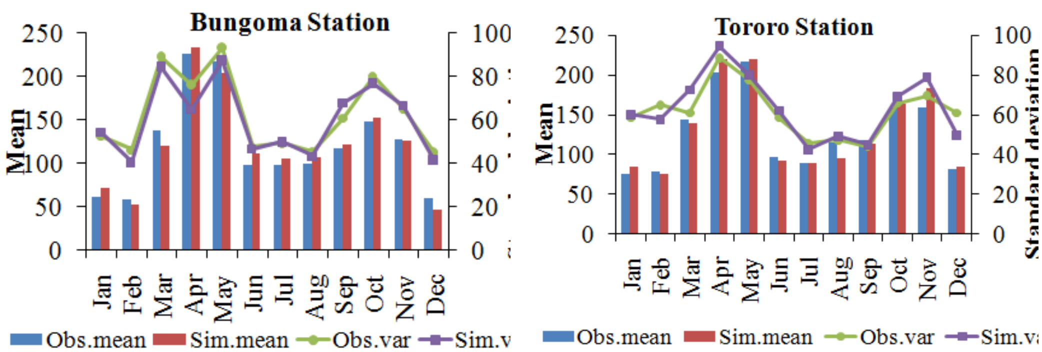


Figure 4.19: Comparison of observed and simulated rainfall at rainfall stations

4.6.1.2 Trend Analysis of Streamflow

The trend of the projected climate variables for all the selected GCMs was determined using Mann-Kendall method and the Theil Sen's slope was used to determine the magnitude of the trend. The results of this analysis are based on the 5% significant level.

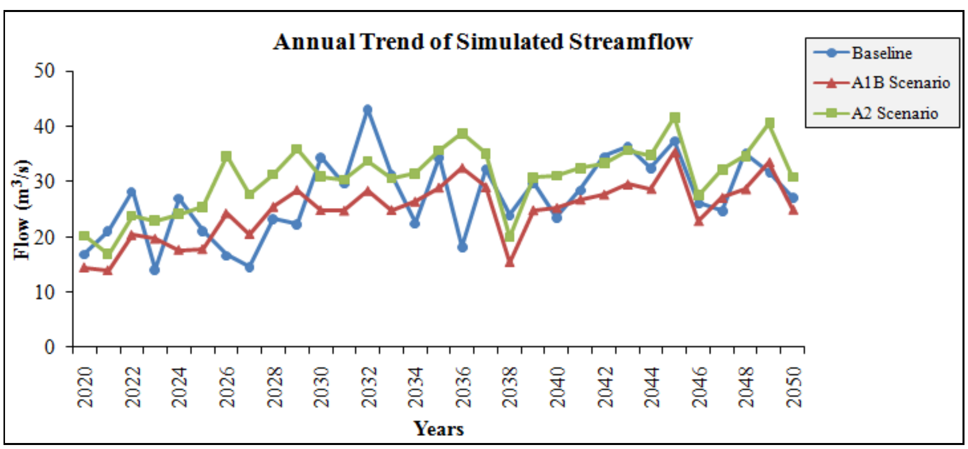


Figure 4.20: Trend of simulated streamflow for A1B and A2 scenarios

Figure 4.20 displays that simulated surface flow for A1B scenario has an increasing annual trend of 0.243 m^3/s and A2 scenario also has an increasing annual trend of 0.264 m^3/s.

4.6.1.3 Change Analysis of Simulated Streamflow

The main aim of determining the monthly changes was to determine whether there would be a shift in seasonality of flow. The analysis of projected changes in Malaba River includes the bais of the climate model that are contained in the models outputs. But since climate models biases exist in the projected data and also the baseline, the comparison of projected future discharge to the baseline is still viable in evaluating the impact of climate change on the changing river discharge.

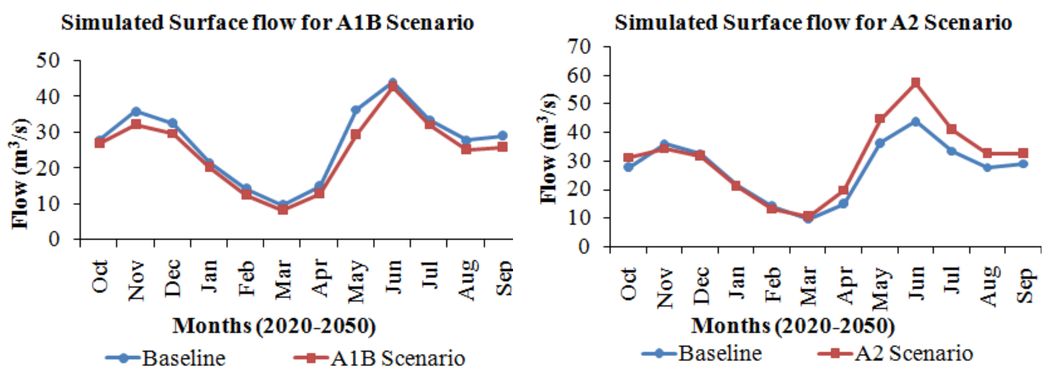


Figure 4.21: Change analysis of simulated flow for A1B and A2 Scenarios

From Figure 4.21, simulated surface flow of A1B scenario follows the trend of the baseline period with the high flows being in June and low flows being in March. But the A1B displays monthly low flows as compared to the baseline with an average of $2.3m^3/s$.

For the A2 scenario, the simulated surface flow follows the trend of the baseline period. The simulated surface flow has highest flows in the month of June and the lowest flows in the month of March. However, the simulated surface flow is higher than the baseline period by an average of 3.5m^3/s monthly.

4.6.1.4 Simulated Flow Variation Assessment

FDC was developed for both the observed (1980-2010) and SWAT simulated flow (2020-2050 for both A1B and A2 scenarios) for comparison purposes. The FDCs were presented in one graph as shown in Figure 4.22, showing the flow percentile exceedence. Also, the percentile exceedence of very high flows (Q_5), median flow (Q_{50}) and very low flows (Q_{95}) are summarized in Table 4.21. In the table additionally there is Q_{25} and Q_{75}.

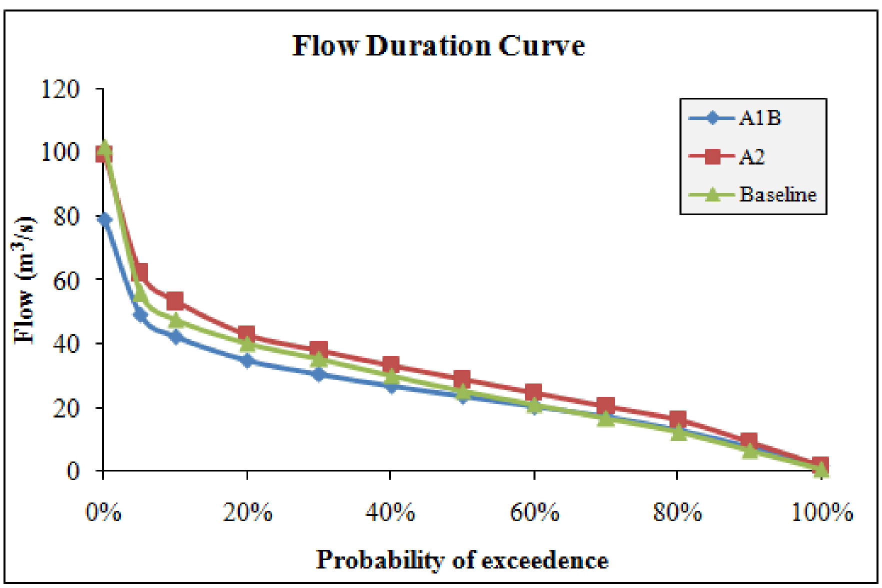


Figure 4.22: Simulated flow variations by flow duration curves

Table 4.12: Flow variations from FDC for the selected percentiles

No.	Percentile exceedence	A1B scenario	A2 scenario	Baseline
1	5%	49.4	62.3	55.9
2	25%	32.7	40.3	38.0
3	50%	23.7	28.8	25.4
4	75%	15.4	18.6	14.6
5	95%	5.1	6.5	3.8

From Figure 4.22 and Table 4.12, A1B scenarios has lower flows for percentiles less than 50 and equal or slightly higher flows for percentiles greater than 50 as compared to the baseline flows. A2 scenario has higher flows for all the percentiles as compared to the baseline flows. Therefore this means that higher floods are to occur and the lower flows will increase in A2 scenario as compared to the baseline period. Higher median flows are to also occur in the A2 scenario.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

LARS weather generator was used to gap fill observed data and also to project the climate variables of the catchment based on observed data. A hydrological model, SWAT was used to simulate streamflow from projected climate. Irrespective of insufficient observed data, the SWAT model proved to be applicable in Malaba River catchment. This study has revealed outcomes in the assessment of climate change on streamflow of Malaba River Catchment. The following are the important findings.

An analysis was carried out on the hydroclimatic variables in the study area and the results showed that fluctuations in rainfall have an impact on streamflow. Therefore the historic climate change has contributed to fluctuations in stream flow. The climate of the catchment was projected and both the mean areal precipitation and temperature showed an insignificant increase for A1B and A2 scenarios. The monthly areal rainfall for A1B scenario is 1% less than the one for baseline period while for the A2 scenario it is 9% more than the value for baseline period. The SWAT model was successfully calibrated (1992-1999) with a NSE of 55%, R^2 of 0.59, p-factor of 44% and r-factor of 0.57. The validation period was from 2000-2004 with NS of 35%, p-factor of 40% and r-factor of 59%.

The simulated streamflow for A1B scenario is averagely 2.3 m^3/s less than the one for baseline period per month whereas for the A2 scenario, it is averagely 0.1 m^3/s more than the value baseline period per month.

It is therefore concluded that the A2 scenario is most likely going to be experienced which will impact on the surface water flow of Malaba River. The simulated flow will start to increase from April and reach its peak in June which is 13.3 m^3/s higher than the value of baseline period and gradually decrease till it intersects with the baseline period in November. The flow from November to March is similar to the baseline period with March having the lowest flows.

5.2 Recommendations

From this study, I the author, propose some issues which limited the study undertaking in one way or another.

The accuracy of SWAT model can be improved by ensuring data quantity and quality of the measured hydroclimatic variables such as rainfall, temperature and flow. Therefore the Ministry of Water and Environment, Uganda should maintain the equipment used for measuring the hydroclimatic variables to minimize on the data gaps.

A higher NSE of 0.8 for the calibration period for Malaba River catchment should be attained to determine whether a NSE higher than 0.5 for the validation period can be attained.

Also, the simulated flows did not take into account the current or growing water demands. Therefore, a research on the water availability for all water users in Malaba River catchment is proposed. It is clear that the changing climate has impacts on the streamflow of Malaba River; therefore the Directorate of Water Resources Management, Uganda must address these issues within an integrated framework. The Ministry of Water and Environment Uganda should also carry out a study on how the Land use change within the catchment impacts the streamflow.

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REFERENCES

Abbaspour, K. (2015), SWAT-Calibration and uncertainty programs User Manual, Swiss Federal Institute of Aquatic Science and Technology.

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., Van Griensven, A., Liew, M.W., Kannan, N., and Jha, M.K. (2012), SWAT Model Use, Calibration, and Validation Journal of Hydrology, Volume 55, No.4, pp 1491–1508.

Barker, T. (2007), An Assessment of the Intergovernmental Panel on Climate Change, Spain.

Bates, B.C., Kundzewics, Z., Wu, S., and Palutikof, J. (2008), Intergovernmental Panel on Climate change. Report on Climate Change and Water, p 210.

Cayan, D.R., Maurer, E., Dettinger, M., Tyree, M., and Hayhoe, K. (2007), Climate Change Scenarios for the California Region Journal of Climatic Change, Volume 87.

Chai, S.G., Yoon, K.S., and Han, K.H. (2011), Estimation of SCS Runoff Curve Number for Agricultural Reservoir Watershed by Analysis of Reservoir Operation Record, ICID 21st International Congress on Irrigation and Drainage.

Chiew, F., and Siriwardena, L. (2005), Trend/Change Detection software User Guide, www.toolkit.net.au/trend retrieved on Monday, 29th February, 2016.

Cunderlik, J.M., and Simonovic, S.P. (2007), Hydrologic Models for Inverse Climate Change Impact Modeling, 18th Canadian Hydrotechnical Conference.

Das, S.K., and Perera, B.J. (2013), Sensitivity analysis of SWAT model in the Yarra River catchment, 20th International Congress on Modelling and Simulation.

Dibike, Y.B., Gachon, P., St-Hilaire, A., Ounda, M.J., and Nyugen, E.V. (2008), Uncertainty analysis of statistically downscaled temperature and precipitation regimes in Northern Canada Journal of Theoretical and Applied Climatology, Volume 91, No.1-4, pp 149–170.

Directorate of Water Resources Management (DWRM). (2011), The Declining Trends of Water Resources in Uganda, pp 1–16.

Elshamy, M.E., Seierstad, I. A., and Sorteberg, A. (2008), Impacts of Climate Change on Blue Nile Flows Using Bias-corrected GCM Scenarios Journal of Hydrology and Earth System Sciences Discussions, Volume 5, pp 1407–1439.

Gunasekara, N., Kazama, S., Yamazaki, D., and Oki, T. (2014), Analysing Regional Aspects of Climate Change and Water Resources Journal of Water Resources Management, Volume 28, No.1, pp.169–184.

Hamby, D. (1995), A comparison of sensitivity analysis techniques Journal of Health Physics, Volume 4, No.2, pp 1–20.

Hastenrath, S. (2001), Variations of East African climate during the past two centuries, pp 209–217.

Hayhoe, H.N. (2000), Improvements of stochastic weather data generators for diverse climates Journal of Climate Research, Volume 14, No.2, pp 75–87.

Hepworth, N., Goulden, M., and Hammond, G. (2008), Climate Change in Uganda: Understanding the Implications and Appraising the Response Journal of Proceedings of the Institution of Civil Engineers - Energy, Volume 161, pp 1–48.

Houghton, J.T., Ding,Y., Griggs, D.J., Noguer, M., Van Der Linden, P.J., Dai, X., Maskell, K., and Johnson, C.A. (2001), Climate Change 2001: The Scientific Basis, Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press.

Intergovernmental Panel on Climate Change (IPCC). (2007). Climate Change 2007 Synthesis Report, p 104.

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

IPCC-TGICA. (2007), General Guidelines on the Use of Scenario Data for Climate Impact and Adaptation Assessment Journal of Finnish Environment Institute, Volume 312, p 66.

Jassogne, L., Läderach, P., and Van Asten, P. (2013), The impact of Climate Change on Coffee in Uganda, Lessons from a case study in the Rwenzori

Mountains, Oxfam Research Reports.

Lo, K.F., and Koralegedara, S.B. (2015), Effects of Climate Change on Urban Rainwater Harvesting in Taipei City, Taiwan Journal of International Development Research, Volume 5, No.2, pp 3300-3310.

Ministry of National Planning and Devolution (MNPD). (2013), Busia County Integrated Development Plan.

Ministry of Water and Environment (MWE). (2012), Water and Environment Sector Performance Report, pp 12–14, 236.

Ministry of Water and Environment (MWE). (2015), Republic Of Uganda, Thematic report – Detail on hydrology and surface water resources assessment.

Moses, M. (2009), Progress Report on the Implementation of 6 months Action Plan on Intellectual Disability in Community Activity in Tororo District from August 2008 - January 2009.

Muys, B., Garcia-quijano, J., and Heuvelmans, G. (2004), Innovations in Land Use Impact Assessment for LCA, Department of Land Management and Economics Netherlands.

Mwiturubani, D.A. (2010), Climate change and access to water resources in the Lake Victoria basin, Institure for Security Studies.

Nasr, A., Michael, Bruen., Jordan, P., Moles, R., Kiely, G., and Byrne, P. (2007), A Comparison of SWAT, HSPF and SHETRAN/GOPC for Modelling Phosphorus Export from three Catchments in Ireland Journal of Water

Research, Volume 41, No.5, pp 1065–1073.

Nawaz, R., Bellerby, T., Sayed, M., and Elshamy, M. (2010), Blue Nile Runoff Sensitivity to Climate Change Journal of Open Hydrology, Volume 44, pp 137–151.

Ndomba, P.M., Mtalo, F.W., and Killingtveit, A. (2007), Sediment Yield Modelling Using SWAT Model at Larger and Complex Catchment Journal of Urban and Environmental Engineering, Volume 2, No.2, pp 53-62.

Neitsch, S.L., Arnold, J.G., Kiniry, J., and Williams, J.R. (2005), Soil and Water Assessment Tool User's Manual Version 2005.

Niang, I., Ruppel, O.C., Abdrabo, M.A., and Essel, A. (2014), Climate Change 2014: Impacts, Adaptation, and Vulnerability, Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, pp. 1199-1265.

Nile Basin Initiative (NBI). (2014), Sub-Catchment Management Plan Malaba for Middle Malaba Subcatchment of Malakisi-Mpologoma River Basin, Kenya / Uganda, Period 2014- 2024.

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

Pisinaras, V. (2016), Assessment of Future Climate Change Impacts in a Mediterranean Aquifer Journal of Global NEST , Volume 18, No.1, pp.119–130.

Salathe, E.P., Steed, R., Mass, C., Zalm, P.H. (2008), A high-resolution Climate Model for the United States Pacific Northwest: Mesoscale feedbacks and local responses to climate change Journal of Climate, Volume 21, pp 5708–5726.

Salmi, T., Maata, A., Anttila, P., Ruoha-Airola, T., and Amnell, T. (2002), Detecting Trends of Annual Values of Atmospheric Pollutants by the Mann-Kendall Test and Sen's Slope Estimates - The Excel Template Application Makesens, Finnish Meteorological Institute.

Santhi, C., Kannan, N., Arnold, J.G., and Luzio, M.D. (2008), Spatial Calibration and Temporal Validation of Flow for Regional Scale Hydrologic Modeling Journal of the American Water Resources Association, Volume 44, No.4, pp 829–846.

Semenov, M. (2010), LARS-WG 5 : A Stochastic Weather Generator for Climate Change Impact Assessments, Quick Start Manual.

Semenov, M. A., and Barrow, E.M. (2002), A Stochastic Weather Generator for Use in Climate Impact Studies User Manual, Hertfordshire, UK.

Shrestha, D.L. (2009), Uncertainty Analysis in Rainfall-runoff Modelling: Application of Machine Learning Techniques.

Socolow, R.H., and Pacala, S.W. (2006), A plan to Keep Carbon in Check Journal of Scientific American, Volume 295, No.3, pp 50–57.

Taylor, J.C., Miller, S.A., and Bibby, D.M. (1986) Predicting Future Changes in

Temperature and Precipitation in Arid Climate of Kutch, Gujarat: Analyses based on LARS-WG Model, India Meteorogical Department.

Trenberth, K.E., and Josey, S.A. (2007), Observations: Surface and Atmospheric Climate Change to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press.

UNESCO. (2007), Predicting and Managing the Impacts of Climate Change on World Heritage and Strategy to Assist State Parties to Implement Appropriate Management Responses Journal of World Heritage Reports, Volume 22, pp 1–55.

Van Griensven, A. (2009), Sensitivity, Auto-calibration, Uncertainty and Model Evaluation in SWAT 2005.

Van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., and Srinivasan. (2006), A global sensitivity analysis tool for the parameters of multi-variable catchment models Journal of Hydrology, Volume 324, No.1-4, pp 10–23.

Vorosmarty, C.J., Leveque, C., Revenga, C., Bos, R., Caudill, C., Douglas, E.M., Meybeck, M., Prager, D., Patricia, Balvanera., Barker, S., Maas, M., Nilsson, C., Oki, T., and Reidy, C.A. (2005), Findings of the Condition and Trends in Current State and Trends of Ecosystems and Human Well-Being, Cambridge University Press.

Wagener, T., Boyle, D., Lees, M.J., Wheater, H.S., Gupta, H.V., and Sorooshian, S.

(2001), A framework for development and application of hydrological models. Journal of Hydrology and Earth System Sciences, Volume 5, No.1, pp 13–26.

Wilby, R.L., Wigley, T., Conway, D., Jones, P., Hewitson,B., Main, J., and Wilks, S. (1998), Statistical Downscaling of General Circulation Model Output: A comparison of methods Journal of Water Resources Research, Volume 34, No.11, p 2995.

Yang, J., Reichert, P., Abbaspour, K.C., Xia, J., Yang, H. (2008), Comparing Uncertainty Analysis Techniques for a SWAT Application to the Chaohe Basin in China Journal of Hydrology, Volume 358, No.1-2, pp 1–23.