International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

A Predictive Model for Quantifying the Combined Effect of Land Use Change and Climatic Variability on Sedimentation in Malaba Sub Catchment

Ologe Hector Daniel

Student, Busitema University

ABSTRACT

Over the previous years, sedimentation in Malaba sub catchment has become a major problem, this research aimed at using SWAT as a predictive model to assess the impacts of historical and future climate change and land use changes on sedimentation in Malaba sub catchment. Two variables rainfall and temperature were considered under climate change. Four scenarios were modeled in SWAT during this study, the first scenario focused on historical sedimentation in the catchment, land use data of 2000 and weather data of 1990 to 2005 was used to simulate flow and sediment yield in the catchment. The second scenario focused on the current sediment yield in the catchment where land use data of 2020 and weather data of 2003 to 2020 was used to simulate the sediment yield and flow. Calibration and validation was done using SWAT CUP software. The calibrated and validated model was then used to further simulate two future scenarios. The two future scenarios used projected land use data and projected weather data. Land use data was projected using Clerk Labs Terr set software while weather data was projected using the Statistical Downscaling Model (SDSM). The third scenario considered projected land use data of 2035 and projected weather data of 2020 to 2035 to simulate flow and sediment yield of 2023 to 2035. The forth scenario considered projected land use data of 2050 and projected weather data of 2033 to 2050 to simulate catchment flow and sediment yield of 2036 to 2050. The results obtained from climate change analysis indicated un even changes, rainfall over the catchment is expected to increase, maximum temperature is expected to increase, minimum temperature is expected to reduce. Land use change results after comparison between the historical land use and projected land use indicated that from 2020 to 2050 cropland and built up area will increase while forests and water bodies will reduce. Average annual Sediment yield of 1993 to 2020 is expected to generally increase from 4975.4 tons/km2/year to an average annual sediment yield of 5525.6 tons/km2/year from 2023 to 2050. Therefore, mitigation measures should be adopted to ensure sustainable management of the catchment. Some of the recommendations made in this research are; Government through NEMA should put restrictions on cultivation close to the river banks, encourage planting trees within the catchment, bare lands within the catchment should be converted to other sustainable land uses. The study findings of this research shall be relevant for planning, design and management of reservoirs, dams, irrigation systems and sustainability of eco systems in the catchment.

Keywords: Catchment, sediment yield, Land use and land cover, sedimentation, climate change, projection, SWAT, Malaba.

1 CHAPTER ONE: INTRODUCTION

1.1 Background of the study

The International Geosphere Biosphere Program (IGBP) initiated by the International Council of Scientific Unions (ICSU) in 1987 (Steffen *et al*., 2004), as well as a number of related initiatives, have focused increasing attention on the changes in the functioning of the Earth system caused by human activity and on the problems associated with the sustainable management of this changing system over the coming centuries. Much of this attention has been directed to the increased emission of greenhouse gases, leading to climate change.

Sediment yield estimation along with identification of soil erosion mechanisms is essential for developing sophisticated management approaches, assessing, and balancing different management scenarios and prioritizing better soil and water conservation planning and management, at a watershed scale, land management practices are commonly utilized to minimize sediment loads (Megersa *et al*., 2023)

Sediment discharge is one of the main water quality concerns in integrated watershed management. A proper identification of sediment sources is therefore important to the success of watershed conservation programs (Yongbo *et al*.,2015)

Historical climate change has been observed and further changes are anticipated (Alava et al., 2018). According to the Intergovernmental Panel on Climate Change (IPCC), the average temperature on the planet has increased by about 0.6 degrees Celsius over the past century, and it is expected to further increase by 4 degrees by the end of the 21st century. Urbanization, agriculture, and deforestation are just a few of the everyday anthropogenic activities that have altered land use and cover over time and space. River sedimentation and stream flow are normally affected by changes in land use and land cover. Surface soil is being eroded from river basins at a rate of 60 billion tons per year, this results in 24 billion tons of sediment being released into the world's water bodies and almost 25 billion tons of soil being removed from agricultural land (Deltares, 2018). Sedimentation and eutrophication are caused by excessive soil erosion, which can make land unsuitable for farming and releases a lot of sediment, phosphorus, and nitrogen.

A study was done on the world’s 145 major rivers with consistent long term sediment records and the results indicated that about 50 % of the rivers have statistically a significantly downward flow trend due to sedimentation (Walling and Fang, 2003). Roughly 25% of the population in Africa is at present experiencing water shortages (Bates *et al*., 2008). In recent years, hydrological simulation models have been widely utilized to assess the impact of changing land use and cover on the hydrologic cycle (Lin et al., 2008).

A study on sediment impacts in Africa's transboundary lake/river basins; a case study of the East African Great Lakes indicated that the current population pressure, inappropriate cultivation practices, forest removal and high grazing intensities on forests, wetlands, rangelands and marginal agricultural lands leads to unwanted sediment and stream flow changes that mainly impacts the downstream human and natural communities. Forests and bushes are cleared, and wetlands are encroached to create space for human settlement, road construction and to satisfy wood fuel energy demands. Similarly, pastoral areas are subjected to growing human and livestock populations, leading to land degradation, soil erosion and an increase in the load from non-point pollutants (Olago and Odada, 2007).

River sediment yield is directly influenced by climate and land use variation (Guo *et al*., 2018). According to research done on River Ruaha catchment in Tanzania, annual total sediment load increased as a result of modifications to land use and land cover (Nathalie and Gutierrez, 2022).

Uganda is a land-locked country located in East Africa and lies in both the northern and southern hemispheres. The country is approximately 241,500 km2 and is bordered by Kenya to the east, South Sudan to the North, Tanzania and Rwanda to the south, and the Democratic Republic of the Congo to the West. 17% of the country is covered by water and swamp land. The central part of Uganda is a plateau, surrounded by four main mountain ranges that is to say Rwenzori, Elgon, Mufumbiro, and Moroto, the tallest point is the peak of Mt. Rwenzori at 5,110 meters above sea level. Uganda has substantial natural resources, including relatively fertile soils, a high degree of biodiversity, rich vegetation, abundant water resources, small deposits of copper, gold and oil (WBG, 2021).

On the eastern shore of Lake Kyoga, the Malaba River flows continuously (ILM, 2004). The river rises from the Mount Elgon slopes and empties into Lake Kyoga, which is situated in central and mid-northern Uganda. This is a transboundary basin shared by Uganda and Kenya. (MWE, 2016). Malaba River is very vulnerable to climate change because it relies heavily on rainfall as its main flow contributor (Kangume, 2016). The major tributaries OF River Malaba include Okame, Aturukuku, Solo, Malakisi, and Lwakhakha Rivers. Malaba sub catchment has experienced several flooding events due to heavy rainfall and decreased river capacity caused by high sediment loads in the river (Mubialiwo *et al*, 2022).

Effects of Floods and Sedimentation; Because contaminants adsorb in fine silt, the huge volume of sediment produced by riverbank erosion has an influence on ecosystems by affecting water quality. Toxins can also collect in sediment sinks (such as reservoirs, impoundments, and ponds), producing ecological problems. The heat absorbed by sediment particles from the sun raises the temperature of the water. As a result, several fish species may be stressed. Plants, invertebrates, and insects can be dislodged from the stream bed by large amounts of floating sediment. This influences fish food supplies, which may result in smaller and fewer fish available.

Motivation

Global climate change is predicted to have severe and far-reaching effects on humans and biological systems including riverbanks sedimentations, disproportionately harming the most physically and economically disadvantaged populations and the eco-system. Society can respond to these risks in two ways: mitigation and adaptation. Individuals, if willing to change their behaviors, can contribute significantly to these efforts, as can industry, trade, and government. Human activities are certainly contributing to global climate change and floods that destroy communities' livelihoods. Individuals, as well as the business and public sectors, must take strategic action to mitigate the harmful effects of climate change on the environment. Thus, the motivation to understand climate change effects on river catchment areas derives from the fact that we need to be able to predict climate-related phenomena, such as natural disasters and sedimentations along riverbanks catchment areas.

1.2 A Statement of the Problem

Unsustainable land management practices in Malaba sub catchment such as cultivation on the river banks, wetland encroachment, uncontrolled cultivation in hilly areas, disposal of untreated wastes from industries into the environment, deforestation and charcoal burning have been the major causes of climate change and land use land cover changes in Malaba sub catchment, these have resulted into; extensive catchment degradation, increased occurrence of disasters like floods and landslides; and significantly increased sediment loads in River Malaba (Nile Basin Initiative, 2015; MWE, 2018; MWE, 2016; Barasa *et al*., 2016). The excess sediment loads have; caused water quality deterioration and reduced the river channel capacity hence causing floods, these have resulted into loss of human life and property, outbreak of diseases like cholera and malaria and increased costs of water treatment (MWE, 2018) Therefore there is great need for a multi-disciplinary approach for proper water resources planning and catchment sustainability to reduce the impacts of sedimentation in Malaba sub catchment through assessing the historical, present and future impacts of climate change and land use land cover changes on sedimentation and flow of R. Malaba in Malaba sub catchment.

1.1.1 Main objective

To assess the impacts of historical, current and future land use changes and climate change on sediment yield and flow of R. Malaba in Malaba sub catchment.

1.1.2 Specific Objectives.

The study aimed to;

1. To assess and project land use land cover changes and climate change in Malaba sub catchment.
2. To assess the impacts of historical, current and future land use land cover changes and climate change on flow of R. Malaba in Malaba sub catchment
3. To assess the impacts of historical, current and future land use land cover changes and climate change on sedimentation of R. Malaba in Malaba sub catchment
4. To identify areas prone to sedimentation in Malaba sub catchment.

1.2 Significance of the study

This research aimed at achieving; SDG 6 (Clean water and sanitation for all), SDG 13 (Take urgent action to combat climate change and its impacts), SDG 3(Good health and wellbeing), NDP III whose major goal is to increase household incomes and improve quality of life of Ugandans, Vision 2040 by indirectly increasing the income levels of the local people through reducing the flood risk.

1.3 Scope of the study

Conceptual scope

This study mainly focused on the application of SWAT to assess the impacts of historical and future climate and land use changes on sedimentation and identification of areas prone to sedimentation in Malaba sub catchment

Geographical scope

This study was carried out on River Malaba located in Malaba sub catchment which is a trans boundary sub catchment shared by Kenya and Uganda. Its covers the following areas; Bududa, Namisindwa, Manafwa, Tororo, Busia, Namayingo, Butaleja, Namutumba, Bugiri districts in Uganda, Bungoma and Busia divisions in Kenya.

Time frame of the study

This study was executed in a period of nine (9) months.

1.7 Conceptual framework

A **conceptual framework** for the study was developed to illustrate the expected relationship between the dependent and independent variables. It defines the relevant objectives for the research process and maps out how they come together to draw coherent conclusions.

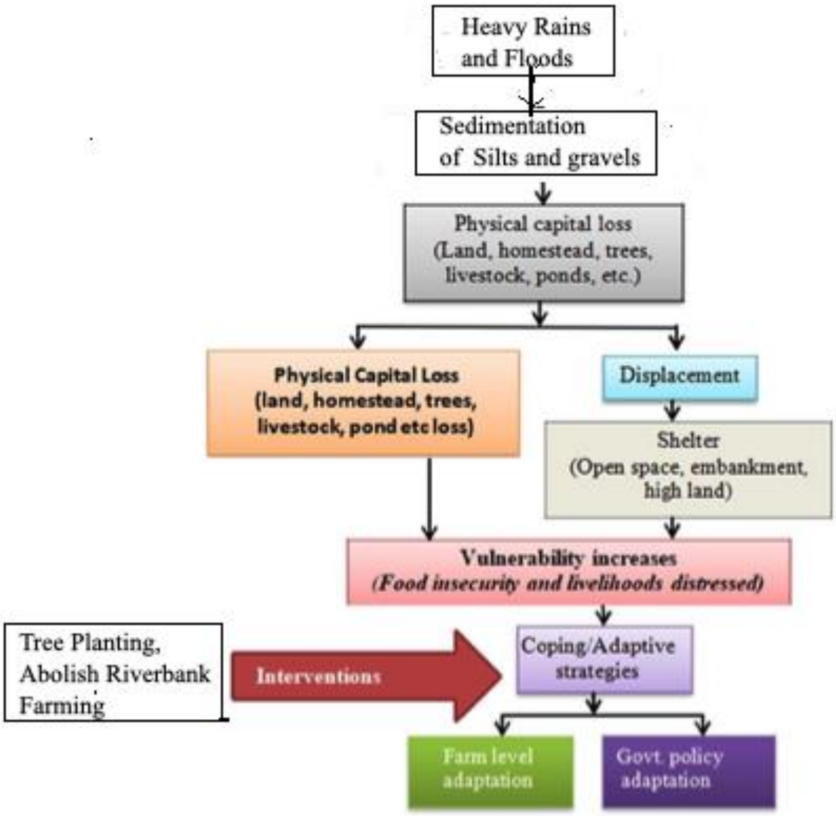

Figure 1.0 Conceptual Framework

2 CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

2.1.1 Uganda's Climate

The two rainiest seasons of the year in Uganda are from September to December and March to May. The northern section of the nation, which is beyond the tropical zone, only has one wet season from March to October. The topography, prevailing winds, lakes, and rivers generate significant variations in rainfall patterns around the nation. The remainder of Uganda is located in an equatorial climatic zone that is very humid. The large-scale Indian Monsoon, Congo air mass, Indian Ocean Dipole (IOD), and Inter Tropical Convergence Zone are responsible for determining the country's weather and seasons due to its location in the tropics and across the equator (WBG, 2021).

2.1.2 General Overview of Water Resources in Uganda

Uganda has abundant surface water throughout most of the country with the White Nile and Lake Victoria constituting the majority of renewable surface water resources (MWE, 2014). Other major water bodies in the country include lakes Kyoga, Albert, George and Edward while OTHER major rivers include the Rwizi, Katonga, Kafu, Mpologoma and Aswa (UN and MWE, 2005). Approximately 35 percent of Uganda's water resources originate from neighboring countries, which could create water availability or water quality challenges if there is extensive pollution or over-abstraction in upstream regions (USAID, 2021)

Urbanization and agricultural expansion are rapidly degrading extensive wetlands. Over 40 percent of Uganda's wetlands have been lost since 1994, threatening biodiversity and reducing wetland infiltration capacity to protect water quality in lakes (USAID, 2021)

2.1.3 Sedimentation

Sedimentation is a process whereby soil particles are eroded and transported by flowing water or other transporting media and deposited as layers of solid particles in water bodies such as reservoirs and rivers. It is a complex process that varies with watershed sediment yield, rate of transportation and mode of deposition (Ezugwu, 2013). Sediment deposition reduces the storage capacity and life span of reservoirs as well as river flows (Eroglu *et al*., 2010)

Sedimentation is one of the biggest threats to river ecosystems around the world (Nakatinda, 2021). Estimation of sedimentation in reservoirs helps in the management and design of the reservoir's useful capacity (Abebe and Wenhong, 2019). The earth's seismic regions are often where sediment output is largest, whereas desert and permanent ice zones have the lowest yield (G.W. Annandale, 2008).

Knowledge of the rate of loss of materials through sedimentation is critical to the determination of the mass budget of nutrients, the fate of pollutants, and the estimation of relative importance of internal loading of nutrients and pollutants relative to external loading (Mwebembezi and Hecky, 2005)

2.1.4 Overview of Malaba sub catchment

River Malaba is a significant tributary of River Mpologoma, therefore, the sub catchment forms part of Mpologoma catchment (MWE, 2018). The Lwakhakha River, Malakisi River, Aturukuku River, and Okame River are among the Malaba River's other significant tributaries, and Solo River (Barasa, 2014). The sub catchment has been affected by rainfall-induced landslides in the highland districts of Manafwa and Bududa. Within the same area, annually, disastrous floods have been experienced in the low-lying districts of Butaleja and Manafwa (Mubialiwo, 2021). These disasters could be linked to impacts of human factors on the sub-catchment hydrology. Besides, the study area hydrometeorology could be influenced by climate variability, some of the major challenges in Malaba sub catchment include; deforestation, soil erosion, dependence on rain fed agriculture, encroachment on wetlands for sugar cane and rice growing, mining of sand & Laterite leading to soil degradation, biodiversity loss, and water pollution. (MWE, 2018).

2.2 Climate Change

Future climate is partly determined by the magnitude of future emissions of greenhouse gases, aerosols and other natural and man-made forcing (Collins *et al*., 2013). Policymakers, planners, investors and vulnerable communities need information about future climate so that they can prepare for expected trends and changes. Climate predictions are estimates of future natural conditions, while climate projections are estimates of future climates under the assumptions of future human related activities such as socioeconomic and technical developments (UNITAR, 2015). In Uganda, particularly in the southwest, the typical temperature is rising in semi-arid regions. The National Adaptation Program of Action (NAPA) of Uganda reports that, between 1960 and 2010, the country's average temperature increased by 0.28°C every decade, with the months of January and February being the most impacted, with an average increase of 0.37°C per decade. In contrast to a decline in the number of cold days, the country now experiences many more hot days than cold ones. According to earlier records of Uganda's glaciers, the ice caps on the Rwenzori Mountains have drastically diminished during the past century. Mount Baker (96%), followed by Mount Speke (91%), has the highest percentage of ice loss. 68 percent of the ice has been lost from Mount Stanley. The changing temperature patterns in Uganda have been linked with drought and consequent increases in cattle deaths in the cattle corridor (MWE, 2015)

Precipitation in the country is highly variable, but overall, Uganda has experienced a statistically significant reduction in annual as well as seasonal rainfall. Seasonal rainfall for March, April and May has been most affected, with decreases of 6.0 mm per month. Decline in rainfall has been observed in some Northern districts: Gulu, Kitgum, and Kotido. While trends in extreme rainfall conditions are more difficult to define due to the lack of data and seasonal variability, droughts have increased in Uganda over the past 60 years. (WBG, 2021)

Flooding, particularly in low-lying areas of the country, presents the largest risk. Each year, floods impact nearly 50,000 people and costs over $62 million.39 Uganda experiences both flash floods and slow-onset floods, which are common in urban areas, low-lying areas, areas along river banks and swamplands (WBG, 2021)

2.2.1 Climate change modeling

Climate models are mathematical representations of the climate developed by scientists to understand and predict the climate system. In order to be able to do this, the models divide the earth, ocean and atmosphere into a grid. Simulating climate change at the regional and national levels is essential for policymaking. However, Global Climate Models (GCMs) have a coarse spatial resolution that is not suitable to understand the climate at a smaller scale. (UNITAR, 2015)

2.2.2 Global Circulation Models (GCMs)

A Global Climate Model (GCM) combines a series of models of the Earth's atmosphere, oceans, and land surface (Randall *et al*., 2007). GCMs divide the earth into many layers and thousands of three-dimensional gridded spaces. These models are skilled at replicating past and current climate. For example, GCMs accurately reproduce observed temporal warming trends, sea ice dynamics, and extreme weather events. The climate models project possible future climate shifts under the conditions of the specific scenarios. These models are run multiple times using various scenarios of future conditions, such as population levels and anticipated emissions of carbon dioxide (CO2) or other greenhouse gases. Each GCM is distinct and has a different sensitivity to greenhouse gas emissions. (Meehl *et al*., 2007; Schcramm *et al.*, 2016). This range, taken as a whole, is important to researchers for providing a sense of the uncertainty surrounding possible future events given a particular scenario and period. To capture this range and make use of the complement of projections, ensembles of multiple global climate model simulations are often used. (Schcramm *et al*., 2016).

Climate models are being subjected to more comprehensive tests, including, evaluations of forecasts on time scales from days to a year. This more diverse set of tests increases confidence in the fidelity with which models represent processes that affect climate projections (Randall *et al*., 2007). GCMs are complex, three dimensional models that are continually evolving to incorporate the latest scientific understanding of the atmosphere, oceans, and Earth's surface. Originally, "GCM" stood for General Circulation Model, since the original focus of these physics-based models was to simulate the circulation of the atmosphere and ocean. Today, however, global climate models incorporate many other facets of the Earth's climate system, including chemistry, biospheric processes, land use, etc. (Hayhoe and Stoner, 2015). Some GCMs are better than others at reproducing important large-scale features of certain regions, such as sea ice in the Arctic (Wang *et al*., 2007).

Some of the CMIP5 models include;

Table 2-1 CMIP5 Global Climate Modeling groups

No	Origin	CMIP5 model(s)
1	National Center for Atmospheric Research, USA	CCM 4
2	Centre National de Recherches Météorologiques, France	CNRM-CM5
3	Commonwealth Scientific and Industrial Research Organization, Australia	CSIRO-MK3.6.0
4	Max Planck Institute for Meteorology, Germany	MPI-ESM-LR
5	UK Meteorological Office Hadley Centre	HadGEM2-CC
6	Institute for Numerical Mathematics, Russian	INMCM4
7	Institut Pierre Simon Laplace, France	IPSL-CM5A-LR
8	Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies, Japan	MIROC5
9	Meteorological Research Institute, Japan	MRI-CGCM3
10	Canadian Earth System Model	CanESM

Source: Hayhoe and stoner, 2015, '*Climate Change Projections for the District of Columbia'* ATMOS Research & Consulting for Kleinfelder.

2.2.3 Regional circulation Models (RCMs)

RCMs operate at much higher resolution and often, with more detailed topography and use of physical parameters. This downscaling can be extended to even finer detail in local models. Most RCM simulations use GCM fields from pre-computed global simulations as boundary conditions. This approach allows RCMs to draw from a broad set of GCM simulations, such as CMIP5, but does not allow for possible two-way feedbacks and interactions between the regional to global scales. Dynamical downscaling can also be conducted interactively through nesting a higher-resolution regional grid or model into a global model during a simulation (Hayhoe *et al.*, 2017).

2.2.4 Coupled Model Intercomparison Project Phase 5 (CMIP5)

This presents an unprecedented level of information on which to base projections including new Earth System Models with a more complete representation of forcings, new Representative Concentration Pathways (RCP) scenarios and more output available for analysis (Hayhoe and Stoner, 2015). The four RCP scenarios used in CMIP5 lead to a total radiative forcing (RF) at 2100 that spans a wider range than that estimated for the three Special Report on Emission Scenarios (SRES) scenarios (B1, A1B, A2) used in the Fourth Assessment Report (AR4), RCP2.6 being almost 2 W m–2 lower than SRES B1 by 2100. The magnitude of future aerosol forcing decreases more rapidly in RCP scenarios, reaching lower values than in SRES scenarios through the 21st century. Carbon dioxide (CO2) represents about 80 to 90% of the total anthropogenic forcing in all RCP scenarios through the 21st century. The ensemble mean total effective RFs at 2100 for CMIP5 concentration-driven projections are 2.2, 3.8, 4.8 and 7.6 W m–2 for RCP2.6, RCP4.5, RCP6.0 and RCP8.5 respectively (Collins *et al*, 2013)

New types of model experiments have been performed, many coordinated by the Coupled Model Intercomparison Project Phase 5 (CMIP5) which exploit the addition new processes (Taylor *et al.*, 2012). Models may be driven by emissions of GHGs, or by their concentrations with different Earth System feedback loops cut, this allows the separate assessment of different feedbacks in the system and of projections of physical climate variables and future emissions

2.2.5 Representative Concentration Pathways (RCPs)

The standard sets of time-dependent scenarios used by the climate modeling community as input to global climate model simulations provide the basis for the majority of the future projections presented in IPCC assessment reports and U.S National Climate Assessments (NCA) developed by the integrated assessment modeling community, these sets of standard scenarios have become more comprehensive with each new generation, as the original SA90 scenarios (IPCC, 1990) were replaced by the IS92 emission scenarios of the 1990s (Leggett *et al.*, 1992) which were in turn succeeded by the Special Report on Emissions Scenarios in 2000 (Nakicenovic *et al.*, 2000) and by the Representative Concentration Pathways in 2010 (Moss *et al.* 2010)

The most recent set of time-dependent scenarios, RCPs, builds on these two decades of scenario development. However, RCPs differ from previous sets of standard scenarios because, RCPs are not emissions scenarios; they are radiative forcing scenarios. Each scenario is tied to one value: the change in radiative forcing at the tropopause by 2100 relative to preindustrial levels. The four RCPs are numbered according to the change in radiative forcing by 2100: +2.6, +4.5, +6.0 and +8.5 watts per square meter (W/m2) (Vuuren *et al*., 2011; Thomson *et al.*, 2011; Masui *et al*., 2011; Riahi *et al.*, 2011).

2.2.6 Downscaling Models

Despite GCMs' sensitivities of hundreds of kilometers, climate change data is required for many impact assessments at a much smaller geographical scale (Dibike *et al*., 2008). As a result, downscaling techniques have emerged as a means of connecting atmospheric variables to grid and sub-grid scales. The two most common approaches for obtaining data on a regional or local scale from global climate scenario generated by GCMs are through numerical and statistical downscaling models (Wilby *et al.*, 1998). A regional climate model (RCM) is used in numerical downscaling, which is also known as dynamic downscaling. In statistical downscaling, a statistical connection is utilized to compare local fluctuations acquired from historical data records to the large-scale climatic condition.

Table *2-2* shows the strength and weaknesses involved in dynamic and statistical downscaling techniques

Dynamic Downscaling

In this type of downscaling, most RCM simulations use GCM fields from pre-computed global simulations as boundary conditions. This approach allows RCMs to draw from a broad set of GCM simulations, such as CMIP5, but does not allow for possible two-way feedbacks and interactions between the regional to global scales. Dynamical downscaling can also be conducted interactively through nesting a higher-resolution regional grid or model into a global model during a simulation (kotamarthi *et al.* 2016).

Within the global climate model of coarser scale, dynamic downscaling is also referred to as limited area models (LAMs) and involves the climate model of finer scale regionally. A dynamic approach makes use of the conditions of a GCM boundary's outputs for the targeted region. Future environment at a size of a district is determined utilizing an environment model completely actual in nature (Jorge *et al*., 2015)

Dynamic models provide the major benefit of accounting for local circumstances, such as physically regular changes in atmospheric chemistry or surface vegetation. However, in order to calculate the same scenarios, regional climate models (RCMs) require the same amount of processing time as the GCM, and they are not easily adaptable to new regions. The initial conditions, particularly soil temperature and moisture, have a significant impact on RCM results at the beginning (Nasr *et al*., 2007).

Statistical downscaling models

Empirical statistical downscaling models (ESDMs) convert large-scale predictors or patterns into high-resolution forecasts at the size of observations by fusing GCM output with prior historical data. Individual weather stations and gridded datasets can also be utilized as observations in an ESDM. They can provide a variety of outputs, from big grids to assessments tailored for a particular place, variable, or decision-context (Hayhoe et al., 2017).

Statistical models are generally flexible and less computationally demanding than RCMs. A number of databases using a variety of methods, including LOCA (Localized constructed Analogs) provide statistically downscaled projections for a continuous period from 1960 to 2100 using a large ensemble of global models and a range of higher and lower future scenarios to capture uncertainty due to human activities. ESDMs are also effective at removing biases in historical simulated values leading to a good match between the average (multi-decadal) statistics of observed and statistically downscaled climate at the spatial scale and over the historical period of the observational data used to train the statistical model (Pierce *et al.*, 2014)

Numerous statistical downscaling methods have been developed over the past few years, and each falls into one of three categories: regression methods, stochastic weather generators, or weather typing schemes (Hernanz *et al.*, 2021).

Weather typing approaches involve grouping local, 194 meteorological variables in relation to different classes of atmospheric circulation (Hay *et al.*, 1991; Bardossy 196 and Plate, 1992; von Storch *et al*., 1993). Future regional climate scenarios are constructed, either by resampling from the observed variable distributions or by first generating synthetic sequences of weather patterns using Monte Carlo techniques and resampling from observed data. The main appeal of circulation-based downscaling is that it is founded on sensible linkages between climate 204 on the large scale and weather at the local scale. The technique is also valid for a wide variety of environmental variables as well as multi-site applications. However, weather typing schemes are often parochial, an inadequate basis for simulating rare or extreme events, and entirely dependent on stationary circulation-to-surface climate relationships. Potentially, the most serious limitation is that precipitation changes produced by changes in the frequency of weather patterns are seldom consistent with the changes produced by the host GCM

Stochastic downscaling approaches typically involve modifying the parameters of conventional weather generators such as wgen (Wilks, 1999) or LARS-WG (Semenov and Barrow, 1997). WGEN simulates precipitation occurrence using two-state, first-order Markov chains: precipitation amounts on wet-days using a gamma distribution; temperature and radiation components using first-order trivariate auto regression that is conditional on precipitation occurrence. ***Table 2-1***

Table 2-2 Main strengths and weaknesses of statistical and dynamical downscaling.

	Statistical downscaling	**Dynamical downscaling**
Strengths	▪ Station–scale climate information from GCM–scale output ▪ Cheap, computationally undemanding and readily transferable	▪ 10–50 km resolution climate information from GCM–scale output ▪ Respond in physically consistent ways to different external forcings

	▪ Ensembles of climate scenarios permit risk/ uncertainty analyses ▪ Applicable to 'exotic' predictands such as air quality and wave heights	▪ Resolve atmospheric processes such as orographic precipitation ▪ Consistency with GCM
Weakness	▪ Dependent on the realism of GCM boundary forcing ▪ Choice of domain size and location affects results ▪ Requires high quality data for model calibration ▪ Predictor–predictand relationships are often non–stationary ▪ Choice of predictor variables affects results ▪ Choice of empirical transfer scheme affects results ▪ Low–frequency climate variability problematic ▪ Always applied off-line, therefore, results do not feedback into the host GCM	▪ Dependent on the realism of GCM boundary forcing ▪ Choice of domain size and location affects results ▪ Requires significant computing resources ▪ Ensembles of climate scenarios seldom produced ▪ Initial boundary conditions affect results ▪ Choice of cloud/ convection scheme affects (precipitation) results ▪ Not readily transferred to new regions or domains ▪ Typically applied off-line, therefore results do not always feedback into the host GCM

Source; Wilby and Dawson, 2004, 'A decision support tool for the assessment of regional climate change impacts'

Statistical Downscaling Model

Statistical DownScaling Model (SDSM) model is a prominent tool, freely available in the public domain. SDSM is best described as a hybrid of the stochastic weather generator and regression–based methods. This is because large–scale circulation patterns and atmospheric moisture variables are used to linearly condition local–scale weather generator parameters (e.g., precipitation occurrence and intensity). Additionally, stochastic techniques are used to artificially inflate the variance of the downscaled daily time series to better accord with observations. To date, the downscaling algorithm of SDSM has been applied to a host of meteorological, hydrological and environmental assessments, as well as a range of geographical contexts including Europe, North America and Southeast Asia (Wilby and Dawson).

1 facilitates the rapid development of multiple, low–cost, single–site scenarios of daily surface weather variables under current and future climate forcing. Additionally, the software performs ancillary tasks of data quality control and transformation, predictor variable pre–screening, automatic model calibration, basic diagnostic testing, statistical analyses and graphing of climate data (Wilby and Dawson, 2004).

2.2.7 Impacts of Climate Change on sedimentation

Climate change has increased precipitation concentration, volume, and intensity, which has had a considerable influence on runoff and soil erosion in many watersheds (Diodato et al., 2020). The primary component of river sediments and a significant contributor to reservoir or river dam sediment deposition are the sediments produced by watershed erosion, which are carried to rivers by surface runoff (Chen et al., 2006). The amount of soil erosion significantly affects how river channels develop, affecting river stability, flood prevention safety, and river repair planning. Therefore, controlling sediment output is essential for watershed management, especially given that it frequently comes at a significant cost (Chen et al., 2020).

Modeling sediment transport and storage is challenging because of complex relationships between climatic forcing, hydrological connectivity, sediment production, and the different geomorphic thresholds involved (Campforts *et al*.,2020)

2.3 Land Use Land Cover change

Land cover defined as the assemblage of biotic and abiotic components on the earth's surface is one of the most crucial components of the earth system (Turner *et al.*,1994). Land cover also reflects the availability of food, fuel, timber, fiber and shelter resources for human populations, and serves as acritical indicator of other ecosystem services such as biodiversity. Information on land cover is fundamental to many national and global applications including watershed management and agricultural productivity. Thus the need to minotor land cover is derived from multiple intersecting drivers, including the physical climate, ecosystem healthand societal needs. (Sudhakar and Kameshwara, 2006). LULC change can also be defined as the modification of surface features on earth's landscape which is realized by the difference in their surface appearance assessed at two different times (Ayele, 2011).

More than 50% world's population resides in urban areas, and this figure is forecasted to exceed 65% by 2050 (United Nations, 2014). The trend of urbanization is common in Africa, resulting from population agglomeration (Andreasen *et al*., 2017). Land cover change is amongst the most widely increasing and significant sources of today's change in the earth's land surface (Houet *et al*., 2010)

Both direct and indirect factors can influence land cover change, human activities resulting from the continuous use of land, such as urbanization, deforestation, expansion of agriculture, and wood extraction, are examples of direct causes while economic, political/institutional, sociocultural, and technological factors are examples of indirect causes that enhance more direct causes of LULCC (Geist and Lambin, 2002).

2.3.1 Impacts of land use change on sedimentation

Watershed planners and managers are making a great effort to understand sediment yield and soil erosion in dynamic environments and assess likely impacts of changing climate and land use patterns, including assessment of sedimentation in dams, reservoirs, natural channels, and harbors (Si *et al*., 2017). Long-term or short-term change in land use substantially impacts soil erosion and sediment yield within the watershed scale due to its ecological features (Worku *et al.*, 2017). Historically, land use has drastically changed in many parts of the world, affecting the hydrological and ecological processes in the area. Land use change is a long-term process, and changes in land cover caused by human activities are observed daily (Shrestha *et al.*, 2018).

Due to human-made structures and activities, the intensity and characteristics of surface flow and sediment yield have significantly changed and meant a great deal to the watershed stakeholder and manager

2.3.2 Remote sensing (RS) and GIS techniques in LULC change analysis

Remote sensing is the sensing of the Earth's surface from space by making use of the properties of electromagnetic waves emitted, reflected or diffracted by the sensed objects, for the purpose of improving natural resources management, land use and the protection of the environment (United Nations, 1986).

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Lillesand, *et al.*, 2008).

2.3.3 Land use modeling

Land use modeling at the present time plays a pivotal role in many natural resources management and decision making processes, land use models are effective tools to analyze the causes and consequences of land use-land cover change and create an enhanced understanding of the land use system in an area (Verburg, *et al.*, 2004; Stabile, 2012). The use of land change models is multi-dimensional, for example, they were used in biodiversity monitoring for estimating loss of vegetation cover (Echeverria, et al., 2008), for forest management (Kamusoko, *et al.*, 2013)

2.3.4 Land use/land cover change (LULCC) Modelling

Understanding LULCC dynamics and drivers is made easier by modeling LULCC. LULCC models can be partitioned in to two classes for example spatial and non-spatial models. Non-spatial models dissect the pace of LULCC without considering spatial variety while spatial models put accentuation on LULCC at a particular spatial level (for example regulatory units) and recognizes spatial variety of LULCC in the financial and strategy setting (Huang *et al.*, 2007).

Numerous software applications, including IDRISI, DINAMICA EGO, and CA-MARKOV. are accessible for demonstrating future LULC, which are exact methodologies in light of the past LULC (Mas et al. 2014). Modules of Land Use Change Assessment (MOLUSCE) module of QGIS was acquainted as of late with break down the LULCC and can foresee future LULC. This module could get ready change potential/likelihood grid utilizing the Markovian methodology and train reenactment model in view of either Counterfeit Brain Organizations (ANN) or calculated relapse (LR) (Sajan *et al.*, 2022)

The recreation of the land use map depends on a Monte-Carlo cell automata model methodology (Jogun *et al.*, 2019), Logistic Regression for Transitional Potential Modeling. Logistic regression is one of the models utilized in LULCC analysis, the relationship between the drivers and the likelihood of LULCC is quantified. Different researchers have previously utilized the Logistic Regression (LR) model to assist in the projection of future LULCC. These projections are based on previous trends and drivers that determine the conversions between the various categories of LULCC (Millington *et al.*, 2015). It estimates the probability of explicit LULCC process from the accepted drivers (Rossiter and Loza, 2008).

Artificial Neural Network (Multi-layer Perceptron); The ANN Multi-Layer Perceptron method was used in LULCC modeling because its prediction is significantly more powerful than other methods (Jogun *et al.*, 2019).

2.4 Hydrology

Hydrology deals with the occurrence, movement, and storage of water in the earth system while hydrologic science comprises understanding the underlying physical and stochastic processes involved and estimating the quantity and quality of water in the various phases and stores (Jose D Salas et al., 2016). The study of hydrology also includes quantifying the effects of such human interventions on the natural system at watershed, river basin, regional, country, continental, and global scales.

The multidisciplinary geoscience of hydrology, which examines the mechanisms driving the replenishment and depletion of terrestrial water resources, can also be referred to as this. It focuses on comprehending and characterizing quantitatively physical, chemical, and biological elements and processes that interact and function at various spatiotemporal scales and are influenced by human actions. (2000) Schulze and (2009) Savenije

2.4.1 Hydrologic Modeling

Historically, hydrological modelling was undertaken to better understand the relationships between rainfall and runoff in the latter half of the 19th century in response to three main engineering problems urban sewer design, land reclamation drainage systems design, and reservoir spillway design. It is conceivable, however that these types of engineering problems date back to before the Roman Empire, and that planners of that time dealt with similar issues at smaller scales (Hubbart, 2012)

Hydrologists are mainly concerned with evaluation of catchment response in order to plan, develop, manage and operate various water resources schemes. There is continuous circulation of water between earth and atmosphere. This is signified by different phases in the hydrologic Cycle which is the fundamental principle of hydrology (NIH Roorkee, 2017).

In order to quantify the effect of land-use change on hydrological components, hydrological models have been used to conceptualize and investigate the interactions between climate, human activities (such as land use change), and water resources (Barasa, 2014).

2.4.2 Classification of hydrological models

Hydrological models can be classified in different ways;

Based on the description of physical processes, the hydrological models can be classified into three groups namely; empirical (data driven models), conceptual, and physically based. Based on the spatial representation the hydrological models can be classified into: lumped, and distributed. Based on the aspect of randomness the hydrological models can be classified into: deterministic, and Stochastic (Džubáková, 2010, Singh and Frevert, 2002).

Hydrologic models can also be classified as; lumped and distributed parameter models, conceptual and hydrodynamic models, models with fitted and physically determined or empirically derived parameters, event and continuous simulation models (Todini, 1988; Knapp *et al.*, 1991).

Empirical models are the most basic kind of numerical models used to simulate streamflow in a direct relationship with other measurable variables. Although this kind of model may be used by a wide range of people due to its simplicity, the model's output limits its utility. Unit hydrograph is the most typical illustration of a black box model. According to Courault et al. (2005) and Davie (2008), the model linkages are based on empirical data rather than necessarily on physical processes.

Physically-based models are those that are based on physical procedures and are modeled after a knowledge of physical mechanics. These models frequently have high computing and data needs. These models provide more experimental and explanatory strength. Their prediction ability is frequently equivalent to or worse than that of empirical models due to the greater number of assumptions that are required (Beven, 1989; Grayson et al., 1992).

Lumped conceptual models were the initial attempt to numerically represent the many hydrological events within a basin. The catchment region receives additional rainfall, and the water budget technique is utilized to track water losses and flows there. The word "lumped" is used since there is no geographical discretization and all the processes work at the same spatial scale. The scale picked is frequently a catchment, or even a sub-catchment. The word conceptual is employed because it is frequently believed because the equations determining flow rates are conceptually comparable to the physical procedures in use (Refsgaard, 1997; Davie, 2008).

2.4.3 Description of some Hydrological models

The Distributed Hydrology Soil Vegetation Model (DHSVM)

DHSVM provides a dynamic representation of watershed processes at the spatial scale described by Digital Elevation Model (DEM) data. The modeled landscape is divided into computational grid cells centered on DEM nodes, this characterization of topography is used to model topographic controls on absorbed shortwave radiation, precipitation, air temperature, and downslope water movement. Vegetation characteristics and soil properties are assigned to each model grid cell, these properties may vary spatially throughout the basin. In each grid cell the modeled land surface can be composed of a combination of vegetation and soil, at each time step, the model provides simultaneous solutions to energy and water balance equations for every grid cell in the watershed. Individual grid cells are hydrologically linked through surface and subsurface flow routing (Wigmosta *et al.*, 1994)

DHSVM has been used to evaluate changes in flood peaks caused by enhanced rain-on-snow and springtime radiation melt reaction impacts of forest paths and traffic drainage, and the forecasting of erosion of sediment and transportation (Wigmosta et al., 1994).

MIKE-SHE

MIKE SHE uses MIKE Hydro River to simulate channel flow, MIKE Hydro River includes comprehensive facilities for modelling complex channel networks, lakes and reservoirs, and river structures, such as gates, sluices, and weirs. In many highly managed river systems, accurate representation of the river structures and their operation rules is essential. In a similar manner, MIKE SHE is also linked to the MOUSE sewer model, which can be used to simulate the interaction between urban storm water and sanitary sewer networks and groundwater (Zhuhuan and Zhou, 2019)

MIKE SHE is applicable at spatial scales ranging from a single soil profile, for evaluating crop water requirements, to large regions including several river catchments, such as the 80,000 km2 Senegal Basin (Andersen et al., 2001). MIKE SHE has proven valuable in hundreds of research and consultancy projects covering a wide range of climatological and hydrological regimes, many of which are referenced in Graham and Butts (2006). The need for fully integrated surface and groundwater models, like MIKE SHE, has been highlighted in many studies (Dresser and McKee Inc., 2001; Kaiser-Hill, 2001; West Consultants Inc. *et al.*, 2001; Kimbley Horn & Assoc. Inc. *et al.*, 2002; Middlemis, 2004)

2.4.4 Soil Water and Analysis Tools (SWAT)

To predict the long-term effects of rural and agricultural management practices (such as specific agricultural land planting, tillage, irrigation, fertilization, grazing, and harvesting procedures) on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions, USDA-ARS created the physically based SWAT model in the early 1990s. SWAT considers evapotranspiration, channel transmission losses, lateral subsurface flow, groundwater return flow, percolation, and surface runoff. The modified SCS curve number approach is used to estimate runoff volume. While the watershed concentration time is calculated using Manning's formula, taking into account both overland and channel flow, peak runoff forecasts are based on a modified version of the Rational Formula (Grizzetti et al., 2003).

2.4.5 SWAT Model Calibration and Validation

Model Parameter Sensitivity Analysis; Evaluating the input parameters to determine how they affect the model output is called sensitivity analysis of SWAT model parameters. It aids in the reduction of uncertainty not only during the model's development but also during its validation (Hamby, 1995). By taking into account the parameters that have the greatest sensitivity and, as a result have the greatest impact on the behavior of the simulation process. The sensitivity analysis reduces the number of parameters that need to be used in calibration.

3 CHAPTER THREE METHODOLOGY

3.1 Introduction

Research Design

This study is both qualitative and quantitative in nature.

3.2 Description of Study area

3.2.1 Location of the study area

Malaba sub catchment is part of the Mpologoma catchment which is located in Kyoga Water Management Zone(WMZ) one of the four Water Management Zones in Uganda, other WMZs in Uganda include Victoria Nile WMZ, Albert Nile WMZ and Upper Nile WMZ. Malaba sub catchment, covers about 3480 km2. The river origins from the slopes of Mount Elgon at the border of Uganda and Kenya, the catchment area covers parts of Bugiri, Namayingo, Tororo, Busia, Namutumba, Butaleja Namisindwa, Manafwa, and Bududa districts in Uganda, Bungoma and Busia Counties in Kenya. The River empties into the River Mpologoma, whose waters go into Lake Kyoga. Figure 3 1 depicts the position of the Malaba sub watershed in Kenya and Uganda.

3.2.2 Population and resources of Malaba sub catchment

Malaba sub catchment has got an approximate population of 4 million people (NBI, 2012). The watershed is rich in minerals including sand, limestone, gold, and phosphates. Mining operations are carried out on both a big and small scale. For instance, sand is mined on a small basis and supplied to regional construction firms. In the Busia district of Uganda, small-scale artisanal miners mostly extract gold on a small scale. Additionally mined in the Tororo area are phosphates and limestone.

3.2.3 Geology and topography

The watershed is hilly with undulating plains; Mount Elgon, at a height of around 4,299 meters above sea level, has the highest peak. The watershed's midsection and downstream regions include undulating plains, and the entire catchment is underlain by rocks of the Precambrian and Tertiary Pre-Elgon volcanic type. Precambrian basement rocks consist of a range of granites, gneisses, quartzite, and tiny pockets of densely folded metamorphic rocks (DSOER, 2004).

3.2.1 Climate of Malaba sub catchment

The western part of Malaba sub catchment which lies in Uganda experiences two types of climates namely; Tropical rainforest climate and Tropical monsoon climate. The Eastern part of Malaba sub catchment which lies in Kenya experiences Hot summer Mediterranean climate (https://climateknowledgeportal.worldbank.org/country/uganda)

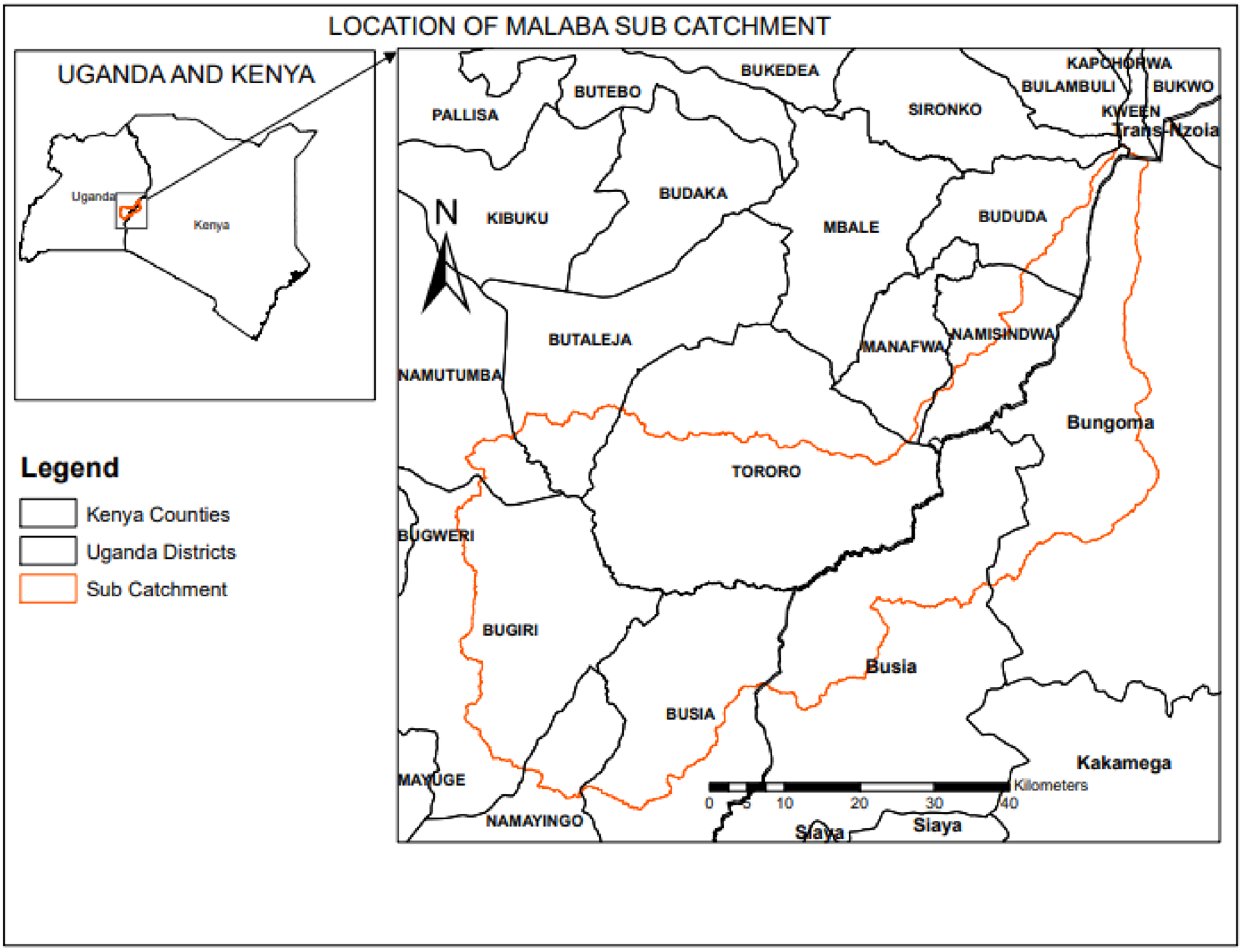

Figure 3-1 Location map of Malaba sub catchment in Uganda and Kenya

Modelling framework for the study

Climate and land use land cover projection to sedimentation.

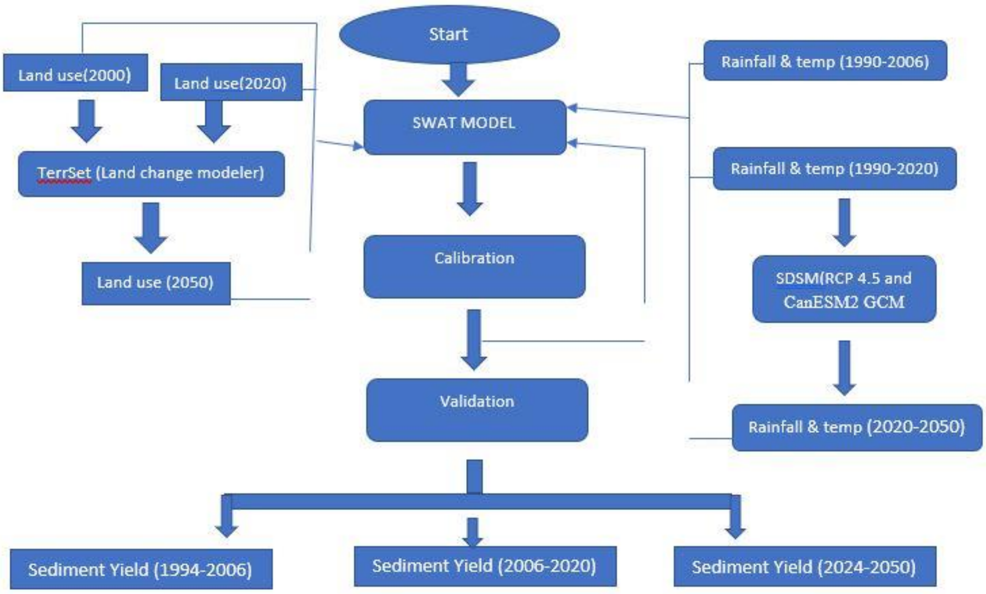

Figure 3-2 Modelling Framework

3.3 Data collection and preparation and

In this study, primary, secondary and tertiary data were used, ***Table 3-1 Secondary data used in this study***Table ***3-1***shows the data sets used in this study with their respective file types and sources.

Data	Source	Type
Land use maps (2020 and 2000)	Google earth pro (Copernicus/Landsat imagery)	Shape file
Weather data (1990-2020)	Tororo weather station	CSV
(Satellite weather data(1990-2020)	NASA (Power access) Website	CSV
Digital Elevation Model (DEM, 12.5m)	Alaska satellite facility	Raster
Soil data	FAO	Shape file
Discharge data	MWE	Excel sheet
Sediment data	MWE	Excel sheet

Table 3-1 Secondary data used in this study

Data preparation and processing

Watershed Delineation was the initial activity carried out in ArcGIS environment using the SWAT automatic watershed delineator, this was aimed at defining the boundaries of Malaba sub catchment which informed the geographical scope during collection of other datasets.

Weather data

Observed weather data was obtained from Tororo weather station. Data Quality check was done using SDSM software, the observed data was found to have a lot of missing values. Bias correction was done using Satellite data of Malaba sub catchment downloaded from NASA's Power Access website, time series of 1990 to 2020 were download with variables of Precipitation, maximum and minimum temperatures

Land use data

Land use data of 2000 and 2020 was obtained from google earth through digitizing the historical imageries of the respective years, other satellite based Land use land cover datasets were not used because they presented a very low accuracy after ground truthing, for example the 2020 Esri Land use map of Malaba sub catchment was not showing any water body in the area yet on ground we actually have River Malaba, USGS land use map of Malaba sub catchment only displayed savannah woody vegetation in places where we expect to find River Malaba. The digitized maps clearly indicated River Malaba and other features within the catchment, the maps were then imported into Arc Map for processing. Land use land cover was classified into 6 six classes namely; Water for all water bodies, Cropland for Agricultural Land, Bare land for any land without any vegetation or water, Forests for area with very many trees, Grasslands for areas with scattered short trees and grass, Built up areas for residential, urban and commercial areas

3.4 Climate projection

Projection of climate change variables from 2021-2050 was achieved using the Statistical Downscaling Model (SDSM) version 4.2, this software was used to project temperature and precipitation data of Malaba Sub catchment from 2021 to 2050

Coupled Model Inter-comparison Project Phase 5 (CMIP 5) was considered and CanESM2(Canadian Earth System Model Version 2) Global Circulation Model, Representative Concentration Pathways 4.5 (RCP 4.5) were used as the most suitable models for Malaba sub catchment climate change projection. RCP 4.5 was chosen because Malaba sub catchment is experiencing a moderate development of industries and other activities that cause greenhouse gases. However, the government of Uganda through its ministry of water and Environment is trying its level best to curb down these greenhouse gas emissions though with a lower rate of success which makes RCP 4.5 a better option compared to RCP 2.6 and RCP 8.5.
The following steps were followed to project/forecast weather data in SDSM environment;
Data quality check; Data quality check was conducted by loading the observed data and checking for missing data. There was no missing data.
Variable screening; This was done by using the analyse and correlation tools. A total of twelve predictor variables were tested to select the most sensitive predictors, six most sensitive predictor variables were selected from the software interface considering a significance of 0.05. The Predictor variables used include; ncepp500gl, ncepp5_zgl, nceps850gl, ncepp8_vgl, nceptempgl, ncepshumgl.
For precipitation projection, conditional process was used with a threshold of one (1) while for temperature projection an un conditional process was considered with a threshold of 0. The statistical model was calibrated using the selected predictor variables for a period 0f 1990 to 2003 and validated for a period of 2004 to 2005. The projected weather data (2020 to 2050) was then generated and results were statistically compared.

3.5 Climate change assessment

Historical rainfall, maximum and minimum temperature are the parameters that were considered during the climate change assessment. Historic data was from 1990 to 2020 while projected data was from 2020 to 2050.
Mean monthly historical values were statistically compared to mean monthly projected values of the three parameters (minimum temperature, maximum temperature and rainfall) using bar graphs to assess the changes
Historical total annual rainfall values were statistically compared to projected total annual rainfall values using bar graphs

3.6 LULC projection

Land use land cover forecasting

This was done in Clark Labs Terr set software, Land change modeler tool was used. Land use land cover change between 2020 and 2000 was analyzed and change maps generated, transition sub-models were grouped into a single transition model (named Anthropogenic disturbance) which was used in the model. Evidence likelihood was used as the transformation type, other transformation types available include natural log, exponential, logit, square root and power. Evidence likelihood was selected because it is a very effective means of incorporating categorical variables into the analysis. The transition sub-model structure was set by importing three static drivers into the model which included; distance to the existing roads within Malaba sub catchment, distance to towns and slope of the sub catchment. Multi-Layer Perceptron (MLP) neural network method was used to run the model, the automatic training and dynamic learning rate options were all considered. The transition sub model was then run and a report was generated.

The default Terr set prediction method by Markov Chain was utilized to estimate the amount of change by comparing the dates of the earlier and later land cover maps. The process develops a transition probabilities file and calculates the precise amount of land that would be anticipated to transition from the later date to the prediction date based on a future projection of the transition potentials. Prediction date of 2050 was considered with two recalculation stages that is to say 2035 and 2050. The model was then run and land use maps of 2035 and 2050 were generated each with a transition potential map.

3.7 LULC change assessment

In the Arc GIS environment, the area covered by each land use and land cover categorization was calculated using the land use maps from 2020 and 2000. Comparing the computed areas of the two LULC maps allowed us to evaluate the gains and losses in land use that took place during the 20-year period from 2000 to 2020.

Clerk Labs Terr Set software was also used to assess land use changes that occurred between 2000 and 2020 using the Land Change Modeler. The transition and persistence maps were developed.

3.8 Sediment Modeling and simulation

This was done through building a rainfall runoff model in Arc GIS environment using the Soil and Water Analysis Tool (SWAT). SWAT model is a flexible and physically distributed model which was developed as a river basin scale to quantify and predict runoff, sediment yield, nutrients and sediment transport from watersheds and river basins.

3.8.1 Scenarios considered

Sediment modelling was done considering four scenarios namely;

1. Historic sediment model which involved the use of 2000 LULC data and weather data of 1990 to 2005 to estimate catchment sediment yield and stream flow from 1993 to 2005.
2. Current sediment model which involved the use of 2020 LULC data and weather data of 2003 to 2020 to estimate catchment sediment yield and stream flow from 2006 to 2020
3. The first Projected sediment model which involved the use of projected LULC data of 2035 and projected weather data of 2020 to 2035 to estimate catchment sediment yield and stream flow from 2023 to 2035
4. The second projected sediment model which involved the use of projected LULC data of 2050 and projected weather data of 2030 to 2050 to estimate catchment sediment yield and stream flow from 2035 to 2050

3.8.2 General Modeling and simulation procedures

The Rainfall-run off modeling and simulation process generally followed the following steps;

1. Model set up
2. Watershed delineation
3. Land use, soils and slope definition
4. Definition of HRUs
5. Weather data definition
6. SWAT simulation

Model set up involved setting up the ArcGIS environment, projecting the data frame and the DEM data to WGS 1984 UTM Zone 36^0 N and saving the model.

Watershed delineation was done using the Automatic watershed delineator, a 12.5 m resolution DEM data was used. Under the stream definition, the flow direction and accumulation was obtained which later produced the stream network through creating streams and outlets. The sub-basin outlets and inlets were defined using a point source input, the whole watershed outlet was defined, the watershed was finally delineated and sub-basin parameters were calculated.

Land use, soils and slope definition was carried out using soil data, and land use data of Malaba sub catchment of 2000, reclassification of data for both soils and land use was performed using information from the SWAT2012 database.

Definition of Hydrologic Response Units (HRUs), Hydrologic response unit definition was carried out by defining the threshold proportions of coverage of different soil and land use classifications; multiple HRU was chosen and given suitable percentages (Land use,10%; soil data, 10%; and slope, 5%). From the elevation bands, the HRUs were created and the HRU analysis report was generated.

Weather data definition was done by considering user defined variables that is to say rainfall and temperature, these were fed into the model considering a daily time step, years from 1990 to 2005 were considered. Under the SWAT input tables, tables were built. From the Edit SWAT inputs, Potential Evapotranspiration (PET) method of Penman monteith was selected, SCS Run off curve number method was selected for estimation of run off. Each land use land cover classification automatically generated a unique Curve number and manning's coefficient which were used to estimate run off in the model using the modified Universal Soil Loss Equation inbuilt in SWAT.

SWAT simulation

The warm up period was set to three years to increase accuracy of the model. The model was **Run** with a starting date of 01/01/1990 and ending date of 31/12/2020. The total simulation period was from 1990 to 2005 and the first 3 years were used as warm up period, which helped to stabilize the model hence minimizing possible model errors.

The warm up period allows "buckets" in SWAT (reservoirs, wetlands, soil moisture, aquifers) to fill up and reach stable values. Sediment yield in the first few years are usually underestimated because of this, 1990-1992 period was used for warm up of the model to establish the initial soil water conditions

The above steps basically explain how the first scenario was achieved, the second scenario was achieved using the same procedures while changing only LULC data and Weather data. The third and fourth scenarios were done using a calibrated and validated model whilst changing the LULC data and weather data to the respective years.

3.8.3 Calibration and Validation

SWAT CUP (Soil and Water Analysis Tool Calibration and Uncertainty programs) 2012 Version 5.1.6 was used, the sequential Uncertainty fitting version 2 (SUFI-2) was used as the calibration method. Initially, twelve input parameters were considered for optimization.

The available Malaba sub catchment sediment yield data was insufficient to carryout calibration and validation therefore only observed stream flow data was used as the observed variable. The calibration period was from 1997 to 2005 a period of 9 years; the validation period was from 2008 to 2010 a period of 3 years. Five iterations were considered each with 500 simulations, a daily time step was considered. NSE (Nash serticlif efficiency) and R^2 (coefficient of) were prioritized as measure of accuracy methods. Table ***3-2*** shows the model parameters that were initially used for model sensitivity analysis, the most sensitive parameters were then selected and used for model calibration and validation

No	Parameter	Description	Absolute Value	
			Min	Max
1	USLE_K	Soil erodability factor	0	0.65
2	SURLAG	Surface runoff lag coefficient	0.05	24
3	ALPHA_BF	Base-flow alpha factor (days)	0	1
4	CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/hr)	-0.01	500
5	CH_N2	Manning's "n" value for the main channel	-0.01	0.3
6	CN2	SCS runoff curve number	35	98
7	GW_DELAY	Ground water delay (days)	0	500
8	SOL_K	Saturated hydraulic conductivity (mm/hr)	0	2000
9	SOL_Z	Depth of soil (mm)	0	3500
10	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	5000
11	CH_EROD	Channel Erodibility factor	-0.05	0.6
12	LAT_SED	Sediment concentration in lateral flow and groundwater flow	0	5000

Table 3-2 In put Parameters initially considered for model calibration.

Sensitivity Analysis

Sensitivity analysis is a process of determining the rste of change in model output with respect to changes in model inputs (parameters). It is necessary to identify key parameters and the parameter precision required for calibration (Ma et al.,2000).

Sensitivity analysis was conducted to identify the most sensitive parameters in the catchment, the most sensitive parameters were then used for calibration of the model. Global sensitivity analysis method was adopted in this model and the sensitivities of the different parameters were identified and ranked.

Model Validation

Malaba sub catchment Observed Stream flow data of 2008 to 2010 was used for model validation, the respective NSE and R2 values were recorded.

4 CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Land use Land Cover maps

Table 4-1 shows the description of the historical and projected land use land cover maps of Malaba sub catchment

Figure	Description
Figure ***4-1***	LULC map of 2000, shows the land use types that existed in 2000 in the catchment
Figure ***4-2***	LULC map of 2020, shows the land use types that existed by 2020 in the catchment
Figure ***4-3***	Persistence LULC map showing the land use types that remained unchanged between 2000 to 2020

Figure ***4-4***	LULC change map, showing land use types that changed between 2000 to 2020
Figure ***4-5***	Projected LULC map of 2035, shows the land use types that are predicted to exist by 2035 in the catchment
Figure ***4-6***	Projected LULC map of 2050, shows the land use types that are predicted to exist by 2050 in the catchment
Table ***4-2***	Shows the summary statistics of LULC changes between 2000 and 2050

Table 4-1 Description of LULC maps of Malaba sub catchment

4.1.1 Historical LULC maps

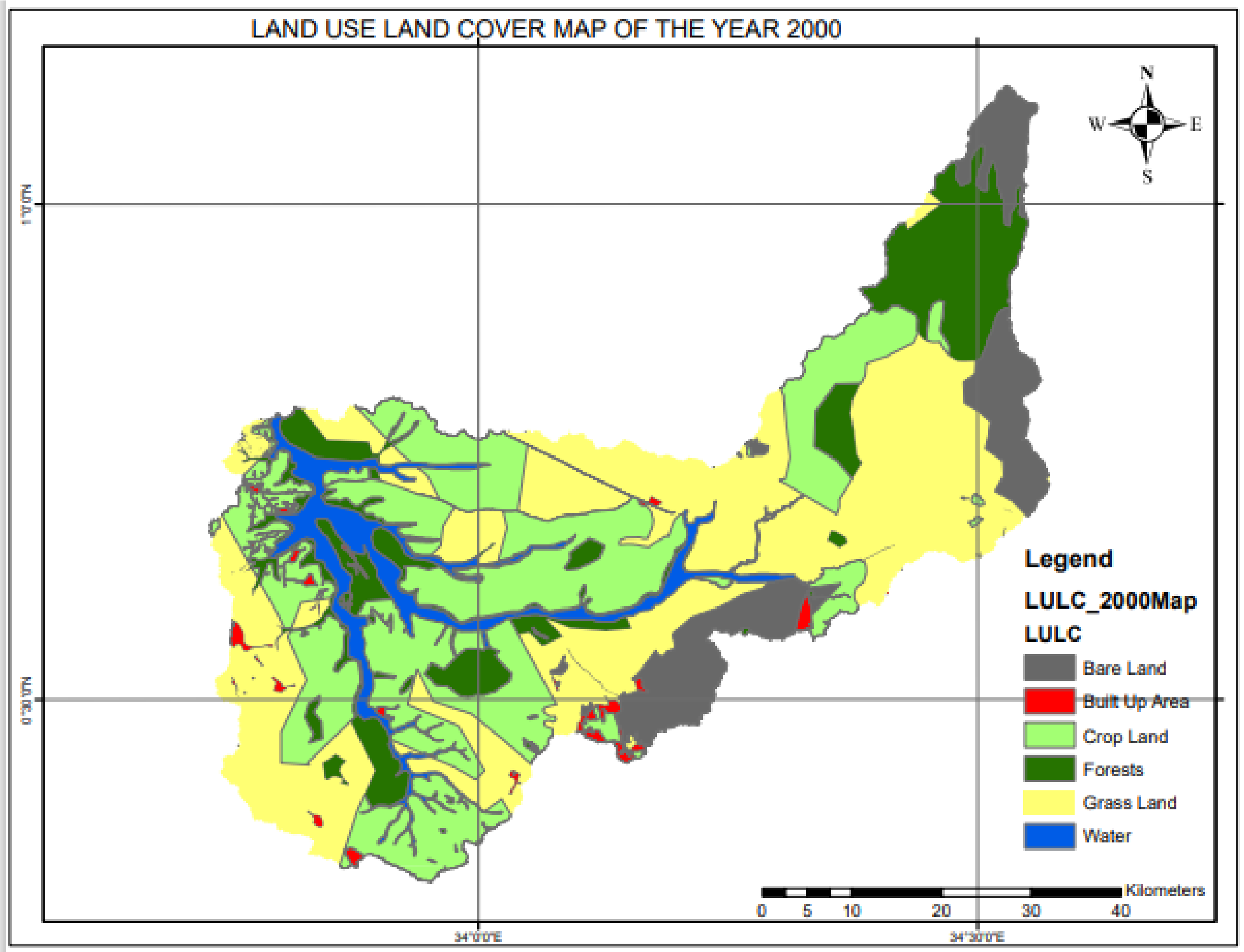

Figure 4-1 Land use land cover map of the year 2000

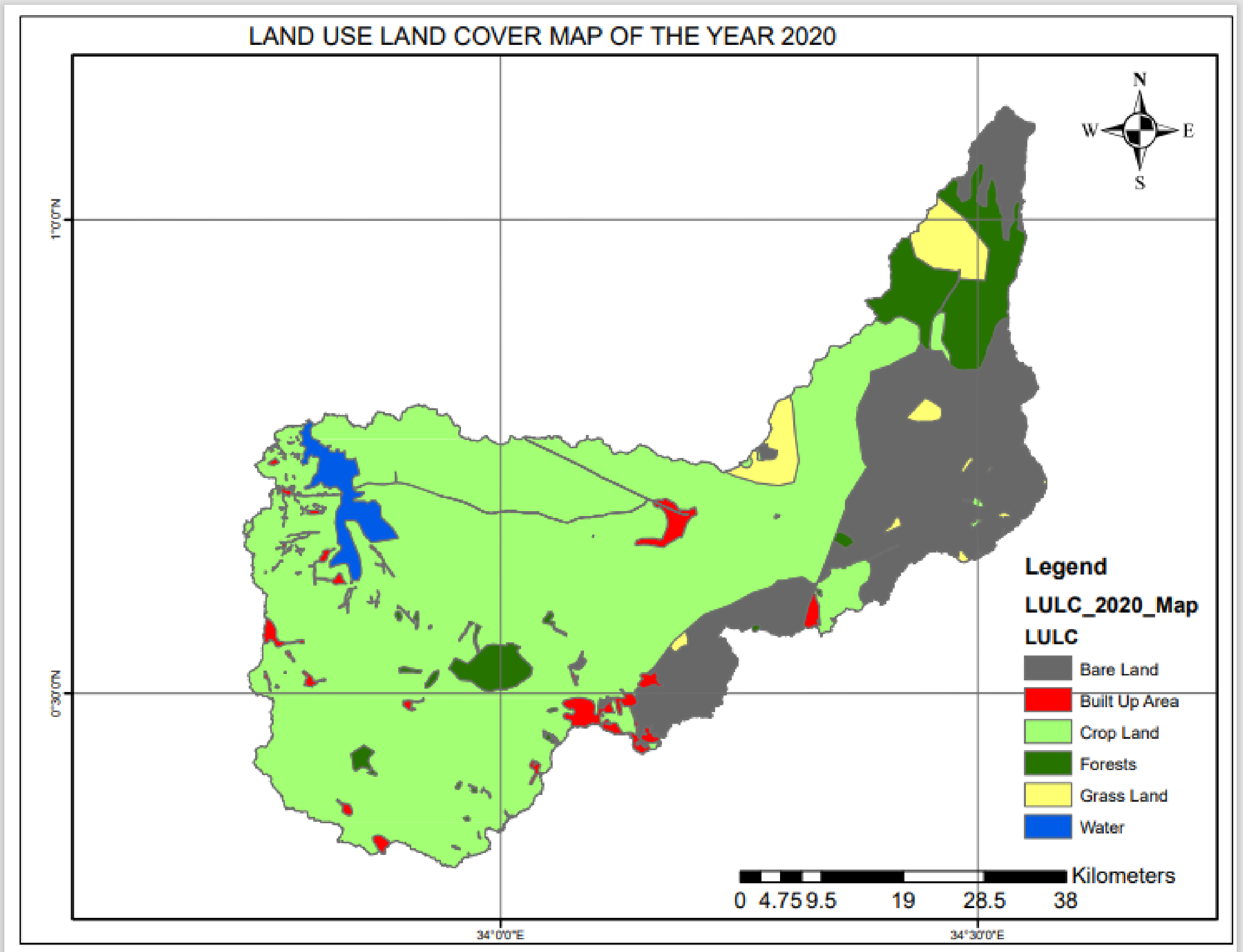

Figure 4-2 Land use land cover map of the year 2020

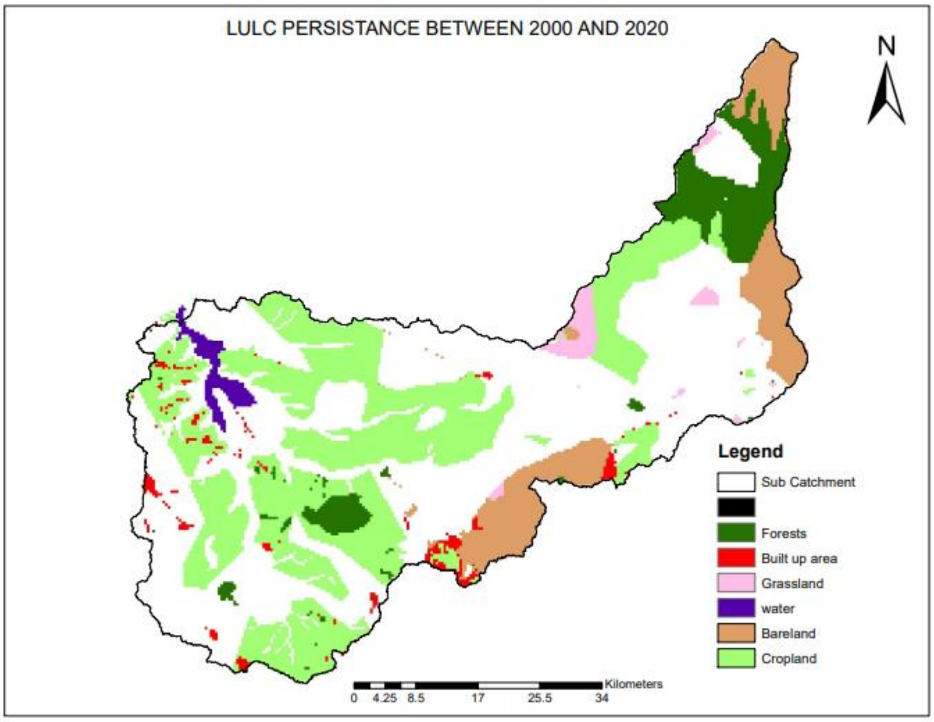

Figure 4-3LU LC persistence map between 2000 and 2020

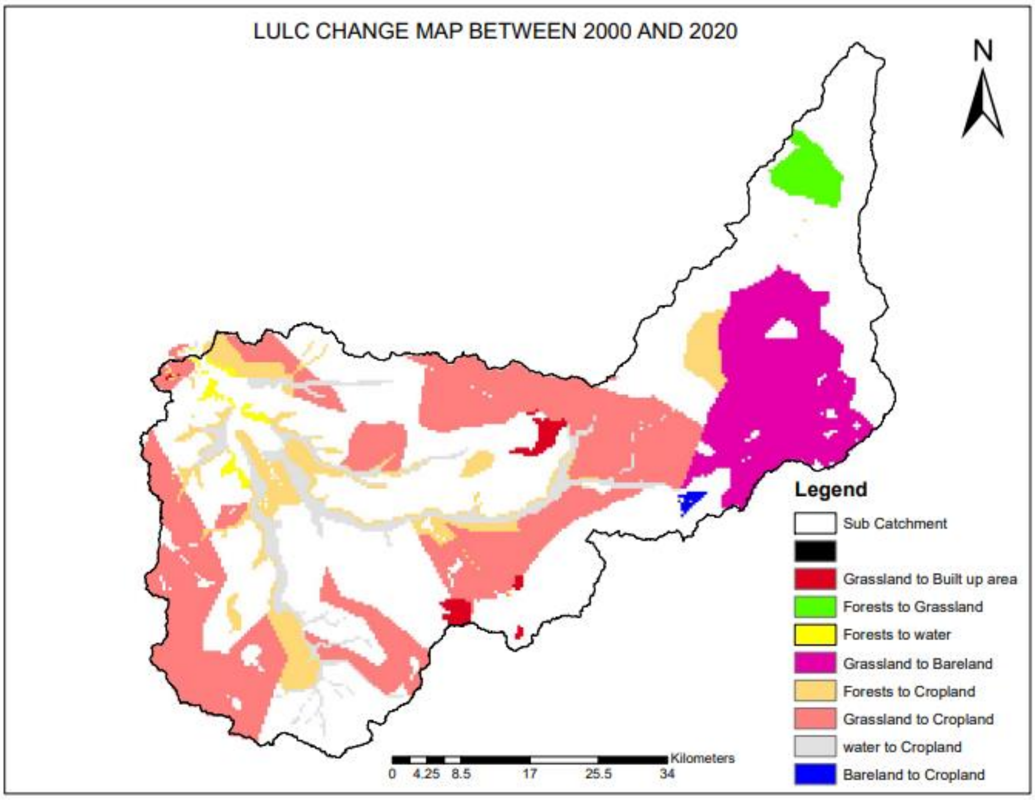

Figure 4-4 LULC change map between 2000 and 2020

4.1.2 Projected LULC maps

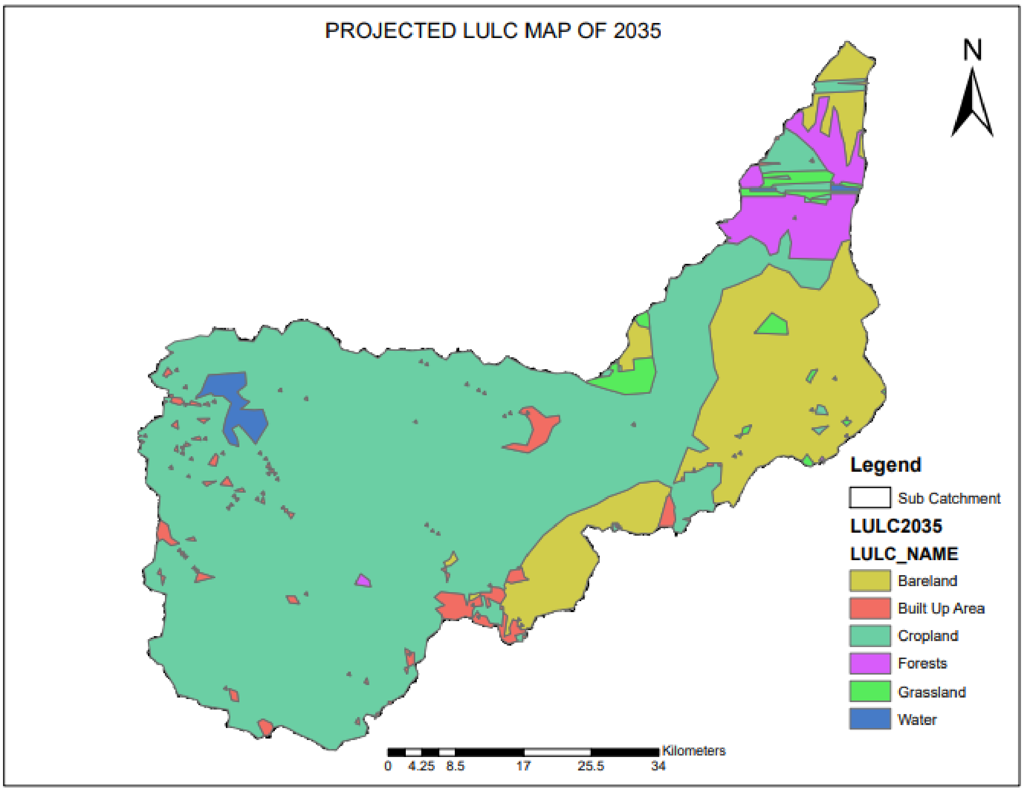

Figure 4-5 Projected LULC map of the year 2035

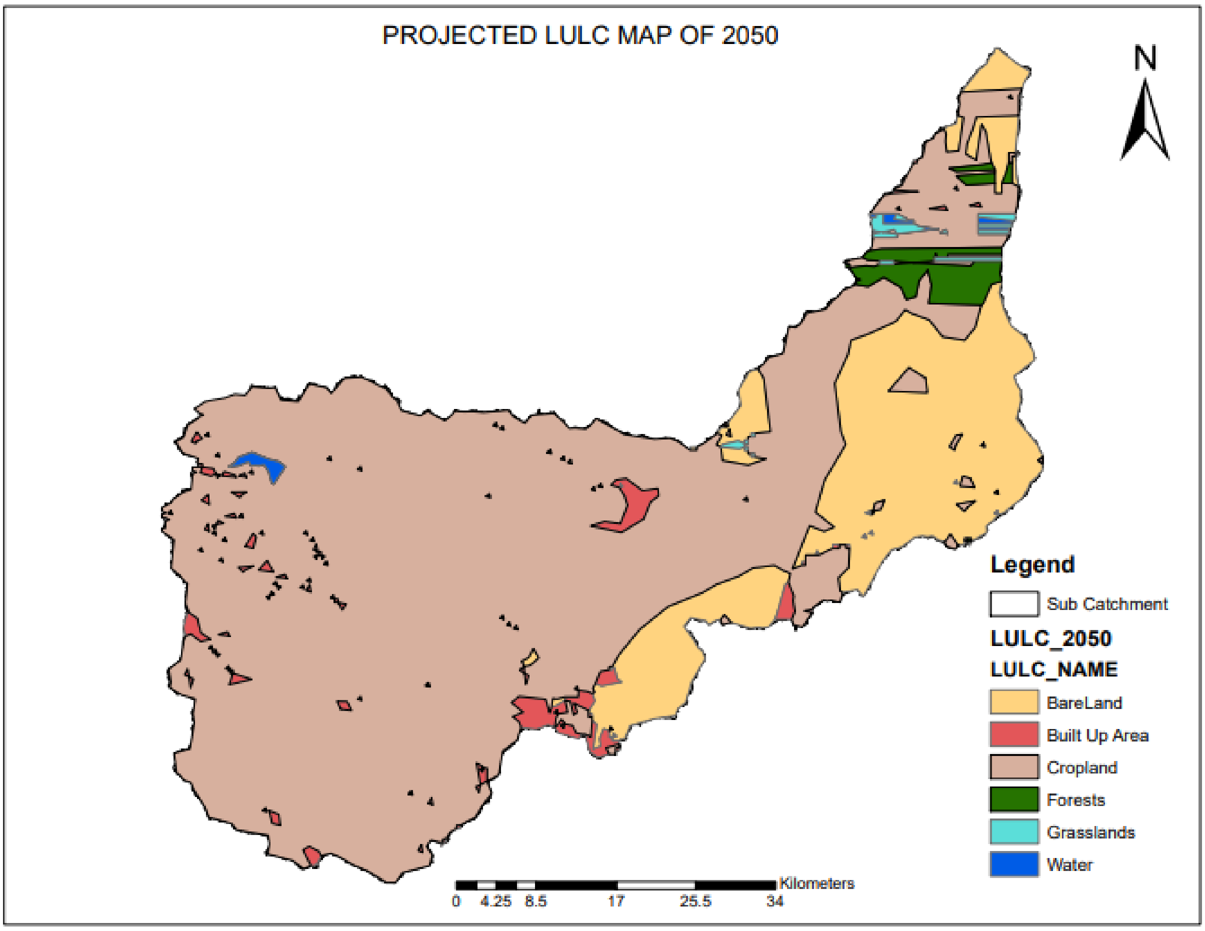

Figure 4-6 Projected LULC map of the year 2050

4.2 Land Use Land Cover Change Analysis

LULC	**Area_km2 (2000)**	2000_Area (%)	**Area_Km2 (2020)**	2020_Area (%)	**Area_Km2 (2035)**	2035_Area (%)	**Area_Km2 (2050)**	2050_Area (%)
Built Up Area	51.6	1.48	79.0	2.27	85	2.436	91	2.61
Crop Land	1062.3	30.44	2324.1	66.61	2469	70.759	2598	74.46
Bare Land	328.3	9.41	692.8	19.86	699	20.033	705.3	20.21
Grass Land	1311.9	37.60	106.7	3.06	55.3	1.585	17	0.49
Water	206.6	5.92	59.5	1.71	37	1.060	12	0.34

Forests	528.7	15.15	227.1	6.51	144	4.127	66	1.89
Total	**3489.3**	**100.00**	**3489.3**	**100.00**	**3489.3**	**100.000**	**3489.3**	**100.00**

Table 4-2 Summary of LULC coverage in square kilometers and percentage

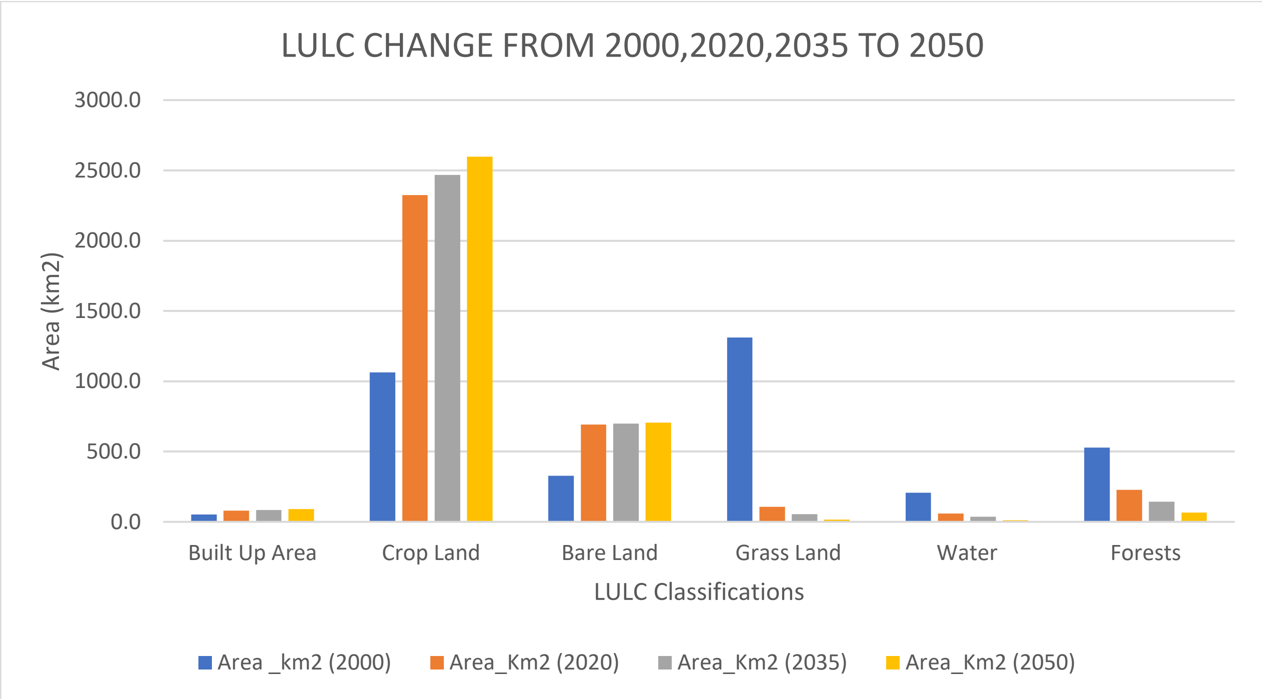

Figure 4-7 Bar chart showing LULC Changes from 2000,2020,2035 to 2050

Considering the above historic and projected LULC maps, tables and the bar chart, it is observed that;Built up area increased from 51km2 in 2000 to 79km2 in 2020, an increment of 18km2 occurred. This study projected that built up area will increase to 85km2 by 2035 and to 91 km2 by 2050. Cropland area increased from 1062 km2 in 2000 to 2324 km2 in 2020, an increment of 1262 km2 occurred. This study projected that Cropland area will increase to 2469 km2 by 2035 and to 2598 km2 by 2050 Bare land area increased from 328 km2 in 2000 to 693 km2 in 2020, an increment of 365 km2 occurred. This study projected that bare land area will increase to 699 km2 by 2035 and to 705 km2 by 2050. Approximately 70% of the bare land in Malaba sub catchment falls in the western part of Kenya. Grassland area decreased from 1312 km2 in 2000 to 107 km2 in 2020, a reduction of 1205 km2 occurred. This study projected that Grassland area will decrease to 55 km2 by 2035 and will further diminish to 17 km2 by 2050 The area covered by water bodies decreased from 207 km2 in 2000 to 60 km2 in 2020, a reduction of 147 km2 occurred. This reduction was majorly caused by encroachment on river Malaba, its tributaries and wetlands. This study projected that the area covered by water bodies will decrease to 37 km2 by 2035 and will further diminish to 12 km2 by 2050 Forest area decreased from 529 km2 in 2000 to 227 km2 in 2020, a reduction of 302 km2 occurred. This study projected that forest area will shrink to 144 km2 by 2035 and will further diminish to 66 km2 by 2050

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

4.3 Climate change Analysis

4.3.1 Precipitation changes

Annual change analysis

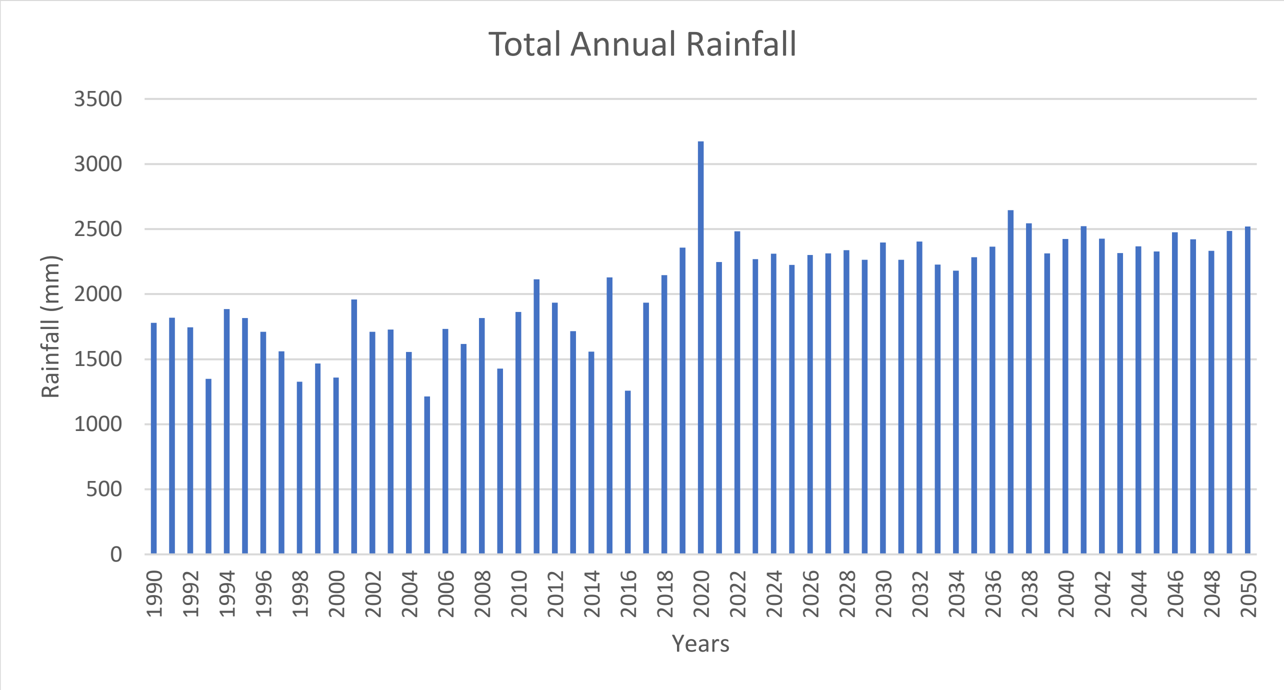

Figure 4-8 Total Annual Rainfall comparison between 1990 to 2050

Figure ***4-8*** indicates that, from the historical rainfall data, the maximum total annual rainfall was observed in 2020 of about 3174mm. This study projected that the rainfall trends and patterns will change un evenly throughout the years from 2020 to 2050. Rainfall is projected to generally increase throughout the years from 2021 to 2050 as indicated in Figure ***4-8*** above with the highest rainfall predicted to occur in 2037 with a total annual value of 2646mm

Average monthly change analysis

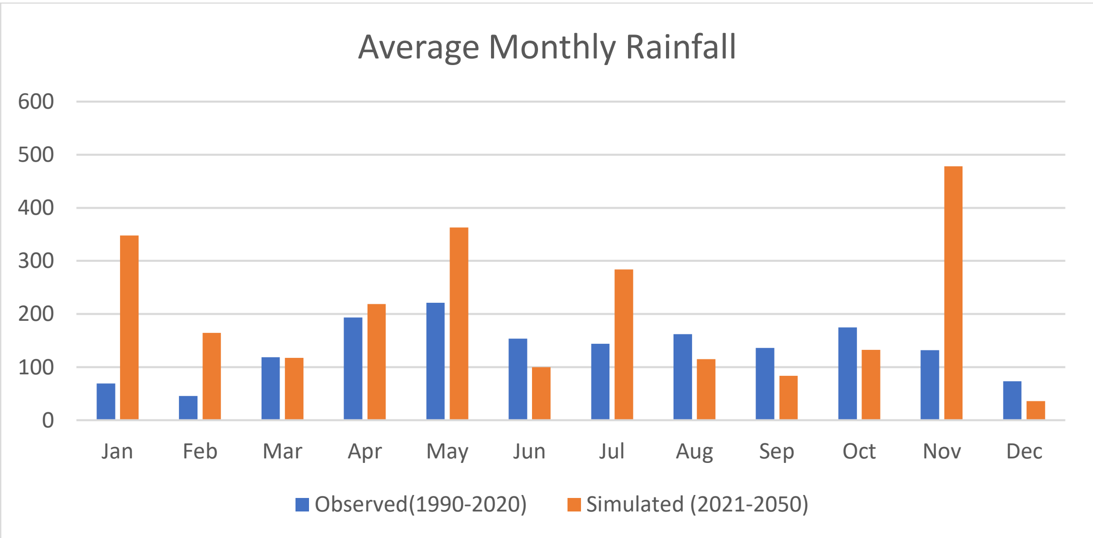

Figure 4-9 Comparison between projected and historic Mean monthly rainfall

From Figure ***4-9***, rainfall is generally projected to un evenly increase throughout the Months of the years from 2021 to 2050 as indicated in figure 4-9. Rainfall will increase from January to May, then decrease from June to October, increase in November and finally decrease in December.

4.3.2 Temperature changes

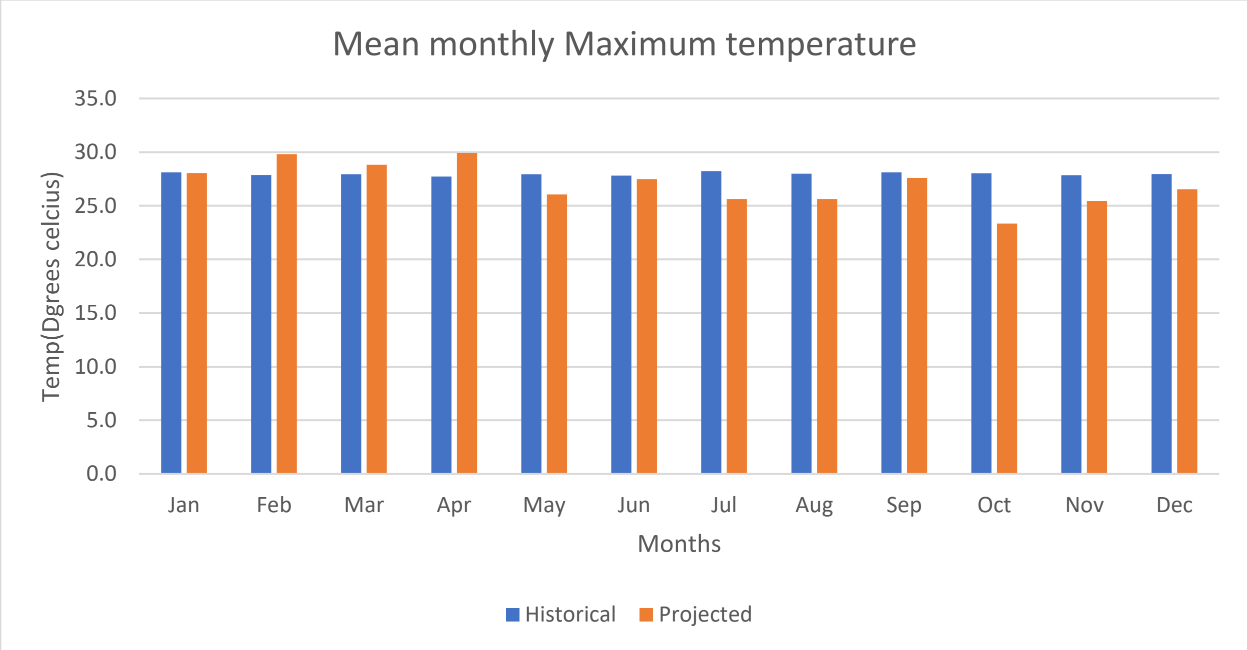

Figure 4-10 Mean monthly maximum temperature comparison

From Figure ***4-10***, maximum temperature in the catchment is expected to increase (become hotter) from February to April, then reduce from May to January.

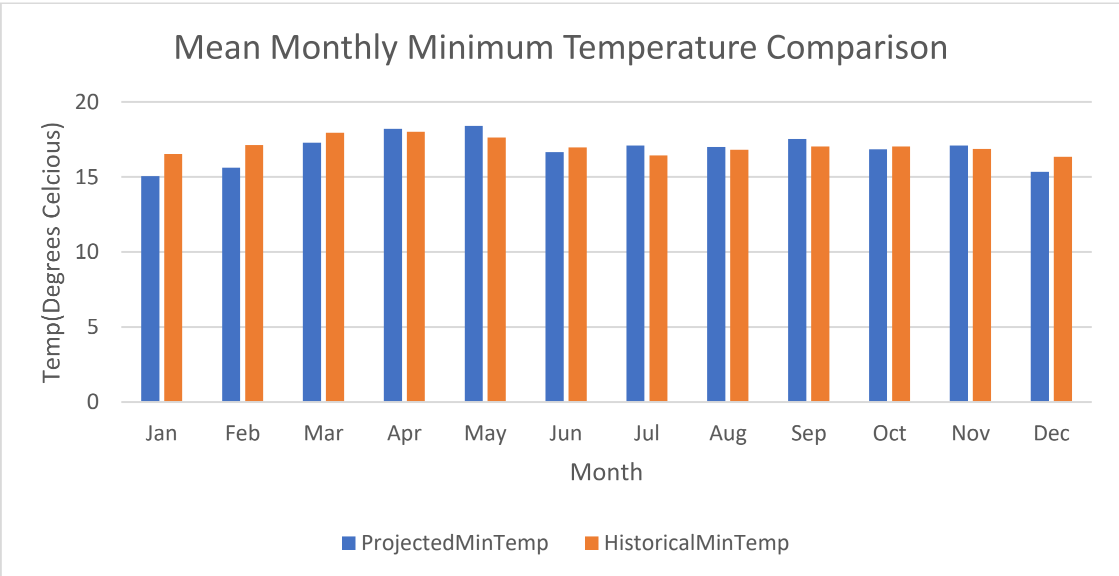

Figure 4-11 Mean Monthly Minimum Temperature Comparison

From Figure ***4-11***, the minimum temperature is expected to reduce (become colder) from December to March, increase from April to September.

4.4 Results from Calibration and Validation of the Rainfall runoff model.

Sensitivity analysis of the model parameters

The global sensitivity analysis indicated that 9 parameters were very sensitive to discharge and sediment yield. *Table **4-3*** shows the most sensitive parameters used for model calibration and validation.

Parameter Name
R__SOL_K(..).sol
R__CN2.mgt
R__SOL_AWC(..).sol
R__CH_K2.rte
V__GWQMN.gw
R__CH_N2.rte
V__ALPHA_BF.gw
R__USLE_K(..).sol
V__GW_DELAY.gw

Table 4-3 Calibration Parameters

Calibration and validation

NSE of 45% and R2 of 3% was obtained during calibration.

4.5 Assessment of Sediment yield in the catchment

4.5.1 Total annual sediment yield at Catchment outlet (tons)

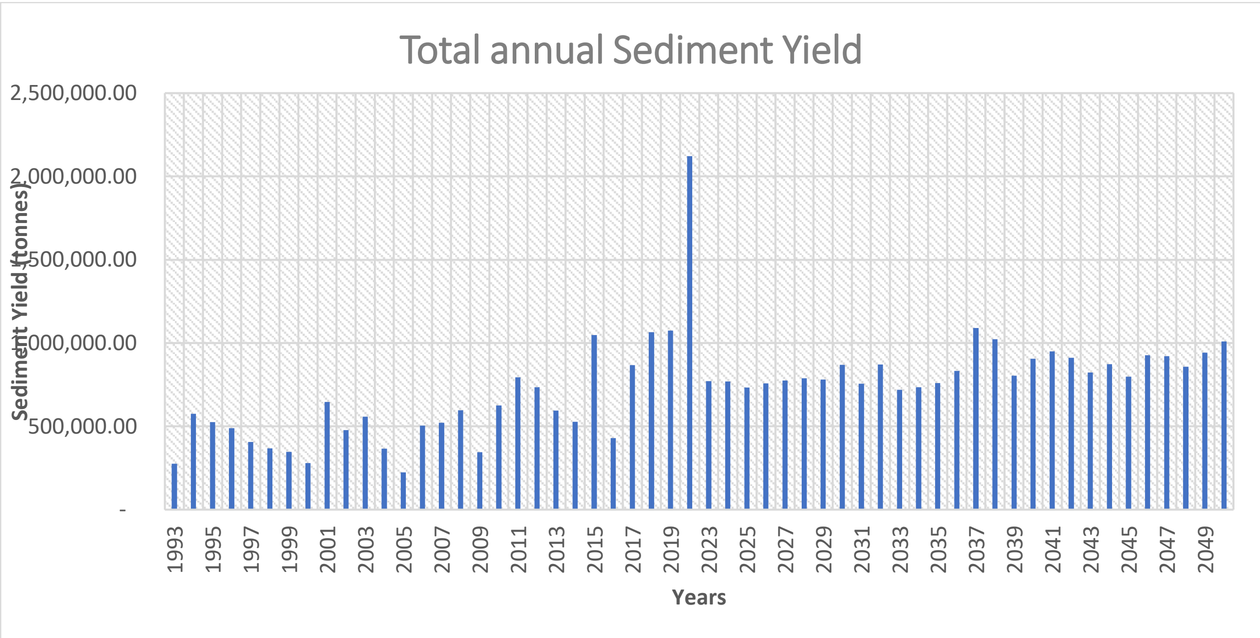

Figure 4-12 Total annual sediment yield from Malaba sub catchment outlet (Point data)

The results indicated in Figure ***4-12*** were extracted from the model outlet of the whole catchment, results from the model indicated that Sediment yield from Malaba sub catchment was highest in 2020, about 2 million tons of sediments were recorded. This was because of the very high rainfall that was received within the catchment in 2020.

The model indicated that Sediment yield in the sub catchment is projected to generally rise from 2023 to 2050 as indicated in *Figure **4-12***

4.5.2 Total Annual Sediment yield from whole catchment (tons)

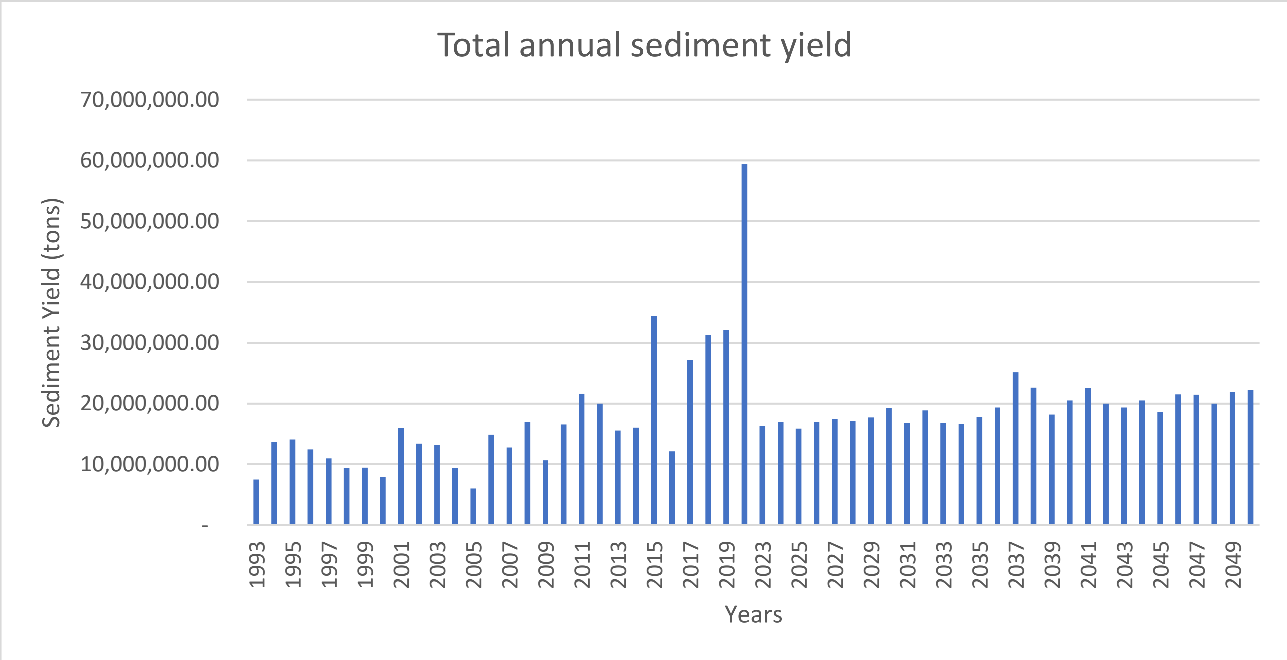

Figure 4-13 Total annual sediment yield from the whole catchment

The total annual sediment yield indicated in Figure ***4-13*** was obtained by summing up the total sediment yield from all the 26 sub basins, the year 2020 had the highest sediment yield of approximately 59 million tons. Among the projected years, 2037 is expected to have a high sediment yield of about 2500 tons.

4.5.3 Total Annual Sediment yield in the catchment (tons/km^2)

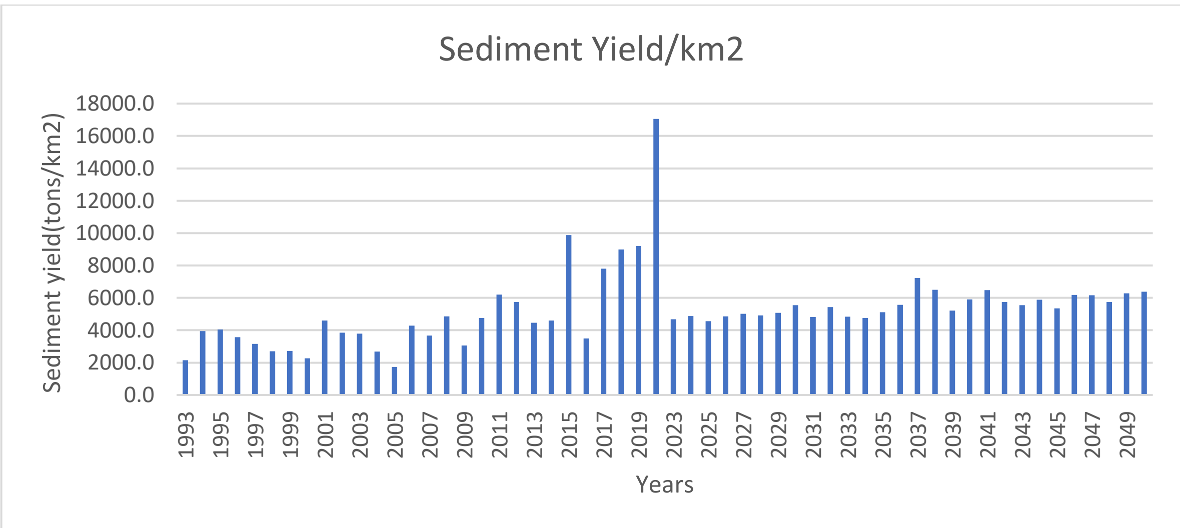

Figure 4-14 Annual Sediment Yield per square kilometer in the catchment

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

The sediment yield/km^2 indicated in Figure ***4-14*** was obtained by dividing the total annual sediment yield in the catchment by the total catchment area. From 1990 to 2020, the highest sediment yield/km2 was observed in 2020. Among the projected years, 2037 is expected to have a high sediment yield of about 7224 tons/km^2.

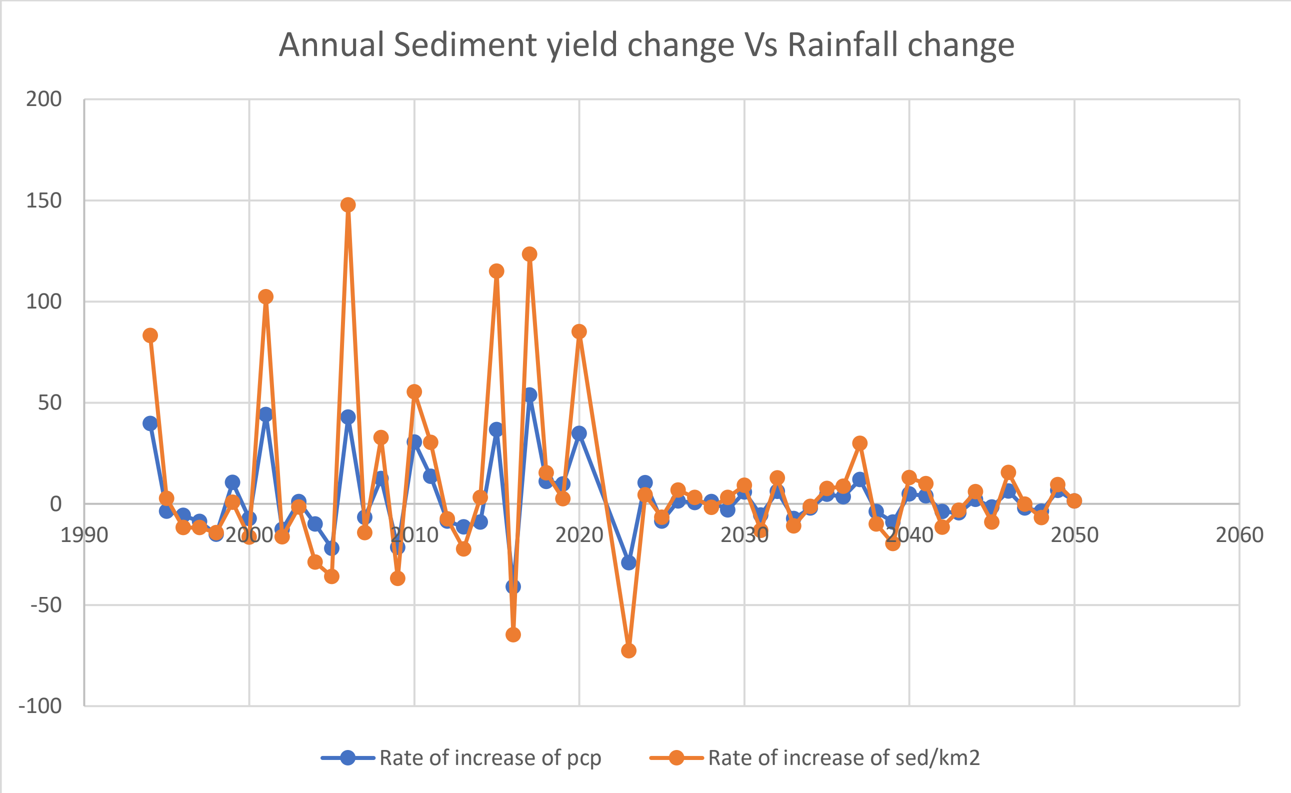

Figure 4-15 Rate of change of Annual sediment yield Vs rate of change of Annual Rainfall in the catchment

From Figure ***4-13***, the sediment yield of the sub catchment was directly proportional to the rainfall. As noticed, from 1994 to 1998 a decrease in rainfall caused a decrease in sediment yield in the sub-catchment. From 2016 to 2017 there was an increase in rainfall which led to rise in sediment yield. The trend continues thought out the years.

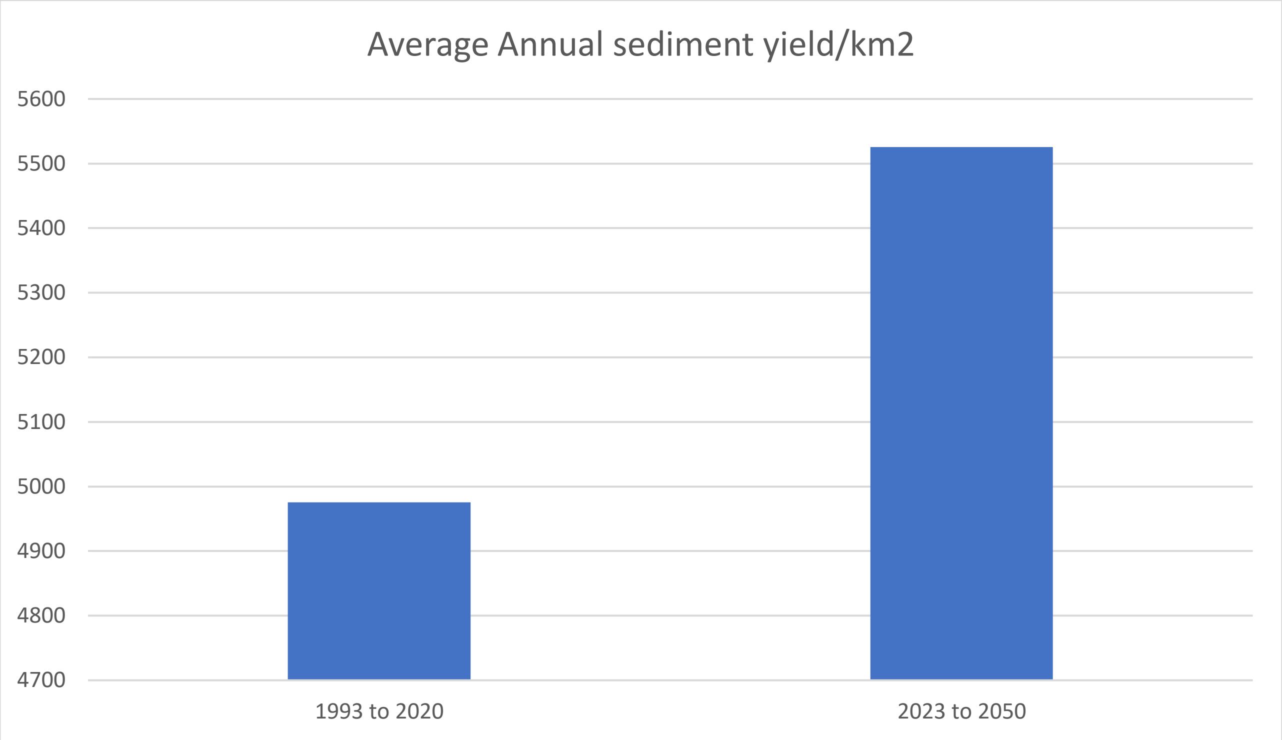

Figure 4-16 Average Annual sediment yield/km2 in the catchment

Figure ***4-16*** indicates that from 1993 to 2020, the average annual sediment yield in the catchment was 4975 tons/km2 per, sediment yield is anticipated to increase to about 5525 tons/km2 per year between 2023 to 2050.

4.6 Flows in River Malaba

Annual average flows

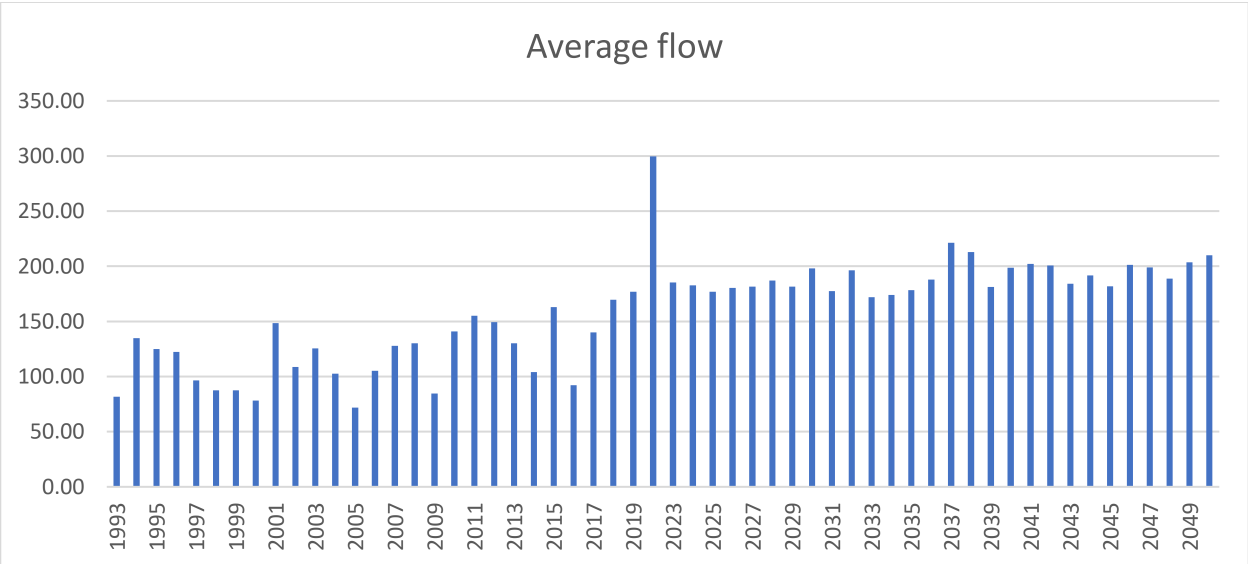

Figure 4-17 Historical and Projected Annual Peak flows in River Malaba

Figure ***4-17*** indicates that flows in River Malaba have been changing un evenly from 1993 to 2020, some of the highest peak flows were observed in 2020 with a discharge of 299m3/s and 2019 with 177m3/s. Flows are projected to generally increase from 2020 to 2050 as indicated in figure 4-18, the highest flow is projected to occur in 2037 with a flow of approximately 221m3/s

4.7 Sub basins in Malaba sub catchment

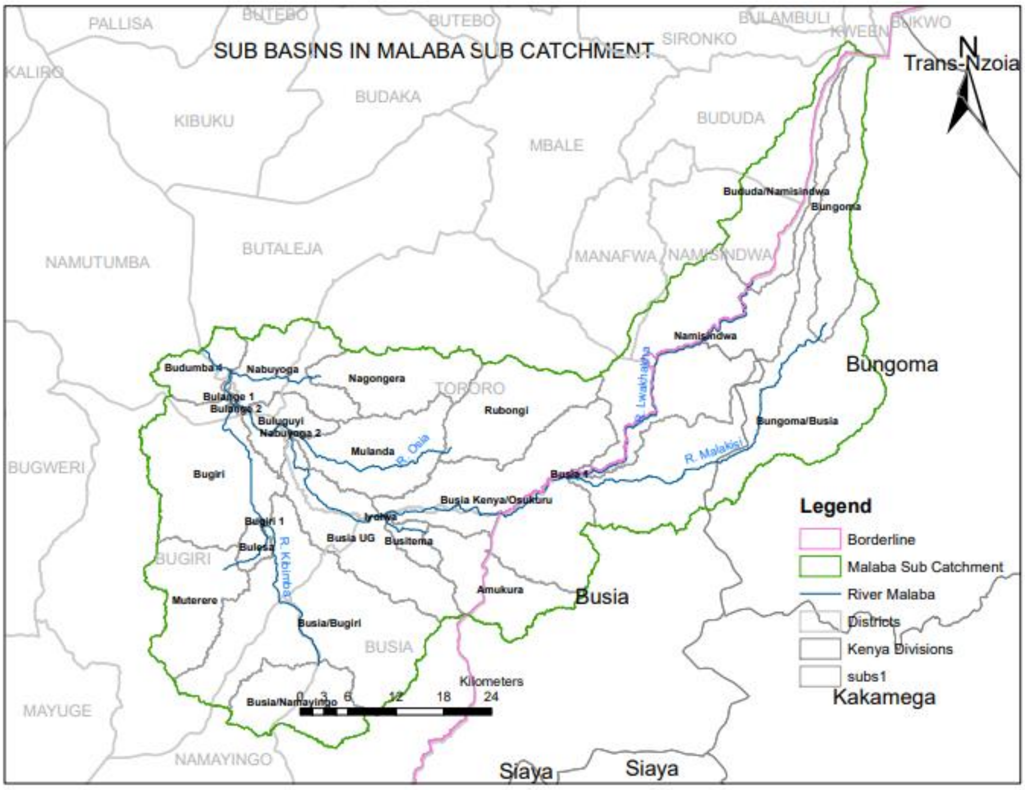

Figure 4-18 Map showing sub basins in Malaba sub catchment

The sub basins indicated in Figure ***4-18*** were named according to the geographical location of the sub basins.

Table 4-4 Description of Sedimentation hotspots Malaba sub catchment

The sediment hotspots were identified according to sub basins, the above table 4-2 shows the sub basins worst hit by sedimentation in Malaba sub catchment together with the sediment yield.

4.8 Sedimentation Hotspots

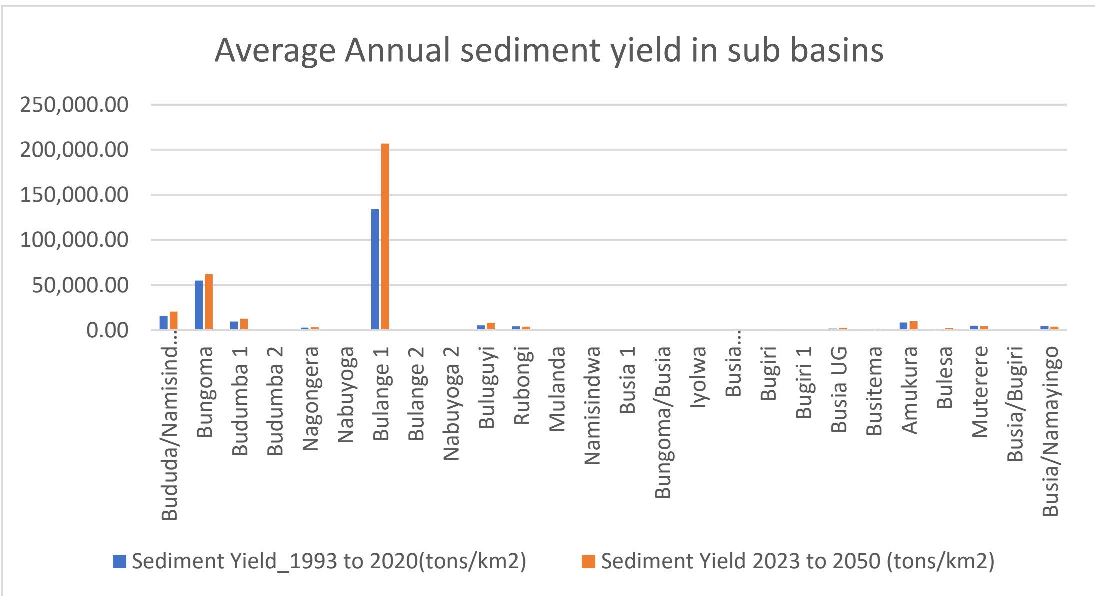

Figure 4-19 Average Annual sediment yield in the sub basins

Sub basin name	Location	Sediment yield (tons/km2/year)	
		Historical (1993-2020)	Projected (2023-2050)
Bulange 1	Bulange sub county in Namutumba District,	134,193.19	206,641.30
Bungoma	Bungoma Division in Kenya	54,836.99	62,089.99
Bududa/Namisindwa	Bukalasi, Bubiita, Nalwanza in Bududa and Mukoto, Bupoto, Bukokho, Bumbo, Bukiambi in Namisindwa	15,857.28	20,397.40
Budumba 1	Budumba subcounty in Butaleja and Bulange sub county in Namutumba district	9,480.35	12,854.27
Buluguyi	Nabuyoga sub county in Tororo district, Buluguyi sub county in Bugiri district, Busabi sub county in Butaleja district	5,332.73	8,201.83
Amukura	Nambale and Amukura in Busia division in Kenya Buteba, Sikuda and Busitema sub counties in Busia Uganda.	8,347.99	9,838.97

Table 4-5 Description of Sedimentation hotspots Malaba sub catchment

*Table **4-5*** shows the sub basins worst hit by sedimentation in Malaba sub catchment together with the estimated sediment yield.
Figure ***4-19*** shows the historical and projected average annual sediment yield in all sub basins in Malaba sub catchment.

4.9 Comparison and contrast between the previous studies and this present study

1. A study done by Barasa in 2014 in the same Malaba sub catchment indicated that changes in land use and land cover type presented an improvement of land use for farm land with about 36% gain, the major losses in land cover were observed in wetlands, about 24% (Barasa, 2014). In this research the

highest gain in land use was also observed in agricultural land which gained by about 36% from 2000 to 2020 while the highest loss was realized in grassland rather than wetlands as indicated by (Barasa, 2014). However, Barasa, 2014 did not project the future scenarios.

2. A study done by Kangume Charity, 2016 indicated that projected rainfall and R. Malaba flows are expected to increase annually from 2020 to 2050. This current research also indicated that rainfall is expected to increase from 2020 to 2024. However, Kangume, 2016 did not deal with land use changes and sedimentation in the catchment.
3. This current research addresses the knowledge gap from both (Barasa, 2014; kangume,2016) because it considers both the historical and projected land use and climate change simultaneously which was not done earlier.

4.10 Limitations of this research

1. In adequate observed sediment data which did not permit long term calibration and validation of the model using sediment as a variable, instead flow was used a calibration and validation variable.

5 CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSION

The climate projection conducted in this study indicated that from 2020 to 2050 climate variables are expected to change un evenly, maximum temperature is expected to increase, minimum temperature is expected to reduce, rainfall over the catchment is expected to increase. The land use projection carried out in this study predicted that from 2020 to 2050 Land use types of cropland and built up area are expected increase while forests and water bodies are expected to reduce. Average annual Sediment yield of 1993 to 2020 is expected to generally increase from 4975.4 tons/km2/year to an average annual sediment yield of 5525.6 tons/km2/year from 2023 to 2050. Therefore, mitigation measures should be adopted to ensure sustainable management of the catchment.

The study findings of this research shall be relevant for planning, design and management of reservoirs, dams, irrigation systems and sustainability of eco systems in the catchment. This is because sediment hotspots/points of intervention have been identified in this study, the land use types which have been significantly reducing over the years and those expected to reduce in future have been identified, this can act as a starting point for environmental conservation strategies in the catchment. However, a few challenges were encountered during the modeling processes; In adequate observed sediment yield which could not be used for calibration and validation.

5.2 RECOMMENDATIONS

1. Observed sediment data should always be availed to researchers to ensure accurate modeling through proper calibration and validation.
2. Land suitability assessments should be conducted in the catchment
3. Agroforestry, watershed restoration, biodiversity and wetland conservation, carbon sequestration, water quality monitoring and pollution control should be implemented in the catchment sedimentation hotspots.

REFERENCES

1. Van, O.K.; Govers, G.; Desmet, P. Evaluating the effects of changes in landscape structure on soil erosion by water and tillage. Landsc. Ecol. **2000**, 15, 577–589. [Google Scholar]
2. Zhang, X.C.; Liu, W.Z. Simulating potential response of hydrology, soil erosion, and crop productivity to climate change in Changwu tableland region on the Loess Plateau of China. Agric. For. Meteorol. **2005**, 131, 127–142. [Google Scholar] [CrossRef]
3. Khoi, D.N.; Suetsugi, T. Impact of climate and land-use changes on hydrological processes and sediment yield—A case study of the Be River catchment, Vietnam. Hydrol. Sci. J. **2014**, 59, 1095–1108. [Google Scholar] [CrossRef]
4. Li, Z.Y.; Fang, H.Y. Modeling the impact of climate change on watershed discharge and sediment yield in the black soil region, northeastern China. Geomorphology **2017**, 293, 255–271. [Google Scholar] [CrossRef]
5. Boix-Fayos, C.; Martínez-Mena, M.; Arnau-Rosalén, E.; Calvo-Cases, A.; Castillo, V.; Albaladejo, J. Measuring soil erosion by field plots: Understanding the sources of variation. Earth Sci. Rev. **2006**, 78, 267–285. [Google Scholar] [CrossRef]
6. Montgomery, D.R.; Brandon, M.T. Topographic controls on erosion rates in tectonically active mountain ranges. Earth Planet. Sci. Lett. **2002**, 201, 481–489. [Google Scholar] [CrossRef]
7. Wang, H.; Saito, Y.; Zhang, Y.; Bi, N.; Sun, X.; Yang, Z. Recent changes of sediment flux to the western Pacific Ocean from major rivers in East and Southeast Asia. Earth Sci. Rev. **2011**, 108, 80–100. [Google Scholar] [CrossRef]
8. Langbein, W.B.; Schumm, S.A. Yield of sediment in relation to mean annual precipitation. EOS **1958**, 39, 1076–1084. [Google Scholar] [CrossRef][Green Version]
9. Stockwell, J.D.; Doubek, J.P.; Adrian, R.; Anneville, O.; Carey, C.C.; Carvalho, L.; Domis, L.N.D.S.; Dur, G.; Frassl, M.A.; Grossart, H.P.; et al. Storm impacts on phytoplankton community dynamics in lakes. Glob. Chang. Biol. **2020**, 26, 2756–2784. [Google Scholar] [CrossRef][Green Version]
10. Shi, Z.H.; Huang, X.D.; Ai, L.; Fang, N.F.; Wu, G.L. Quantitative analysis of factors controlling sediment yield in mountainous watersheds. Geomorphology **2014**, 226, 193–201. [Google Scholar] [CrossRef]
11. Wang, M.; Hamilton, D.P.; McBridea, C.G.; Abellc, J.M.; Hicksa, B.J. Modelling hydrology and water quality in a mixed land use catchment and eutrophic lake: Effects of nutrient load reductions and climate change. Environ. Modell. Softw. **2018**, 109, 114–133. [Google Scholar]
12. Lü, X.X.; Ran, L.S.; Liu, S.; Jiang, T.; Zhang, S.R.; Wang, J.J. Sediment loads response to climate change: A preliminary study of eight large Chinese rivers. Int. J. Sediment Res. **2013**, 28, 1–14. [Google Scholar] [CrossRef]
13. Zabaleta, A.; Meaurio, M.; Ruiz, E.; Antigüedad, I. Simulation climate change impact on runoff and sediment yield in a small watershed in the Basque Country, northern Spain. J. Environ. Qual. **2014**, 43, 235–245. [Google Scholar] [CrossRef]
14. Imeson, A.C.; Lavee, H. Soil erosion and climate change: The transect approach and the influence of scale. Geomorphology **1998**, 23, 219–227. [Google Scholar] [CrossRef]
15. Zhao, G.J.; Mu, X.M.; Tian, P.; Wang, F.; Gao, P. The variation trend of streamflow and sediment flux in the middle reaches of Yellow River over the Past 60 years and the influencing Factors. Res. Sci. **2012**, 34, 1070–1078. (In Chinese) [Google Scholar]

16. Nearing, M.A.; Jetten, V.; Baffaut, C.; Cerdan, O.; Couturier, A.; Hernandez, M.; Le Bissonnaise, Y.; Nicholsa, M.H.; Nunesf, J.P.; Renschlerg, C.S.; et al. Modeling response of soil erosion and runoff to changes in precipitation and cover. Catena **2005**, 61, 131–154. [Google Scholar] [CrossRef]
17. Jansen, I.M.L.; Painter, R.B. Predicting sediment yield from climate and topography. J. Hydrol. **1974**, 21, 371–380. [Google Scholar] [CrossRef]
18. Syvitski, J.P.M. The influence of climate on the flux of sediment to the coastal ocean. In Proceedings of the Oceans 2003. Celebrating the Past ... Teaming toward the Future (IEEE Cat. No.03CH37492), San Diego, CA, USA, 22–26 September 2003; Available online: https://ieeexplore.ieee.org/abstract/document/1283423 (accessed on 1 May 2020).
19. Phan, D.B.; Wu, C.C.; Hsieh, S.C. Impact of climate change on stream discharge and sediment yield in northern Viet Nam. Water Resour. **2011**, 38, 827–836. [Google Scholar] [CrossRef]
20. Huang, X. The Effect and Mechanism of Vegetation Cover and Rainfall Change on Runoff and Sediment Yield in Du Watershed, China. Ph.D. Thesis, Huazhong Agricultural University, Wuhan, China, 2019. [Google Scholar]
21. Walling, D.E.; Fang, D. Recent trends in the suspended sediment loads of the world's rivers. Glob. Planet Chang. **2003**, 39, 111–126. [Google Scholar] [CrossRef]
22. Martin, J.M.; Meybeck, M. Elemental mass-balance of material carried by major world rivers. Mar. Chem. **1979**, 7, 173–206. [Google Scholar] [CrossRef]
23. Walling, D.E. The Impact of Global Change on Erosion and Sediment Transport by Rivers: Current Progress and Future Challenges; United Nations Educational, Scientific and Cultural Organization: Paris, France, 2009; pp. 1–26. [Google Scholar]
24. Montgomery, D.R. Soil erosion and agricultural sustainability. Proc. Natl. Acad. Sci. USA **2007**, 104, 13268–13272. [Google Scholar] [CrossRef] [PubMed][Green Version]
25. Sinha, R.K.; Eldho, T.I. Effects of historical and projected land use/cover change on runoff and sediment yield in the Netravati River basin, Western Ghats, India. Environ. Earth Sci. **2018**, 77, 111. [Google Scholar] [CrossRef]
26. IPCC. Climate change 2014: Synthesis report. In Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change; Pachauri, R.K., Meyer, L.A., Eds.; Core Writing Team, IPCC: Geneva, Switzerland, 2014; p. 151. [Google Scholar]
27. IPCC. Global Warming of 1.5 °C. An IPCC Special Report on the Impacts of Global Warming of 1.5 °C above Pre–Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty; World Meteorological Organization: Geneva, Switzerland, 2018; p. 32. [Google Scholar]
28. Vaighan, A.A.; Talebbeydokhti, N.; Bavani, A.M. Assessing the impacts of climate and land use change on streamflow, water quality and suspended sediment in the Kor River Basin, Southwest of Iran. Environ. Earth Sci. **2017**, 76, 543. [Google Scholar] [CrossRef]
29. Thrasher, B.; Maurer, E.P.; McKellar, C.; Duffy, P.B. Technical note: Bias correcting climate model simulated daily temperature extremes with quantile mapping. Hydrol. Earth Syst. Sci. **2012**, 16, 3309–3314. [Google Scholar] [CrossRef][Green Version]
30. Peng, H.; Jia, Y.W.; Qiu, Y.Q.; Niu, C.W.; Ding, X.Y. Assessing climate change impacts on the ecohydrology of the Jinghe River basin in the Loess Plateau, China. Hydrol. Sci. J. **2013**, 58, 651–670. [Google Scholar] [CrossRef]

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

APPENDICES







International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com