KYAMBOGO UNIVERSITY

ASSESSMENT OF THE IMPACTS OF LAND USE AND LAND COVER CHANGES ON SOIL EROSION IN OGWAPOKE MICRO-CATCHMENT, NORTHERN UGANDA

BY

AJIDIRU RITA

19/U/GMSM/19855/PD

A DISSERTATION SUBMITTED TO THE DIRECTORATE OF RESEARCH AND GRADUATE TRAINING IN PARTIAL FULFILLMENT FOR THE AWARD OF THE MASTERS DEGREE OF SCIENCE IN CONSERVATION AND NATURAL RESOURCE MANAGEMENT OF KYAMBOGO UNIVERSITY

OCTOBER 2022

Declaration

I, AJIDIRU RITA hereby declare that the content in this research thesis is original and was fully prepared and written by me and has never been presented in any academic institution for any ward in all cases.

Signature.. Date...27/10/2022........

Reg No: 19/U/GMSM/18955/PD

Approval

This research thesis has been submitted with approval of the University supervisors:

Signed: .... Date....28/10/2022....

Main Supervisor

Dr. Barasa Bernard

Signed: .... Date....07th/11/2022....

Second Supervisor

Dr. Santa Maria Asio

Acknowledgement

I would like to express my sincere gratitude to my research supervisors, Dr. Barasa Bernard and Dr. Santa Maria Asio for their continued commitment, guidance, encouragement, advice, and review of this research project. Without their support, this thesis would not have been completed in time and shape. Special thanks also go to the entire faculty of science and most especially to the Department of Biological Sciences for their support and effort put in that have enabled me to complete this Masters Programme.

I would also want to appreciate my dear husband, Mr. Toko Godfrey and the entire family members for their moral support and encouragement in pursuing this course.

TABLE OF CONTENTS

List of Tables

List of Figures

List of Abbreviations

AGNPS	Agricultural Non-Point Source
ARS	Agricultural Research Services
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BMPs	Best Management Practices
CA	Cellular Automata
CREAMS	Chemical Runoff and Erosion from Agricultural Management Systems
DEM	Digital Elevation Model
EPIC	Erosion/Productivity Impact Calculator
ERDAS	Earth Resources Data Analysis System.
ET	Evapotranspiration
ETM+	Enhanced Thematic Mapper Plus
EUROSEM	European Soil Erosion Model
FAO	Food and Agriculture Organization of the United Nations
HBV	Hydrologiska Byrans Vattenavdelning
HRUs	Hydrological Response Units
K	Kappa statistics
LAI	Leaf Area Index
LULC	Land Use/Cover
MLP-MC	Multi-layer Perceptron-Markov Chain
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner System
NSE	Nash Sutcliffe Efficiency
OA	Overall Accuracy
OLI	Operational Land Imager
PA	Producer's Accuracy
PBIAS	Percent Bias
PESERA	Pan-European Soil Erosion Risk Assessment
RUSLE	Revised Universal Soil Loss Equation
SedNet	Sediment River Network
SEMMED	Soil Erosion Model for Mediterranean Regions
SPOT	Satellite Pour l'Observation de la Terre
STRM	Shuttle Radar Topography Mission
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT-Calibration and Uncertainty Procedures
SWC	Soil and Water Conservation
TM	Thematic mapper
UA	User's Accuracy
USDA	United States Department of Agriculture

USGS	United States Geological Survey
USLE	Universal Soil Loss Equation
VIC	Variable Infiltration Capacity

Abstract

Several land use/cover changes have been observed in Ogwapoke micro catchment. Population increase, poverty, intensified and unsustainable farming practices and deforestation have been cited as the major drivers of land use/cover changes in the micro catchment. Land use/cover changes have been linked with increased surface runoff and soil erosion. However, there is a paucity of information to ascertain the impacts of land use/cover changes on soil erosion in Ogwapoke micro-catchment, Northern Uganda. Therefore, the study aimed to identify conservation measures and drivers that lead to continuous changes in land use/cover in order to combat the long-term effects of soil erosion on hydrological flow in Ogwapoke micro catchment. Specifically, the study aimed to (i) analyze and predict the spatial-temporal changes in land use/cover changes between 1986, 2003, 2020 and 2040 in Ogwapoke micro catchment; (ii) determine the effect of land use/cover change on soil erosion in Ogwapoke micro catchment; and (iii) assess the impact of land use/cover change on hydrological flow in Ogwapoke micro catchment.

Landsat images for the study area for 1986, 2003 and 2020 were downloaded from Earth explorer. Unsupervised classification and the CA-Markov model were used to analyze and predict the land use/cover changes respectively. Questionnaires were also administered to 200 respondents in the study area to understand their perceptions of land use/cover changes including the drivers. The Revised Universal Soil Loss Equation (RUSLE) and the Soil and Water Assessment Tool (SWAT) models were used to assess the soil erosion and hydrological flow components (total yield, base flow, surface runoff, lateral flow, deep aquifer recharge, and actual evapotranspiration), respectively. The Pearson correlation coefficient was applied to assess the effect of land use/cover changes on hydrological flow components.

Results showed that significant land use/cover changes have taken place in Ogwapoke micro catchment. Between 1986 and 2020, small-scale farmlands and built-up areas increased by 35.1% and 2.4%, respectively whereas bushlands, grasslands, wetlands and woodlands decreased by 11.7%, 7.4%, 2.4%, and 15.9% respectively. A similar pattern is projected to further intensify by 2040. Changes in land use/cover are mostly driven by over grazing, deforestation, poverty, bush burning, deforestation, and increased demand for food due to population growth. The changes in land use/cover had an effect on soil erosion in Ogwapoke micro catchment. Small-

scale farmlands has very high soil erosion compared to other land use/cover types. Changes in land use/cover had a significant effect on hydrological flow components in the micro catchment. Between 1986 and 2020, surface runoff and total water yield increased by 15 mm/yr and 2.2 mm/yr, respectively whereas base flow, lateral flow, deep aquifer recharge and actual evapotranspiration decreased by 12.1 mm/yr, 0.09 mm/yr, 1.1 mm/yr and 1.18 mm/yr, respectively. Mixed hydrological responses are expected in 2040 due to future land use/cover changes. Surface runoff and base flow were positively correlated to changes in small-scale farmlands and grasslands (R^2 =0.97; R^2 =0.99 respectively).

The study concludes that the changes in land use/cover in Ogwapoke micro catchment have had a significant impact on soil erosion and hydrological flow components. The study recommends the government to encourage tree planting in the micro catchment and regulate small-scale farming in wetland ecosystems; the communities should be sensitized about the sustainable land management practices; and there is a need for the decision makers to establish a hydro-meteorological network in the micro-catchment.

CHAPTER ONE: INTRODUCTION

1.1 Background

Changes in land use/cover are considered as the most significant indicators of global change (Mahmood et al., 2010). In recent years, land use/cover changes have received a great deal of attention in a variety of sectors, for example remote sensing, political ecology and in the distribution of species and ecosystems in a particular geographic space over time (Hasan et al., 2020). This is because human activities have been affecting the ecosystem for thousands of years as a result of tremendous population growth, migration, and rapid socio-economic activity that have intensified these environmental changes over the past centuries (Chen et al., 2021). Deforestation, agricultural expansion, and urbanization have all contributed to an increase in a variety of environmental issues, including soil acidification, nutrient leaching, and organic matter depletion (Sharma et al., 2011), climate change, water withdrawals, soil erosion, and habitat destruction (Reid et al., 2000; Rao & Pant, 2001; Turner et al., 2007).

Researchers like Wairiu (2017) have identified poor farming techniques, overgrazing, bush burning, and construction as important drivers of soil run-off, which results in air pollution, soil fertility loss, desertification, and the destruction of infrastructure projects in recent years. However, the environmental consequences of soil erosion as a result of intensive land use/cover changes are manifested by human activities such as soil productivity and agricultural output decline (van Oost et al., 2002) and deteriorating water through carrying pollutants such as pesticides and heavy metals into surface water bodies (Boers, 1996; van Oost et al., 2002).

According to Borrelli et al (2016), changes in land use have resulted in organic matter depletion, erosion, soil degradation, salinization, and crusting in Mediterranean areas. Agriculture, grazing, mining, charcoal, and biomass production, as well as traditional land uses, have resulted in low soil fertility and a heavily degraded landscape. In addition, soil erosion caused by unsustainable farming methods in East Africa has resulted in high levels of eutrophication and water hyacinth infestation on Lake Victoria (Raytheon et al., 2002; Albright et al., 2004).

A number of studies have also revealed that changes in land use/cover have a substantial impact on soil erosion. Yang et al (2003) examined the global situation of soil erosion risk, taking into account the past century as well as the present and future, and discovered that Asia was the most impacted region globally. As a result, a number of studies have used historical and current satellite data to investigate land use/cover change (LULC) in relation to changes in soil erosion in order to determine the effect of LULC on soil eroding (Jordan et al., 2005). Several studies (Favis-Mortlock & Boardman, 1995; Jordan et al., 2005; Wynants et al., 2018) have been undertaken in recent years to assess the impact of LULC on soil erosion at various temporal and spatial dimensions, including micro watershed levels.

However, some of these researches concentrated solely on the effect of vegetation on soil erosion under a single-vegetation land use type, such as woodlands (El Kateb et al., 2013), shrub lands (Garcia-Estringana et al., 2013), abandoned land (Li et al., 2016), pasture (de Koff et al., 2011), and cultivated land (Sasal et al., 2010) which are parallel different in this research study of Ogwapoke micro catchment. On the other hand, studies that have generalized and focused on each land covers and its impacts on soil erosion have been carried out in developed Mediterranean and European continents leaving a bigger research gap in developing countries. Other studies (Breuer et al., 2009; Tang et al., 2011) also agree that stream flow generation capacity is dependent on land use/cover changes. As a result, a hydrological model that takes into account spatio-temporal watershed characteristics is required to aid in the accurate prediction of a watershed's dynamic water balance (Costa et al., 2003; He & Hogue, 2012).

However, soil erosion assessment as a result of land use/cover changes has been computed using a number of indicator-based approaches. The USLE model and its modified Revised Universal Soil Loss Equation (RUSLE) model (Bonilla & Johnson, 2012) that is integrated with GIS is still widely used because of its simplicity and variety of inputs (soil erodibility, topographic variables, rainfall erosivity, and crop management factors). As a result of the rising population pressure in the micro catchment, which has exacerbated the demand for land despite its terrain, it is vital to explore the effects of these changes on soil erosion at the micro catchment scale. The findings of this study are useful in developing mitigation strategies and increasing local farmers', agricultural extension workers', and policymakers' understanding of the implications of environmental degradation (soil erosion, river siltation).

1.2 Problem Statement

The population in Uganda has greatly increased and the annual growth rate is about 3.3 percent (UBOS, 2016). This has resulted into rapid development that is evidenced in the changes of land use/cover attributed to impervious surfaces, increased agriculture and settlements as seen through bush burning, poor farming methods, over grazing, tree cutting for fuel etc. The changes in land use/cover (LULC) have partially affected a number of catchments and micro catchment within the region including Ogwapoke micro catchment. In order to control on the adverse effects on LULC, there has been several initiatives by the Government of Uganda and communities to carry out conservation measures including re-afforestation, mulching, vegetated stripping, live hedging, and contour ploughing among others.

Despite the government's efforts, land use/cover changes have continued. Between 2000 and 2020, subsistence farmlands and built-up areas in Ogwapoke micro catchment increased by 5.3% and 2.2% respectively whereas grasslands, wetlands and woodlands decreased by 1%, 6.6% and 5.6% respectively (MWE, 2020a). Population increase, poverty, intensified and unsustainable farming practices and deforestation have been cited as the major drivers of land use/cover changes in the micro catchment (MWE, 2016). LULC have been linked with increased surface runoff and soil erosion (Peng & Wang, 2012). This is the case in Ogwapoke micro catchment (MWE, 2016, 2020b).

Besides, most of the studies about land use/cover changes especially in Uganda have been done at either catchment or sub-catchment levels (Nyeko, 2010; MWE, 2016; Barasa et al., 2017; Kiggundu et al., 2018; Bunyangha et al., 2021). There is limited literature of such studies at the micro catchment level, and yet, assessment at the micro catchment level allows a deeper understanding of the effect of land use/cover changes on surface runoff as well as community participation in issues pertaining hydrological conservation (Guzha et al., 2018). Therefore, the study aimed to contribute to this knowledge gap by assessing the impacts of land use/cover changes on soil erosion in Ogwapoke micro catchment. The study is timely to guide the policy and decision makers in the Upper Nile Water Management Zone about the feasible conservation measures to reduce soil erosion and enhance the underground water in Ogwapoke micro catchment.

1.3 Objectives

1.3.1 General objective

The purpose of the research was to identify conservation measures and drivers that lead to continuous changes in land use/cover in order to combat the long-term effects of soil erosion on hydrological flow in Ogwapoke micro catchment.

1.3.2 Specific Objective

1. To analyze and predict the spatial-temporal changes in land use/cover changes between 1986, 2003, 2020 and 2040 in Ogwapoke micro catchment.
2. To determine the effect of land use/cover change on soil erosion in Ogwapoke micro catchment.
3. To assess the impact of land use/cover change on hydrological flow in Ogwapoke micro catchment.

1.4 Research Questions

1. To what extent has land use/cover changed in Ogwapoke micro catchment between 1986, 2003 and 2020?
2. What is the future state of land use/cover trend in Ogwapoke micro catchment in 2040?
3. What is the effect of land use/cover changes on soil erosion in Ogwapoke micro catchment?
4. What is the impact of land use/cover changes on evapotranspiration, surface runoff and total water yield in Ogwapoke micro catchment?

1.5 Conceptual Framework

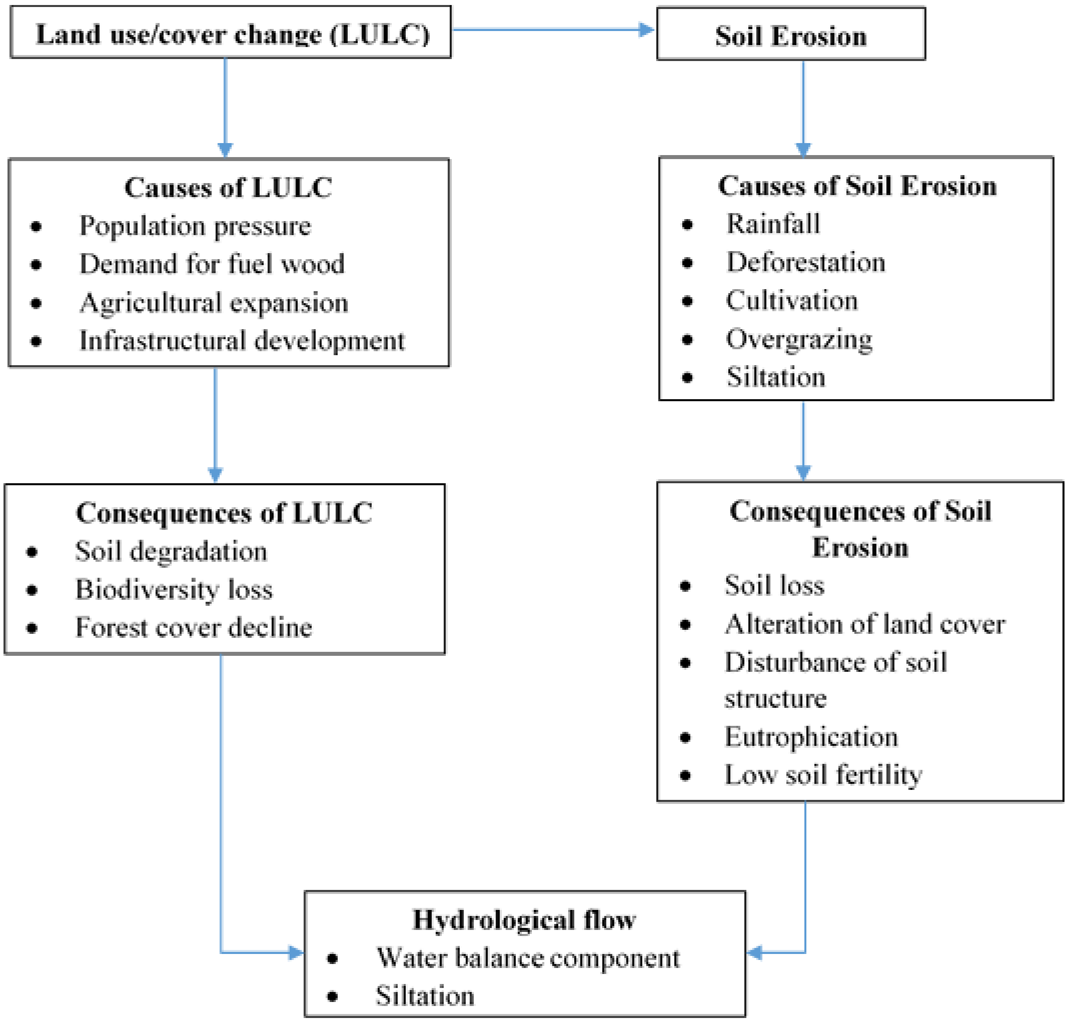

Figure 1. 1: Conceptual framework of the research study

In Figure 1.1, changes in land use/cover have been mainly caused by population growth, intensification of agriculture and infrastructural developments (Onyutha et al., 2021). Land use activities such as deforestation and cultivation lead to forest cover decline, biodiversity loss, and they fuel the decreased soil quality (El Kateb et al., 2013). In the long-term, these lead to land degradation as well as deterioration of water quality through elevated concentration of compounds (e.g. nitrogen, phosphorous) and siltation caused by long-term agricultural and erosion effects (Geissen et al., 2009).

Changes in land use, particularly farming on deforested and unsuitable areas, can rapidly degrade soil quality and cause stream flow declines because ecologically sensitive habitat components are unable to mitigate the negative consequences. Seibert & McDonnell (2010) argued that deforestation and built-up area often exacerbate stream flows especially in hydrologically fragile sites like wetlands. LULC modification lowered water provision and hydrological processes in India's Pennar Basin (Garg et al., 2019). Sampaio et al (2007) reported that the net impact of deforestation is an increase in water yield and stream flow. Therefore, changes in the hydrological balance such as increased stream flow due to LULC may further aggravate the soil erosion in an area.

1.6 Scope of the Research

The analysis was based on changes in land use/cover for a period of 1986-2020 and prediction for 2040, as well as the impact of land use/cover change on soil erosion and hydrological flow. It was carried out in 2021 from Ogwapoke micro catchment in Kitgum, Northern Uganda.

1.7 Significance of the Study

Land use/cover maps will be used to guide land development decisions in urban areas, and create large-scale inventory of resources at the micro catchment, parish, sub-county, and district levels. The assessment will also show the biggest land use driver for land use/cover change in Ogwapoke micro catchment so that it can be regulated.

Studies on the fluctuation of soil erosion in relation to land use can help people understand the phenomenon and apply suitable conservation measures. Estimating soil loss and identifying key places for following optimum management techniques are vital to a soil conservation project's success. The research will also contribute to a better scientific knowledge of the consequences of land use change on hydrological processes in the micro watershed, which will help with the sustainable management of water resources.

The study will also help to improve scientific understanding of the effects of land use change on hydrological processes in the micro watershed, which will aid in the management of sustainable water resources. Thus, the availability of spatial mapping, modeling and evaluating changes in land use land and cover patterns, and soil erosion study will provide land use and cover information for future use or reference.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter presents a literature review on changes in land use/ cover estimates, soil erosion modelling, hydrological flow modelling, and vegetation monitoring approaches and tools. It is divided into four major sections: literature on related studies, land cover change analysis, land cover prediction, soil erosion and hydrological flow. The chapter also reviews literature of different methodologies used in analyzing land cover and soil erosion.

2.2 Analyzing and predicting the spatial-temporal changes in land use/cover

Human interventions in the natural ecosystem are primarily responsible for changes in land use/cover. Meshesha et al (2016) defines "land cover" as the biological and physical characteristics of the land surface, which include vegetation (trees, grass), built-up areas (buildings, roads, paved land), and other land surfaces such as bare soil, water, and rocks. According to Wasige et al (2013), land use refers to anthropogenic activities performed on certain types of vegetations with the obj ective of producing, altering or preserving it. Land use/ cover (LULC) alterations are the modifications to a specific type of vegetation that can alter the severit y of its use as well as its qualitative characteristics.

Rapid population increase, desire for wood and charcoal, building materials, agricultural practices, and policy and tenure ambiguity, are the key driving drivers for change in land use/cover (Wubie et al., 2016; Mwanjalolo et al., 2018). Changes in Lake water and other aquatic resources, soil depletion, habitat loss, and forest cover loss all have an influence on the local livelihoods and the ecosystem (Wubie et al., 2016). The cumulative effect of these consequences result in poverty and ecosystem deterioration. Human actions, particularly habitat conversion and degradation, are causing global biodiversity losses (Newbold et al., 2015). Significant activities include tree cutting, charcoal burning, and poor farming methods, all of which affect ecosystem functionality.

Agriculture techniques and approaches targeted at boosting contemporary agriculture may result in the quick conversion of natural vegetation to agricultural land (Popp et al., 2017). Agriculture practices and tactics aimed at bolstering modern agriculture may result in a quick conversion of natural vegetation to agricultural farmland (Sambou, 2015). In the Democratic Republic of the

Congo, for example, agricultural expansion through shifting cultivation is a direct primary driver of deforestation in the Equatorial region (Samndong et al., 2018). More studies (Godar et al., 2014; Specht et al., 2015), emphasize 76% of families in Brazil's Atlantic forest use firewood on a regular basis, consuming an average of 686 kilograms of tree biomass per person per year; poor people, on the other hand, consume approximately 961 kilograms per year.

Land use/cover types can be categorized based on various classification schemes for example LULC classification scheme by United State Geological survey (USGS), the national land cover classification scheme, and the FAO LULC classification scheme (Yang et al., 2017). In this study, the satellite images were classified into land use/cover types basing on the classification scheme by USGS. This is because the USGS scheme can be customized accordingly based on the region of interest. Despite substantial research on the impact of LULC change on watershed hydrology and erosion, many concerns remain unsolved. For example, the relationship between tree cover and hydrology are not well understood for watersheds including Ogwapoke micro catchment.

Hydrologic circulation's response to land use planning and management is inextricably intertwin ed (Garg et al., 2019; Li et al., 2019). Changes in land use/cover (LULC) are one of the elements that have a direct impact on a watershed's hydrological cycle (Getu Engida et al., 2021). Human activities induce LULC modification and have had a significant impact on the hydrological processes and water resources of the watershed (Marie Mireille et al., 2019). For example, LULC modification lowered water provision and hydrological processes in India's Pennar Basin (Garg et al., 2019).

There are several approaches for researching habitat changes, including GIS, remote sensing, and Google Earth, that can be employed to detect changes in land use/cover (Karakus et al., 2015). Remote sensing is capable of monitoring large and hazardous areas, such as battle zones, where information is required in the past, present, and future. Several studies have employed Geospatial technologies to track changes in land use/cover (Guzha et al., 2018). To capture geospatial information, these systems employ a variety of cameras, multispectral scanners, and sensors (LIDAR and RADAR) with varying spectral and radiometric resolutions. These scanners, cameras and sensors are mounted on space craft platforms to produce satellite imagery (Guzha et al., 2018). The satellite imagery varies in imaging characteristics for example;

MODIS, ERADAS, Sentinel, SPOT, ASTER, LANDSAT, IKONOS, Quick Bird, Geoye and Landsat through its various series of satellites multi-spectral (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus TM sensor (ETM+) sensors (Wang et al., 2010; Schroeder et al., 2019).

2.2.1 Land use/cover prediction modeling

There are many modeling tools in use for predicting changes in land use/cover, however, it is difficult to compare the performance of different modeling tools because the change in land use/cover (LULC) model can be inherently distinct in many ways (Kusuma, 2015; Regmi et al., 2017; Nwaogu et al., 2018). The commonly used land use land cover modeling tools and techniques to model and predict changes in land cover include GEOMOD, Cellular Automata (CA) Markov, Markov chain, etc (Pontius Jr. & Chen, 2006; Yirsaw et al., 2017). Although LULC models have existed for decades, developments in remote sensing, land inventory methodologies and computing power have resulted in the development of a wide range of distinct changes in land-use and land-cover models in the last five to ten years. For example the CLUE model framework, DINAMICO EGO, Markov-chain model among others (Verburg et al., 2004). Various simulation and empirical models have been used to forecast changes in LULC, but few have employed system dynamics models to identify the primary drivers (Rimal et al., 2017).

Spatial simulation models are effective tools for quantitative modeling, and some consider blending the Markov-chain model approach with cellular automata (CA) to be one of the finest solutions for analyzing LULC on different spatial scales (Girma et al., 2022). The CA-Markov model is a prominent model among several LULC simulation tools and methodologies for modeling both spatial and temporal changes (Hamad et al., 2018). Several prior studies investigated land use change patterns modelling using the CA-Markov model (Parsaie, 2016). This is evidenced in the way that, the CA-Markov model was successfully applied at the Arasbaran biosphere reserve in Iran to predict changes in LULC, which assists land use planners and policy makers when making suitable decisions for future land use difficulties. They stated that utilizing a CA-Markov model in land use policy formation can be beneficial, as well as serving as an early warning system.

However, Ozturk (2015) compared CA-Markov chain and Multi-layer Perceptron-Markov Chain (MLP-MC) models to forecast future change in LULC for the Atakum, Samsun urban expansion simulation in Turkey. According to the authors, the MLP-MC model outperformed the CA-Markov model for projected scenario simulation. On the other hand, Regmi et al (2017) compared CA-Markov and GEOMOD models to analyze and model the LULC dynamics in the Phewa lake watershed in Nepal. They discovered that CA-Markov chains worked well as an operational model for anticipating future LULC scenarios. Several planning and management tasks rely on analyzing, modeling, and comprehending the transition of habitant changes (Dezhkam et al., 2017; Regmi et al., 2017). Observing previous LULC aids in recognizing trends of change and future extrapolations. As a result, knowledge about historical, present, and projected change plays an important part in decision-making development (Hamad et al., 2018; Gemitzi, 2021).

The CA Markov model is a hybrid of the CA filter principle with the Markov chain process. The CA model can be represented in equation 2.1.

$$S(t,t+1) = f(S(t),N) \qquad \text{……………………………………………………………………2.1}$$

where S is the set of finite and discrete cellular states, N is the cellular field, t and t + 1 represent separate incidents, and f is the cellular state transformation rule in local space.

The Markov model is a process-based theory that forms a Markov random process system for prediction and optimal control theory. Equation 2.2 calculates the projection of land use/land cover changes based on the conditional probability formula - Bayes.

$$S(t+1) = P_{ij} \times S(t) \qquad \text{……………………………………………………………………2.2}$$

where *S(t), S(t + 1)* represent the system status at *t* or *t + 1*; and *Pij* is the transition probability matrix in a state, and is computed as in equation 2.3.

$$P = (p_{ij}) = \begin{vmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{vmatrix}, \quad \sum_{j=i}^{n} p_{ij} = \quad \text{...2.3}$$

where, *P* is the Markov transition matrix *P, i,* j is the land use land cover type of the first and second time period, and *Pij* is the probability from land use and land cover type *i* to land type *j*.

In this expression, *n* is the number of land use and land cover types in the target area, and “*Pij*” is the probability of transition of type *i* into that of type *j* from the initiation to the end. In the transition matrix, it requests that each rate is a non-negative quantity, and each line factor 0 to 1. The estimate of Markov chain is the relative frequency of transitions observed over the entire time. The result of the estimation can be used for prediction (Hamad et al., 2018). However, different studies have predicted future LULC using this model including (Aithal et al., 2014; Yirsaw et al., 2017). In this regard, there is an urgent need to estimate changes in land use over time and predict future scenarios. Therefore, the CA Markov available in Idrisi was implemented to predict and compare the land uses for some further period.

2.3 Determining the effect of land use/cover change on soil erosion

The processes of sediment dissociation, transport, and deposition generated by raindrop impact and moving water are referred to as water erosion and sedimentation (Julien, 1995; Yue et al., 2019). Raindrop impact and moving water generate the most powerful forces. Erosion is a natural geological phenomenon induced by the movement of soil particles by water or wind, although some human acts, such as agronomic systems, forest conversion, and so on, would accelerate erosion rates. Erosion is triggered by a combination of factors such as steep slopes (Brandolini et al., 2018), climate (e.g. long dry periods followed by heavy rainfall), inappropriate land use, and land cover patterns (Ochoa et al., 2016). Water erosion and wind erosion are the two most common types of soil erosion, although only water erosion is simulated and explored in this study.

Soil erosion is caused by both natural and man-made activities. Climate, land use/cover (LULC), parent rock material, and topography are all elements that might influence the extent of soil loss. Because of the earth's gravity, soil erosion is widespread in hilly and mountainous places with steep slopes and complex topography. Higher slope gradients are more prone to soil erosion (Brandolini et al., 2018). Soil erosion by water is commonly thought to be a purely natural process induced by rainfall and water flow, but human actions considerably exacerbate the erosion through land cover change and soil structure disturbance caused by farming. Today land use/cover change is a significant driving agent of regional and global change (Munthali et al., 2019).

Large-scale land use/cover changes caused by deforestation, agricultural land expansion, and other human activities are causing changes in global systems and cycles. Changes in land use/cover have a direct impact on the atmospheric cycle and climate change, and the principal external agents of water erosion vary with changes in land use/cover and climate (Geist, 2003). The fastest rates of soil erosion occur during heavy rainfall or windstorms. Soil particles are generally separated, transported, or aid in a chemical reaction between rain water and rock minerals, resulting in surface crusting and erosion. Furthermore, parent rock material is a reliable indication of soil erosion vulnerability. Soil made from marl, gypsum, and shale, for example, has lesser erosion resistance than other soil types (Sang-Arun et al., 2006).

Agricultural expansion without soil conservation methods can have significant negative consequences on soil, such as increased erosion and decreased fertility, which can lead to ground water pollution and river and lake eutrophication (Lamek et al., 2016). For example, traditional land uses and human activities such as agriculture, grazing, mining, charcoal and biomass production have resulted in organic matter exhaustion, erosion, soil degradation, salinization, and crusting in Mediterranean lands, resulting in low soil fertility and a highly eroded terrain (Borrelli et al., 2016). The rapid land-use changes taking place in the Lake Victoria basin, including the upper Rwizi micro-catchment, continue to contribute to land degradation. For instance, banana production in the Rwizi-micro catchment of southwestern Uganda is expanding rapidly in response to increasing demand for cooking banana in urban places in Uganda and neighboring countries (Mugonola et al., 2013). Because of this rapid increase, land use is shifting and marginal areas (wetlands, steep slopes, valley bottoms) are being converted to agricultural cultivation. These additional areas, however, may not be able to sustainably maintain agricultural output because they are prone to land degradation due to soil erosion.

Soil erosion has also been identified as a major non-point pollution source in several regions, causing severe damage each year. In the United States, for example, the net damage cost of erosion-related pollutants was estimated to be \$3.2–\$13 billion in 1980 (Olson et al., 2016). Soil erosion leads to preferential removal of a soil's organic carbon and clay contents. As much as 20% of carbon transported by eroded sediments may be released into the atmosphere as CO_2 (Lal, 2003; Polyakov & Lal, 2008). Soil erosion is directly related to food productivity reduction and water pollution, and may also reduce the ability of soil to mitigate the greenhouse effect. Excessive soil erosion, with its associated high rate of sedimentation in reservoirs and diminished fertility, has become a serious environmental issue for the country, with disastrous economic effects (Ganasri & Ramesh, 2016). For example, in Uganda's Rwizi watershed, erosion causes loss of topsoil, organic matter, and poor water penetration and retention. Crop failure and low yield are the outcomes of nutrients and moisture stress (Mugonola et al., 2013).

Smallholder farmers must use water-smart technologies such as mulching, grass strips, runoff diversion, agro-forestry, and water harvesting to reduce soil erosion and land degradation. These methods are classified as soil and water conservation (SWC) technologies and encompass biological, physical, and management-related procedures (Bastiaanssen et al., 2007). Erosion control can take many different kinds in a variety of activities. Mechanical, physical, and biological methods can all be utilized to minimize erosion and control sedimentation (Holz et al., 2015). Many of these technologies are classified as best management practices (BMPs) and are used in agriculture, construction, forestry, mining, and other land uses where erosion is an issue. BMPs are designed to prevent erosion at the lowest possible cost, and they are based on physical principles that govern water energy and soil erodibility (Stuart & Edwards, 2006; Pulley & Collins, 2019).

2.3.1 Modeling Soil Erosion

Several models have been created and are being utilized for research and operational purposes. The most well-known soil erosion models are the USLE (Universal Soil Loss Equation, 1965), Agricultural Non-Point Source model (AGNPS), Chemical Runoff and Erosion from Agricultural Management Systems model (CREAMS), Sediment River Network model (SedNet), EUROSEM (European Soil Erosion Model, 1993), RUSLE (Revised Universal Soil Loss Equation, 1997), EPIC (Erosion/Productivity Impact Calculator, 1984), PESERA (Pan-

European Soil Erosion Risk Assessment, 2003), Rill Grow (a model for rill initiation and development, 1998), SEMMED (Soil Erosion Model for Mediterranean Regions, 1999), and EROSION3D are some well-known soil erosion (De Mello et al., 2016; Defersha et al., 2012). To aid management and decision-making, all of these sophisticated models are connected with the RUSLE model. Although their usefulness varies depending on geographical setting, the models incorporate common physical characteristics discovered to be essential from observational experience or multivariable statistical analysis, such as slope, precipitation/rainfall, vegetation cover, and soil erodibility (Chandramohan et al., 2015; Mello et al., 2016; Igwe et al., 2017). However, all these initiatives have enabled the current global evaluation of soil erosion.

However, the RUSLE model is well-known and widely used (Alewell et al., 2019), and it represents simple to comprehend and easy-to-apply technology that has been of significant assistance to soil conservation and land management. The Revised Universal Soil Loss Equation (RUSLE) is an upgrade and improvement of the commonly used Universal Soil Loss Equation (USLE) (Rowlands, 2019). RUSLE calculates long-term soil loss with more precision than USLE because it incorporates four independent variables: rainfall erosivity (Factor R), soil erodibility (K-factor), terrain, and vegetation cover types (Benavidez et al., 2018). As a result, with correct assessment of these erosion indices, the RUSLE model may be adapted to the Ogwapoke micro catchment, as RUSLE is also suitable for analyzing soil movement at a given place.

2.4 Assessing the impact of land use/cover change on the catchment hydrological flow

Stream flow or discharge refers to the amount of water that flows past a certain point in a stream over a specific time period. The velocity (how fast the water is moving) and volume (the amount of water in the stream) components of stream flow combine to determine the energy of the water. Water energy has a significant impact on the structure of the stream as well as its biological and chemical properties. According to Kelderman et al (2007), wetlands are known for providing various ecological functions, including retention of sediments and nutrients from watersheds. Wetlands can perform the function of protecting water bodies against eutrophication according to Kansiime et al (2007). Studies done by Kyambadde et al (2004) observed that papyrus and other aquatic plants in river beds help in trapping particles by supporting sedimentation and retention of particulate matter. They also help in reducing the speed of runoff by the nature of their roots.

This notion is supported by Stromberg et al (2010), plant canopy has a buffering effect on stream flow. This leads to the slowing of the runoff across the canopy thus promoting sedimentation. The presence of plants lowers the overall velocity of flow, which is a phenomenon that encourages deposition of sediments.

However, according to Seibert & McDonnell (2010), deforestation and built-up area often exacerbate stream flows especially in hydrologically fragile sites like wetlands. According to Coe et al (2009), when forests are replaced with agricultural crops, there is reduced net surface radiation, reduced humidity and recycling and thus rainfall. Reduced evapotranspiration leads to low discharge while decreased rainfall also causes reduced discharge. Therefore, decreased amounts of rainfall and evapotranspiration affects stream flow in a very complex manner. This notion is shared by Sampaio et al (2007) who asserted that deforestation leads to reduction in surface roughness, leaf area and rooting depth reduction, negatively affecting the rate at which water is lost from leaves and soil, impacting on stream flow. Sampaio et al (2007) therefore concludes that the net impact of deforestation is an increase in water yield and stream flow.

2.4.1 Rainfall-Runoff Models for predicting hydrological flow

Hydrological models are mathematical representation of rainfall - runoff processes in a watershed (Devia et al., 2015). These simulations are based on the hydrological cycle that starts with a precipitation event followed by other processes such as surface runoff, infiltration, percolation, base flow, evapotranspiration and discharge that is simulated at the catchment outlet. Hydrological models play a vital role in understanding catchment processes that is key for water resources planning and management. Hydrological models are classified based on their spatial extent, nature of basic algorithm used and model input or parameter requirements (Devia et al., 2015; Trambauer et al., 2013).

The models classified based on input or parameter requirements are either deterministic or stochastic. Deterministic model gives same output from the same input while different outputs are obtained from the same input in stochastic models. Models based on spatial extent are further divided into lumped, semi-distributed or distributed. Lumped model considers the entire catchment as a single unit with disregard for heterogeneity, semi-distributed models divide the catchment into sub-catchment from which simulations are done while distributed models cater for spatial heterogeneity by making simulations from smaller units of the entire catchment. And those classified according to the nature of basic algorithms are grouped into empirical, conceptual or physical.

Empirical model uses data obtained from either observation or experiment as inputs for understanding catchment response to rainfall. Empirical models are simpler and can produce reasonable result with limited data requirements compared to conceptual and physical models. Conceptual model uses simple mathematical equations to describe all the components of the hydrological system while physical models are based on solving governing equation such as the equations of conservation of mass and momentum (Kauffeldt et al., 2016). Physical models use catchment parameters or variables that are measured in the field or assumed based on catchment characteristics. Physical models suffer from the challenge of over parameterization.

Model selection for predicting hydrological flow

Model for a particular study is selected based on the objective, scope, temporal and geographical resolution of the model (Trambauer et al., 2013). Additional criteria my include ease of access, input data requirements, cost, expertise, availability of model code, existing user community, flexibility to grid structure, possibility of calibration with suitable tools, data assimilation and availability of user manual (Kauffeldt et al., 2016). There are many hydrological modelling tools that have been used for watershed scale studies and these includes; MIKE SHE, Hydrologiska Byrans Vattenavdelning model (HBV), Variable Infiltration Capacity model (VIC) and Soil and Water Assessment Tool (SWAT).

a) MIKE SHE

MIKE SHE is an advanced, flexible model created by the Système Hydrologique Européen (SHE) (Abbott et al., 1986). The model can simulate surface and ground water flow including transport of pollutants such as sediments, nutrients and pesticides in a catchment as such it plays a key role in water quantity and quality monitoring. MIKE SHE has a high processing ability but its use is limited to smaller catchment due to large data requirements and inability of users to modify codes (Devia et al., 2015).

b) HBV model (Hydrologiska Byrans Vattenavdelning)

The HBV is a public domain semi-distributed conceptual hydrologic model used in hydrological forecasting and water balance studies (Bergström, 1976). The model divides the entire watershed into sub-watersheds based on vegetation and elevation zones. It simulates catchment discharge using daily rainfall and air temperature and estimate daily or monthly evapotranspiration. The model is less complex and can be run on modest computer. Its outputs are easy to read and it also provide sound hydrological information with limited input data. However, the HBV being a conceptual model does not take into account the complete physical characteristics of the catchment.

c) VIC model (Variable Infiltration Capacity model)

The VIC is a semi-distributed grid based hydrological model created by Liang et al (1994) at the University of Washington. The model simulates the hydrological cycle based on empirical equation of water balance and energy to provide information on the quantity and temporal availability of water within the watershed. The VIC model divides the soil into three layers where the first layer allow quick evaporation, the second layer represents the dynamic response of soil to rainfall event while the third layer characterizes soil moisture levels (Devia et al., 2015). The main model inputs include; precipitation, temperature, wind speed and land use/cover types that are highly differentiated within each grid. The model is open source http://github.com/UW-Hydro/VIC with a very active global user community. The model has no tool provided for incorporating observation stations, channel losses are not represented in routing model and its resolution below 6 km is limited (Kauffeldt et al., 2016).

d) Soil and Water Assessment Tool (SWAT)

SWAT is a water basin scale and semi-distributed watershed model that is commonly used to forecast the future influence of land control methods on agricultural chemical outputs, water, and sediments, across longer timeframes in huge complex watersheds with differing soils, land cover, and management circumstances (Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.;Williams, 2011). It was developed for the United States Department of Agriculture (USDA)-Agricultural Research Services (ARS) to assess the impact of human activities on water quantity and quality (Arnold et al., 1998). The Digital Elevation Model (DEM) is used to divide the catchment into sub-catchments that are further subdivided into Hydrological Response Units (HRUs) based on soil type, land use/cover and slope (Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.;Williams, 2011). HRUs are areas of the catchment which respond to rainfall events in the same way due to homogenous soil, land use/cover and slope characteristics. The HRUs form the basic unit of hydrological response in the SWAT model. Simulation of a catchment hydrology in the model is divided into land and routing phase. The land phase represents the amount of water and pollutants (sediment, nutrient and pesticides) entering the river channel while the routing phase defines the movement of water and pollutants through the river channels to the catchment outlet (Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.;Williams, 2011). The model simulates the hydrological cycle based on the water balance (Equation 2.4).

$$SW_t = SW_o + \sum_{t=1}^{t} (R_i - Q_i - ET_i - P_i - QR_i) \qquad \text{..........2.4}$$

where SW*t* is the final soil water content of the day and *SWo* is the initial soil water content of the day, *t* is time in days, and *R*, *Q*, *ET*, *P*, and *QR* are the daily amounts of precipitation, surface runoff, evapotranspiration, percolation, and return flow, all measured in millimeters.

Because the Model is publicly available via http://swat.tamu.edu/, efficient, adaptable, and continuous-time model that employs easily available data, the model has been effectively deployed in both small and big catchments all over the world (Arnold et al., 1998; Neitsch et al., 2011). The model also has one of the largest and most active global online user support community. The model in addition uses the automatic SWAT-Calibration and Uncertainty Procedures (SWAT-CUP) for calibration outside the SWAT software making the process easier. Therefore, SWAT model was used in this study to simulate the impact of change in and use/cover on the water balance of Ogwapoke micro-catchment.

Evaluation of model performance

A model's performance can be evaluated using a variety of approaches, including the coefficient of determination (R2), Nash Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS) (Moriasi et al., 2007). The R2 is an indicator of strength of linear relationship between the observed and simulated discharge values. It describes the proportion of the variance in observed discharge data is explained by the model (Moriasi et al., 2007). R2 value ranges from 0 - 1, with higher values indicating less error variance. R2 values >0.5 indicate acceptable model performance (Santhi et al., 2001) while a review by Moriasi et al (2015) recommended the use of values >0.6. The NSE measures how efficient the plot of daily monitored and simulated discharge fits the 1:1 line and its value ranges from $-\infty$ - 1 with 1 as the optimal value (Moriasi et al., 2007; Santhi et al., 2001). NSE value of >0.5 is considered satisfactory model performance (Moriasi et al., 2015). The PBIAS calculates the average tendency of the generated discharge data to be larger or smaller than the observed discharge data with zero as the optimal value (Moriasi et al., 2007). PBIAS values $\leq \pm$ 15% is satisfactory for a catchment scale model (Moriasi et al., 2015).

2.4.2 Siltation of the river

River siltation is exacerbated by soil erosion caused by agricultural operations, deforestation, particularly along river banks, clearing of trees and grasses, and trenches along river banks (Terefe, 2020). Siltation from lake basin erosion has a direct negative impact on water creatures like fish by burying breeding grounds, diminishing benthic food supplies, and hindering water clarity for visually feeding animals (Kemp et al., 2011; Wantzen & Mol, 2013). However, increased turbidity may have an indirect impact on Lake Biodiversity. Seehausen et al (1997) and Taabu-Munyaho et al (2016) demonstrated that increased turbidity (due to deforestation and agricultural practices) is to blame for the diversity decline of the cichlid in Lake Victoria by decreasing the impact of sexual selection on sexual isolation.

Actually, colour drives mate selection in these cichlids, and severe assortative mating can quickly lead to sexual isolation of colour morphs, which is accelerating and most likely began in the 1920s. By constraining color vision, turbidity interferes with mate choice (Ehlman et al., 2018; Seehausen et al., 1997). The reduced effectiveness of signals causes relaxation of sexual selection for color, with consequent loss of male nuptial coloration and erosion of species diversity due to a breakdown of reproductive barriers. Dull fish colors, limited color morphs variants, and minimal species diversity are prevalent in turbid environments caused by recent eutrophication. This is proof that human activities that increase turbidity destroy the mechanism of diversification and the maintenance of diversity.

2.5 Emerging literature gaps/synthesis

Despite the availability of various remote sensors in the world, this research used Landsat satellite images (Thematic mapper (TM) and Operational Land Imager (OLI)). This is because of free accessibility and wide temporal availability since 1972 (Wulder et al., 2012). In addition, most of the land use/cover changes worldwide have been conducted using Landsat satellite images (Reis, 2008). In northern Uganda, few studies (3) have been conducted about land use/cover changes therefore, this study is timely (Kilama Luwa et al., 2020).

The study adopted the Markov chain and Cellular Automata (CA-Markov) model to understand the future state of land use/cover in Ogwapoke micro catchment. This model effectively combines the spatial and temporal dynamics in modelling the land use/cover changes of an area (Liping et al., 2018). The model is preferred in land use/cover projection because it is efficient, easy to calibrate, and has a high ability to simulate multiple LULC and intricate patterns (Behera et al., 2012). In addition, the mixed model of CA-Markov incorporates the drivers of land use/cover prediction (Yirsaw et al., 2017). Most of the recent studies of land use/cover prediction have used the CA-Markov model (Amini Parsa et al., 2016; Dezhkam et al., 2017; Kang et al., 2019; Q. Wang et al., 2020). The review of literature showed that several studies have been done globally about the effects of land use/cover changes on soil erosion (Sharma et al., 2011; Bogale, 2020; Kogo et al., 2020; Yu et al., 2021), however, few studies have been done about the same in Uganda (Mukisa, 2021). Therefore, this study aimed to bridge this knowledge gap by assessing the effect of land use/cover changes on soil erosion in Ogwapoke micro catchment.

This research utilized the Revised Universal Soil Loss Equation (RUSLE) model to determine the soil erosion in Ogwapoke micro catchment. This is the mostly used model worldwide to assess the soil erosion due to its simple applicability (Ghosal & Das Bhattacharya, 2020). The factors of the model (rainfall erosivity, soil erodibility, terrain, and vegetation cover types) can be easily integrated with GIS for better analysis (Ganasri & Ramesh, 2016). It also allows to estimate deposition through sediment transport (Biswas & Pani, 2015).

Globally, several studies have been conducted about the effect of land use/cover changes on hydrological flow (Mati et al., 2008; Getahun & Van, 2015; Guzha et al., 2018; Martínez-Retureta et al., 2020). There is also emerging literature about this subject in Uganda (Gabiri et al., 2020; Onyutha et al., 2021; Twesige, 2019), however, no such studies have been done in northern Uganda, and yet, the area has undergone significant land use/cover changes (MWE, 2020b). Therefore, the study assessed the impact of land use/cover changes on hydrological flow in Ogwapoke catchment using the Soil and Water Assessment Tool (SWAT).

SWAT was adopted in this study because it uses the automatic SWAT-Calibration and Uncertainty Procedures (SWAT-CUP) for calibration outside the SWAT software making the process easier (Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.;Williams, 2011). Other models for predicting hydrological flow have limitations for example the use of MIKE SHE is limited to smaller catchment due to large data requirements and inability of users to modify codes (Devia et al., 2015); the Hydrologiska Byrans Vattenavdelning (HBV) model does not take into account the complete physical characteristics of the catchment (Xu et al., 2017); and the Variable Infiltration Capacity (VIC) model does not provide tools for incorporating observation stations, channel losses are not represented in routing model and its resolution below 6 km is limited (Kauffeldt et al., 2016).

CHAPTER THREE: METHODOLOGY

3.1 Introduction

This chapter explains the methodology that was used in data collection and analysis. The contents of this chapter are presented under description of the study, research approach, research design, and methods of data collection.

3.2 Description of study area

3.2.1 Location

The Ogwapoke River, a significant river in the Ogwapoke micro watershed, divides Yepa and Ogwapoke parishes, and it receives water from other tributaries. Ogwapoke micro catchment is located in the Upper Nile basin, Pager Aringa sub catchment in Aswa catchment, found in Kitgum District in North Uganda (MWE, 2020a) (Figure 3.1). Ogwapoke micro catchment covers a land area of 16.5 square kilometers with minimum elevation of about 958 meters and maximum elevation of 1085 meters above sea level. The micro catchment lies between Ogwapoke, Yepa, Pajong and Pubech parishes of Muchuni Subcounty (Figure 3.1) where the research was conducted in order to estimate the impact of change in land use/cover on soil erosion. The Ogwapoke River, a significant river in the Ogwapoke micro watershed, divides Yepa and Ogwapoke parishes, and it receives water from other tributaries.

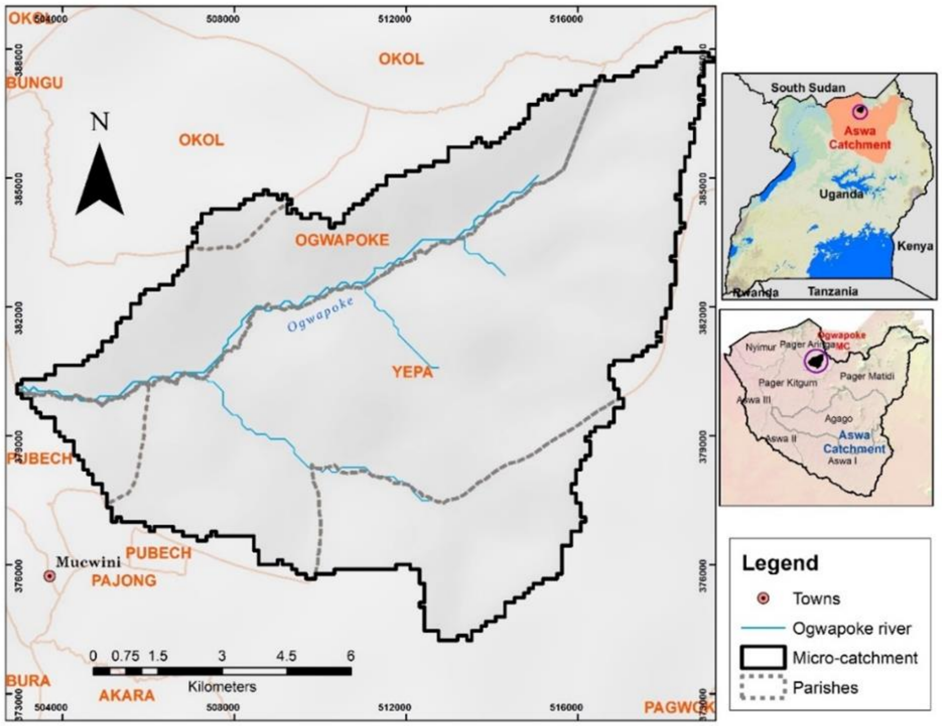

Figure 3:1: Location of Ogwapoke micro catchment

3.2.2 Vegetation

The micro catchment is dominated by patches of subsistence farmland with crops like sorghum, ground nuts, millet, soya beans and sim-sim. The micro catchment is also dominated with grasslands and tree coverage.

3.2.3 Climate

Ogwapoke micro-catchment in Aswa Catchment registers an average annual rainfall of about 1,200 mm, the highest single annual amount being slightly more than 1,420 mm and the lowest being about 1,000 mm (MWE, 2013).The mean temperature during the year within the entire catchment is about 24°C. This area has high evapotranspiration rates, which affects runoff, groundwater recharge, and dry season flows, raising drought hazards (CORDAID & MWE, 2017).

3.2.4 Soils and Geology

The central part of Upper Ogwapoke is underlain by undifferentiated gneisses and granulite facies rocks and sediment of alluvium black soil in the south which were formed some 3,000 million years ago and have been modified and altered by subsequent geological events including the rifting and volcanic activity, as well as the deposition of associated sediments (CORDAID & MWE, 2017).

3.3 Research Design

Quantitative and qualitative research approach were used and these were drawn from remote sensing and questionnaire tool. Remotely sensed Landsat imagery was used for analyzing land cover changes in Ogwapoke micro catchment. The advantages of utilizing remote sensing land cover monitoring is the ability to capture the continuous expression of land cover trends across the landscape as emphasized by Reed et al (2009) and the ability to historically observe land cover changes from archived satellite data sets (e.g. Landsat).

The sample size was determined according to Krejcie & Morgan (1970) (Equation 3.1).

$s = X^2NP(1 - P) \div d^2(N - 1) + X^2P(1 - P)$ ……………………………………………Equation 3.1

where;

s is the required sample size, X^2 is the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841), N is the population size, P is the population proportion (assumed to be .50 which should provide the maximum sample size), and d is the degree of accuracy expressed as a proportion (.05).

The total number of households in Ogwapoke, Yepa, Pajong and Pubech parishes (415) (UBOS, 2016) was used as N. Therefore, a sample size of 200 households was selected in this study. Semi structured questionnaires were used to conduct the household survey in randomly selected households within the micro catchment (Nath et al., 2010). The research considered farm owners/households that have been resident in the area for 5 years and above to participate in the survey. Household heads or the next of kin in each household were considered for the interview. Therefore, the sampling unit was a household while the unit of observation was the head of the house or next of kin. The household survey was conducted with the support of respective parish and village heads within the selected parishes to ease access to households and prevent conducting the survey beyond the micro catchment parish boundaries. Prior to undertaking the survey, the questionnaire was pre-tested on ten households within the study area (these were exempted from the main survey) to check for errors and ambiguity and hence improve the validity of the survey tools (Grimm, 2010).

Empirically derived equations and models based on the soil distribution process that combined the use of remote sensing, GIS and other advanced scientific and technological means were used for soil erosion modelling. These include USLE (Universal Soil Loss Equation) and RUSLE (Revised Universal Soil Loss Equation).

3.4 Analyzing and predicting the spatial-temporal changes in land use/cover

The Thematic mapper (TM) Landsat imagery for both 1986 and 2003, and Landsat 8 Operational Land Imager (OLI) for 2020 were freely acquired from USGS (htpps://earthexplorer.usgs.gov) at a 30 m spatial resolution. To generate the land use/cover (LULC) maps using satellite imagery, pre-processing was performed, and a classification scheme that defines the LULC classes was explored. Six major LULC classes were identified for mapping in Ogwapoke micro catchment. These included; built-up areas, croplands/ small scale farming, bushlands, grasslands, woodlands and wetlands as described in Table 3.1.

Under Image processing and classification, Landsat TM/ETM images was resampled from 30m spatial resolution prior to image analysis. To reduce the impact of the dust and noise on the sensor, the resampled images (30m) were atmospherically adjusted using the Dark Object Subtraction process. The method searches and removes dark pixel values. The Landsat imageries were classified using a hybrid classification algorithms (supervised and unsupervised classification) (Caprioli & Tarantino, 2003) in Arc Map software version 10.8 for spectral reflectance clustering. This algorithm provided land use/cover spectral classes in Ogwapoke micro catchment. Auxiliary data that included ground-truthing data in form of reference data points was captured using the Geographical Positioning System (GPS). The reference data points were mainly used to validate the current year (2020) image classification and accuracy assessment of the results. Prior to post classification, 500 training sites were randomly mapped for validation purposes, which was essential in enhancing the classification accuracy.

Table 3.1: Description of land use/cover types

LULC types	Description
Built-up areas	Commercial areas, urban settlements, industrial parks, government and institutional buildings, highways, hard surfaces, parking lots, and recreational places
Bushlands	Disturbed vegetation that is not cultivated but with trees, shrubs and other vegetation
Grasslands	Land covered with grasses and other soft vegetation characterized by narrow leaves and hollow stems but not with bushes and trees
Croplands	Agricultural areas characterized with crops like beans, maize, simsim, soya beans etc. grown on a small scale
Wetlands	Areas that are seasonally or permanently waterlogged with vegetation
Woodlands	Sparsely scattered trees that have a height beyond the underneath grass

3.4.1 Socio-economic data

A set of well-structured questions both close and open ended were designed (Appendix 1) and the micro-catchment area was clustered by parishes, which included Yepa, Ogwapoke and Pajong.

The questionnaires targeted household heads who were residents in the micro catchment for the last 5 years, since they gave detailed insight on the previous and current trends on land use/cover and soil eroding within the micro-watershed. The questionnaire tool focused on land use/cover changes, status of erosion, drivers of LULC changes & soil erosion, soil conservation method, impacts and recommendations for the changes in the micro catchment. The different land covers were mapped using the Global positioning system (GPS) in order to verify the land changes generated by the satellite images. The drivers of change, impacts of change and soil conservation methods were brain stormed by the respondents and filled in the questionnaire tool. The sampling methods employed during the research study included sampling clusters for the parishes according to the population and simple random sampling for the respondents in the study area. The questionnaire method was preferred because it drew information from a wide category of respondents (Zohrabi, 2013). Other data collection methods like interviewing, observation and recording were used alongside the main questionnaire tool. The questionnaire approach also helped to have a better comparison of the outputs obtained from remote sensing approach.

Data cleaning and coding were done prior to data analysis to obtain accurate information about the land use/cover types that may be prone to soil erosion, existing soil and water conservation practices, and drivers of change in the last 17-34 years in the micro catchment. IBM SPSS, a statistical software widely known as general approach to data analysis was used for data analysis of the different variables (Arbuckle, 2012).

3.4.2 Accuracy Assessment

The accuracy of the information derived from remotely sensed data is determined through accuracy evaluation. It performs best when combined with ground reference data with data acquired from aerial images (Zhou et al. 2009). The research captured approximately 500 ground truthing points to depict the land use and cover classes on ground within the case study area. These were used to calculate the confusion matrix in Ogwapoke micro-catchment. The confusion matrix is performed to assess the accuracy of the land cover classification process relative to reference data (Comber, 2013). The overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA) and Kappa statistics (K) were derived from the confusion matrix (Reis, 2008). The Kappa (K) statistics combines the off diagonal elements of the error matrices and reflects agreement obtained after removing the proportion of an agreement that could be expected to occur by chance (Wu et al., 2006). Overall accuracy is a percentage that reflects the likelihood that a pixel will be correctly identified/classified by the thematic map. Producer's accuracy denotes the proportion of pixels on the ground that are correctly classified by the one on the map, and quantifies the proportion of pixels excluded from a reference classis (omission error). User's accuracy represents the fraction of a category that is incorrectly included in another category (commission error) (Foody, 2002).

The overall accuracy is calculated as in equation (3.2)

Overall accuracy = $1/N \sum_{i=1}^{n} xii$ ……………………………………………………Equation (3.2)

where;

x is the individual cell values, xii is the total number of observations in a row i and column i, N=total number of samples.

On the other hand, Kappa coefficient was computed as in equation (3.3).

Kc= $N \sum_{i=1}^{r} xii - \sum_{i=1}^{r} \frac{(xit \times xti)}{N^2 \quad -} \sum_{i=1}^{r} (xit \times xti)$ ……………………………………Equation (3.3)

where Kc is the kappa coefficient, N is total number of samples, xii is the sum of correctly classified pixel, r is the number of rows in the matrix, xit and xti, are the marginal totals of row i and column *i* respectively.

The IDRISI software's Cellular Automata (CA)-Markov model was used to forecast future LULC scenarios. The CA-Markov model was adopted because of its great data efficiency, and ease of calibration, as well as its capacity to model different land covers and complicated patterns (Memarian et al., 2012; Hyandye et al., 2017) hence qualifying to be widely-used tool for land use dynamic simulation capability (Singh et al., 2015;Pan et al., 2017; Lu et al., 2018;). The model was built on the Cellular Automata and Markov models, which were created to anticipate land cover changes in complex and unpredictable urban areas (Ozturk, 2015). The procedures of projecting land use/covers changes with CA-Markov from Clark Labs outlined by Pan et al., (2017) and Liping et al., (2018) in the framework of IDRISI software was used in this study. Calculating the transition matrix, generating suitability maps, and predicting the land use/cover map were all part of this process. The Land use/cover transition matrix was computed from the land use/cover map using the: (I) Markov model; (II) Suitability which was based on the assessment indicators (road proximity, water body proximity, elevation, slope, and urban and built areas) in the multi-criteria evaluation module; and (III) The spatial distribution of land use/cover was simulated by the CA model based on the transition matrix and suitability maps. As a result, the land use maps of 2003 and 2020 were utilized as a baseline map, and CA-Markov in IDRISI software was used to anticipate and evaluate future land use maps of 2040.

To ensure model reliability, the CA–Markov model was used to predict land cover status in 2020 before performing reliable prediction of future land cover patterns. The land cover change map was projected using various iteration numbers, i.e., optimum iteration number, to achieve significant performance of the used model. The projected LULC map was compared with the classified LULC map for validation purposes using the Kappa index statistic (Equation 3.3) (Zhang et al., 2011). The validation results were aimed at giving a high level of agreement between the actual and predicted maps.

3.5 Determining the effect of changes in land use/cover on soil erosion

In order to determine the micro catchment study area boundary, a freely acquired digital elevation model (DEM) with a 30-metre resolution was obtained from https://earthexplorer.usgs.gov/. The Uganda soil layer downloaded from www.fao.org, and the annual meteorological satellite rainfall data for 2020 from https://power.larc.nasa.gov/data-access were used in the research. The satellite rainfall data was considered because it was more consistent and had no missing data gaps throughout the years than the locally available rainfall data. All data used in the research were considered because it was freely acquired. The RUSLE Model was employed to generate soil-erosion in the study area. The RUSLE model was preferred because it is widely used globally due to its practicality to generate and compute the average annual soil erosion rate for different soils and weather conditions (De Mello et al., 2016). Besides, the model utilizes seemingly low data requirements (Benavidez et al., 2018) compared to more complex soil loss models, making it easier to apply in areas with scarce data like Ogwapoke micro catchment. The integration of slope length factor in RUSLE enables the prediction of soil loss due to overland flow. Therefore, in this research, the soil erosion was calculated by multiplying four natural parameters (rainfall erosivity, soil erodibility and slope length and slope steepness factors) to identify areas of high vulnerability (Panagos et al., 2015). In contrast, the estimated soil erosion (Equation (3.4) was calculated by combining natural and anthropogenic components (rainfall erosivity, soil erodibility, slope length and slope steepness, cover management, and support practice factors) (Kogo et al., 2020).

$A = R \times K \times LS \times C \times P$……………………………………………………………..Equation (3.4)

where A denotes the soil loss per unit of area ($t\ ha^{-1}\ year^{-1}$); R represents rainfall erosivity factor ($MJ\ mm\ ha^{-1}\ h^{-1}\ year^{-1}$); K is soil erodibility factor ($t\ ha^{-1}\ MJ^{-1}\ mm^{-1}$), LS (unit-less) denotes topographic factor, C (dimensionless) is a crop management factor, and P (dimensionless) is a conservation practice factor.

The R factor was estimated using (Equation (3.5)) as proposed by (Moore, 1979).

$R = 0.029*(3.96*P+3122)-26$……………………………………………………………Equation (3.5) where P is the mean annual precipitation in mm. The long-term mean annual precipitation from 2019 was determined using NASA's Prediction of Worldwide Energy Resources (NASA POWER).

K Factor

The K factor expresses the susceptibility of soil erodibility as a result of its soil properties (Cassol et al., 2018) as described in table 3.2. The FAO-compiled sand, clay, silt, and organic carbon 3fractions were used to determine the soil erodibility factor of the Ogwapoke micro catchment using (Equation (3.6)) as proposed by (Anache et al., 2015). Practically, to convert the K factor from the American system to the metric system unity/International System of Units (SI), A, B, and C were multiplied by 0.1317. However, K factor is derived from a sub equation of

K = A * B * C * D * 0.1317…………………………………………………………....Equation (3.6)

Table 3.2: K factor detailed description

K=	**A x B x C x D x 0.1317**		
A	Is the factor that gives low soil erodibility factors for soils with high *coarse-sand contents* and high values for soils with *less sand*	= (0 .2+ 0.30exp (-0.0256 SAN(1-SIL/100))	***SAN*** is the percent sand content (0.05–20.00 mm diameter particles) ***SIL*** is the percent silt content (0.002–0.05 mm diameter particles)
B	is a factor that gives low soil erodibility factors for soils with *high clay to silt* ratio	$=(\frac{SIL}{(CAL+SIL)})^{0.3}$	***CLA*** is the percent clay content (<0.002 mm diameter particles)
C	is a factor that reduces soil erodibilit y for soils with *high organic carbon* content	$=(1-\frac{0.0256co}{co+\exp(3.72-2.95co)})$	***co*** is the percent organic carb on content of the layer and
D	is a factor that reduces soil erodibilit y for soils with *extremely high sand* contents	$=(1-\frac{0.7SN1}{SN1+\exp(-5.51+22.9SN1)})$	***SN1*** =1-SAN 1 /100

Using an updated soil data, the K value was computed in excel spread sheet for each soil type using the A, B, C, D parameters (**Error! Reference source not found.**) and later an excel table was joined to the Soil dbf in ArcGIS using the Join and Relate tool. The joined soil map was further converted to raster format using the conversion tool in order to be used for analysis while creating a raster K factor map.

Slope Length and Slope Steepness (Factor LS)

The slope length and steepness factor (LS) is a product of two separate factors: slope length *(L)* and steepness *(S)*, LS Factor. Digital Elevation Model (DEM) (is a raster representation of a continuous surface in which each cell represents the elevation at a location) was used as the main layer. Slope was derived from Ogwapoke micro catchment masked Uganda's Digital Elevation Model-DEM (STRM) of 30 m spatial resolution using spatial analyst tool in degrees. Flow accumulation was also derived from the hydrology tool of spatial analyst. Therefore, factor LS was computed and derived (equation 3.7) using the Raster Calculator of Spatial Analyst Extension in the ArcGIS environment to obtain a final spatial distribution map.

$$L = \left(\frac{FlowaccumulationXGridsize}{22.13}\right)^m$$ ………………………Equation (3.7)

where;
Grid size = 110m, and slope length exponent ***m*** is taken from m-map for respective grid.
whereby;

$$Factor\_M = \frac{Factor\_F}{(1+Factor\_\mathrm{F})}$$ ……………………………………………..Equation (3.8)

To calculate Factor F before getting Factor M.

where;

Factor F= ((Sin ("Slope"* 0.01745) / 0.0896) / (3 * Power (Sin ("Slope"* 0.01745),0.8) + 0.56)…………………………………………………………………………....Equation (3.9)

Therefore, from equation (3.8),

Factor L=Power (((“Flow accumulation” *grid size)/22.13),” Factor M”)…………Equation (3.10)

And;

Factor S =Con ((Tan ("**Slope**" * 0.01745) < 0.09), (10.08 * Sin ("**Slope**" * 0.01745) + 0.03), (16.8 * Sin ("Slope" * 0.01745) - 0.05))…………………………………………………. Equation (3.11)

Then;

Factor LS = Factor L * Factor S……………………………………………………Equation (3.12)

Conservation Practice Factor

In order to compute the conservation practice Factor C, land use/cover (LULC) map for 2020 was generated through ArcGIS using the "*Iso-cluster unsupervised and maximum like hood*" tools. The values of conservation practice Factor C were assigned to all the land use/cover classes using ArcGIS raster calculator after adding a field in the table of attributes. The Factor C attributes ranging between 0-1 for different management practices (Table 3.3) are widely used as emphasized and tabulated by (Panagos et al., 2015; Borrelli et al., 2017; Fenta et al., 2020).

Table 3.3: Land use/land cover classes and respective C-factor value

Class	**Small scale farming**	**Grasslands**	**Bushlands**	**Built-up areas**	**Wetlands**	**Woodlands**
Factor C	0.38	0.15	0.015	0	0	0.015

Support practice factor (Factor P)

However, support practice factor (Factor P) is rarely taken into account in soil erosion modeling at large scale, as it is difficult to estimate for large areas. P factor was taken as a unit assuming no erosion control practices, it was therefore, assigned to 1.

GPS points were mapped with high erosion seen in deep valleys along the entire study area and the points were overlayed on the RUSLE model for accuracy assessment, areas with steep slope had high values as reflected in the model analysis whereas areas with low erosion were seen in the low areas with low values.

The final map that shows the annual soil loss of the micro catchment was produced by overlaying the above five parameters (K, R, LS, C, and P) using (Equation 3.4), and raster calculator geo-processing tools in Arc GIS 10.8 environment. Each layer was organized in a grid format with a resampled cell size (55×55) of the DEM. Furthermore, the statistical tool was used to estimate the amount of soil loss and to classify the level of the soil loss in the Ogwapoke micro catchment. After computing the soil erosion loss using the main factors of soil erosion (Rainfall erosivity, soil erodibility, slope, and C factor from land use map), results derived from the soil erosion model were used as a base factor to determine the estimated soil loss for each land use/cover. Soil erosion index was classified and categorized in four classes as follows; low erosion, moderate erosion, high erosion and very high erosion based on the rate of erosion (t/ha/year). Therefore, more erosion corresponds to very high erosion and least rate of erosion correspond to low erosion (Srinivasan et al., 2019). Therefore, the study considered rate of erosion > 1 t/ha/year as low and values > 5 t/ha/year as high. Secondly, the land use/cover 2020 was overlaid on the classified erosion indexed layer and area for each index corresponding to a particular land use/cover was computed.

3.6 Assessing land use/cover change impact on the Ogwapoke catchment hydrological flow/water balance

The Land use/cover change effect on stream flow was simulated using the Soil and Water Assessment Tool (SWAT model, Arnold *et al.*, 2012). SWAT has been worldwide utilized and fully tested for hydrologic modeling at various spatial scales to examine the land use and land cover change impacts on watershed water supplies. The SWAT model (Neitsch *et al.,* 2009; Arnold *et al.,* 2012) is a physically based, process-oriented, computationally efficient, semi-distributed, time continuous catchment model. The model was developed to simulate and predict the impacts of land management practices on water quantity and quality over long time periods in complex catchments with varying soils, land use, and management conditions. Using topographic information, the catchment was partitioned into a number of sub basins in the model. Sub-basins are subsequently separated into hydrological response units (HRUs), which are made up of a variety of soil, land cover, and slope classes (Arnold *et al.,* 2012). On a daily time scale, the model replicates hydrological processes. The hydrological cycle was divided into two parts: land and routing (Figure 3.2). The land phase regulates the amount of water, sediment, nutrients, and pesticides that enter each sub-main catchment's channel. The land phase involves processes like climate, hydrology, erosion, and management operations. The routing phase involves the movement of water, through the channel network to the catchment outlet (Neitsch *et al.* 2009).

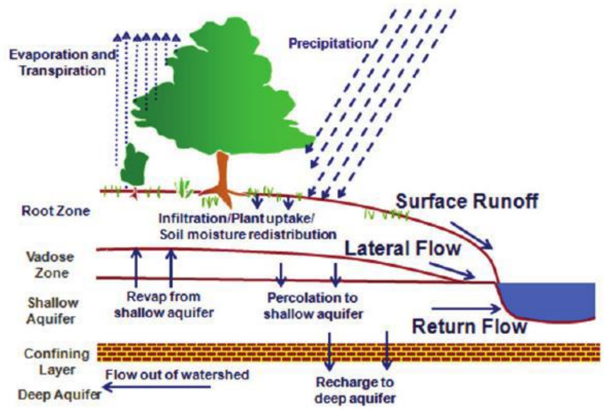

Figure 3:2: SWAT schematic representation of hydrological cycle. Adopted from Neitsch et al. (2009)

In SWAT, five storages were considered to calculate the water balance and these include the canopy storage, the soil profile, snow, a shallow aquifer and a deep aquifer. The water balance is expressed as in equation 3.12

$SW_t = SW_0 + \sum_{t=1}^{t}\left(R_i - Q_i - ET_{a,i} - W_{seep,i} - Q_{gw,i}\right)$.................................(Equation 3.12)

where SWt is the final soil water content [mm], SW0 is the initial soil water content on day i [mm], t is the time [days], R_i is the net precipitation on day i [mm], Q_i is the amount of surface runoff on day i [mm], $ET_{a,i}$ is the amount of evapotranspiration on day i [mm], $W_{seep,}$i is the amount of water entering the vadose zone from the soil profile on day i [mm], and $Q_{gw,i}$ is the amount of return flow on day i [mm] (Neitsch *et al.* 2009).

Model setup, calibration and validation

The basic initial model setup was carried out with the ArcSWAT interface. This involved catchment delineation using a 30 m DEM, subdivision of sub-catchment into HRUs and generation of daily climate input files. After the initial setup of ArcSWAT, sensitivity analysis, calibration (1986-2003) and validation (2003-2020) was conducted using a standalone program, SWAT-CUP (Calibration and Uncertainty program) at the catchment outlet using daily forecast reanalysis stream flow (downscaled from Princeton climate for the periods of calibration and validation), following the guidelines of (Abbaspour, 2015). Reanalysis of stream flow data was used in the calibration and validation because there were huge data gaps in the measured discharge data from the gauging station at the outlet of the catchment, thus, this never rave a representative picture within the catchment. The optimization algorithm, SUFI-2 (Sequential Uncertainty Fitting) (Abbaspour, 2015) integrated in SWAT-CUP was adopted for sensitivity analysis, calibration and uncertainty analysis. Sensitivity analysis was conducted to determine how various sources of uncertainty in a mathematical model contribute to the model's overall uncertainty. An uncertainty analysis is crucial to evaluate the strength of a calibrated model (Abbaspour, 2015). There exist several uncertainties in hydrological modelling which include according to Shen et al (2012), (1) uncertainties in the model structure; (2) uncertainties in model parameter estimates; (3) uncertainties in the model drivers (initial and boundary conditions such as rainfall, soil and land use); (4) uncertainties that are overlooked by the modeller and not included in the model (can be unknown or known processes).

In SUFI-2, uncertainty of parameters accounts for all sources of uncertainties stated above. Accumulation of uncertainties in the parameters results into uncertainties in the model output variables, which are expressed as 95% prediction uncertainty. 95% prediction uncertainty (95PPU) was calculated at the 2.5 and 97.5 percentiles of the cumulative distribution of an output variable attained through Latin Hypercube sampling, ignoring 5% of the very bad simulations due to bad parameter combination. The uncertainty band of 95PPU was used to account for the modelling uncertainty (Arnold et al., 2012). The degree and strength of uncertainties in the model output were measured by the P-factor and the R-factor respectively (Abbaspour, 2015). The P-factor is the percentage of measured discharge enveloped by the 95PPU. The P-factor ranges between 0 and 1, in which 1 means 100% bracketing of the measured discharge by the model. The R-factor is the thickness of 95PPU envelop calculated by Equation 3.13. The R-factor divides the average distance between 2.5 and 97.5 percentiles with the standard deviation of the measured (Arnold et al., 2012). The R-factor ranges from 0 to infinity, with values below 1, indicating a small uncertainty band (Arnold et al., 2012). A P-factor of one and R-factor of zero is a simulation that exactly corresponds to the measured discharge. The strength of calibration is judged by the degree of deviation of these numbers. A larger P-factor is achieved at the expense of a large R-factor (equation 3.14).

$$\mathrm{R} - factor = \frac{1}{n\sigma_o}\sum_{n=1}^{n}(S_U - S_L) \ldots\ldots \text{(Equation 3.14)}$$

where n is the number of observations, σ_o is the standard deviation of the measured discharge, S_U and S_L are the 97.5th and 2.5th percentiles of the simulated 95PPU, respectively.

Model evaluation

SWAT model performance during calibration and validation was evaluated based on three statistics, specifically: (1) the coefficient of determination (R2), (Equation 3.15); (2) the Nash-Sutcliffe efficiency (NSE) (Equation 3.16) (Nash and Sutcliffe, 1970); and the percent bias (PBIAS) (Equation 3.17) (Gupta et al., 1999), The coefficient of determination (R2) was used to describe the proportion of variance explained by the model and ranges between 0 and 1.0, with high values indicating less error variance (Rathjens and Oppelt, 2012a). The NSE is a dimensionless model evaluation index, used to determine the relative magnitude of the residual variance between the simulated and measured data variance (Nash and Sutcliffe. 1970) and ranges from -∞ to1.0. An NSE of 1.0 indicates a perfect fit between the simulated and observed data and it is very responsive to the peak flows (Moriasi *et al.* 2007). PBIAS was calculated to measure the average tendency of the simulated data to be larger or smaller than the measured values. The optimal value of PBIAS is 0%, with positive and negative values indicating model underestimation and overestimation bias, respectively (Gupta *et al.*, 1999).

The model performance was considered to be satisfactory if NSE > 0.50, R^2 > 0.50, PBIAS ±25% (Moriasi *et al.*, 2007). These three statistic criteria were enough to evaluate the model performance for the study purpose since they capture the low and high flows in the hydrograph. Further, these lumped metrics have been established as key model performance benchmarks (Moriasi et al., 2015). They provide an average measure of error and are intentionally biased towards large magnitude flows and this was partly the objective of the calibration to maximize the peaks since the catchment is mainly characterized by low flows for most of the periods due to the low rainfall received. NSE is slightly better than R^2 for many model applications as it is sensitive to the observed and model simulated means and variances (Krause et al., 2005).

$$R^2 = \frac{\left[\sum_{i=1}^{n}(O_i-\bar{O})(P_i-\bar{P})\right]^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2\sum_{i=1}^{n}(P_i-\bar{P})^2} \qquad \text{(Equation 3.15)}$$

$$NSE = 1-\frac{\sum_{i=1}^{n}(O_i-P_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2} \qquad \text{(Equation 3.16)}$$

$$PBIAS = 100 * \frac{\sum_{i=1}^{n}(O_i-P_i)}{\sum_{i=1}^{n}O_i} \qquad \text{Equation 3.17)}$$

where O_i and P_i are the measured and simulated data, respectively, $\bar{O}$ and $\bar{P}$ are the mean of measured and simulated data, n is the number of observations.

CHAPTER FOUR: RESULTS

4.1 Analyzing and predicting the Spatial-temporal changes in land use/cover

Between 1986 and 2003, bushlands, grasslands, wetlands and woodlands continued to shrink although slight increases in both small-scale farming and built-up areas were observed. The same pattern was still observed between 2003 and 2020 while the main land covers were shrinking in area. The estimates of LULC changes show that the built-up and small-scale farming land uses have both increased significantly (Table 4.1). In 1986, built-up areas covered 0.1 sq.km which increased to 1.6 sq.km and 2.5 sq.km by 2003 and 2020 respectively indicating a 4 % growth in the 34 years interval. Table 4.1 also shows that between 1986, 2003 and 2020, small scale farming increased to approximately 5.5%, 21.5% and 40.7% respectively. Over the same period, bushlands decreased from 23.3% to 20.1%, and to 11.6%. Grassland decreased from 26.2% to 20.5% and then to 18.8%. Wetlands decreased from 12.9%, 10.5%, and 10.3% whereas woodlands decreased from 32.1% to 26.1% and 16.2% over the same study period (Table 4.1).

However, under the ground survey it was observed that between 1986 and 2003 and 2003-2020, built up areas (1.3%, 1.1%) and small-scale farming (16%, 19.2%) respectively increased in favour of other land covers (bushlands, grasslands, woodlands and wetlands). The highest decrease between 1986 and 2003 was observed in woodlands (6%) followed by grasslands (5.7%) whereas 2003-2020, highest decrease was observed in woodlands (9.9%) followed by bushlands (8.5%). Wetlands were observed to have the least decrease in changing trends with 0.1%, 0.2% (Table 4.1)

Table 4.1: Land use/cover spatial statistics in Ogwapoke micro catchment from1986-2020

	1986		**2003**		**2020**		**Change 1986-2003**		**Change 2003-2020**	
Land use/ cover	**Area (Sq.km)**	**%**	**Area (Sq.km)**	**%**	**Area (Sq.km)**	**%**	**Area (Sq.km)**	**%**	**Area (Sq.km)**	**%**
Built-up areas	0.1	0.1	1.6	1.4	2.9	2.5	1.5	1.3	1.3	1.1
Bushlands	27.1	23.3	23.4	20.1	13.5	11.6	-3.7	-3.2	-9.9	-8.5
Grasslands	30.5	26.2	23.9	20.5	21.9	18.8	-6.6	-5.7	-2	-1.7
Small scale	6.5	5.5	25	21.5	47.4	40.7	18.5	16	22.4	19.2

farming										
Wetlands	15	12.9	12.2	10.5	12.1	10.3	-2.8	-2.4	-0.1	-0.2
Woodlands	37.4	32.1	30.4	26.1	18.8	16.2	-7	-6	-11.6	-9.9
TOTAL	**116.5**		**116.5**		**116.5**					

Table 4.2 shows results from household survey indicating that small scale farming was replacing other land use/cover with a score of 41.5%, followed by woodlands (32.5%) and then grasslands (15%). Besides, a number of questionnaires also showed that the earlier years (1986-1990s) woodlands, grasslands and bushlands had the highest coverage compared to the 2000s. Therefore, the shrinking of land covers from 1986 to 2003 (Table 4.1) and the increasing patterns of land uses from 1986 to 2003 shows that this was the same obtained with the observed results from the respondents as shown in Table 4.2.

Table 4.2: Response to the major land use/cover that has been the main replacement of other land covers at least in the last 17years

Land use/cover	**No. Respondents**	**%**
Built-up areas	14	7
Bushlands	8	4
Grasslands	30	15
Small scale farming	83	41.5
Wetlands	0	0
Woodlands	65	32.5
Total	**200**	**100**

Spatial patterns of LULC changes in the study area for 1986, 2003 and 2020 are shown in Figure 4.1. The research revealed six land use/cover (LULC) classes that were evenly distributed throughout Ogwapoke micro catchment between 1986, 2003 and 2020 (Figure 4.1). These LULC classes included built-up areas, bushlands, grasslands, small scale farming, wetlands, and woodlands with a total coverage of approximately 116.5 sq.km.

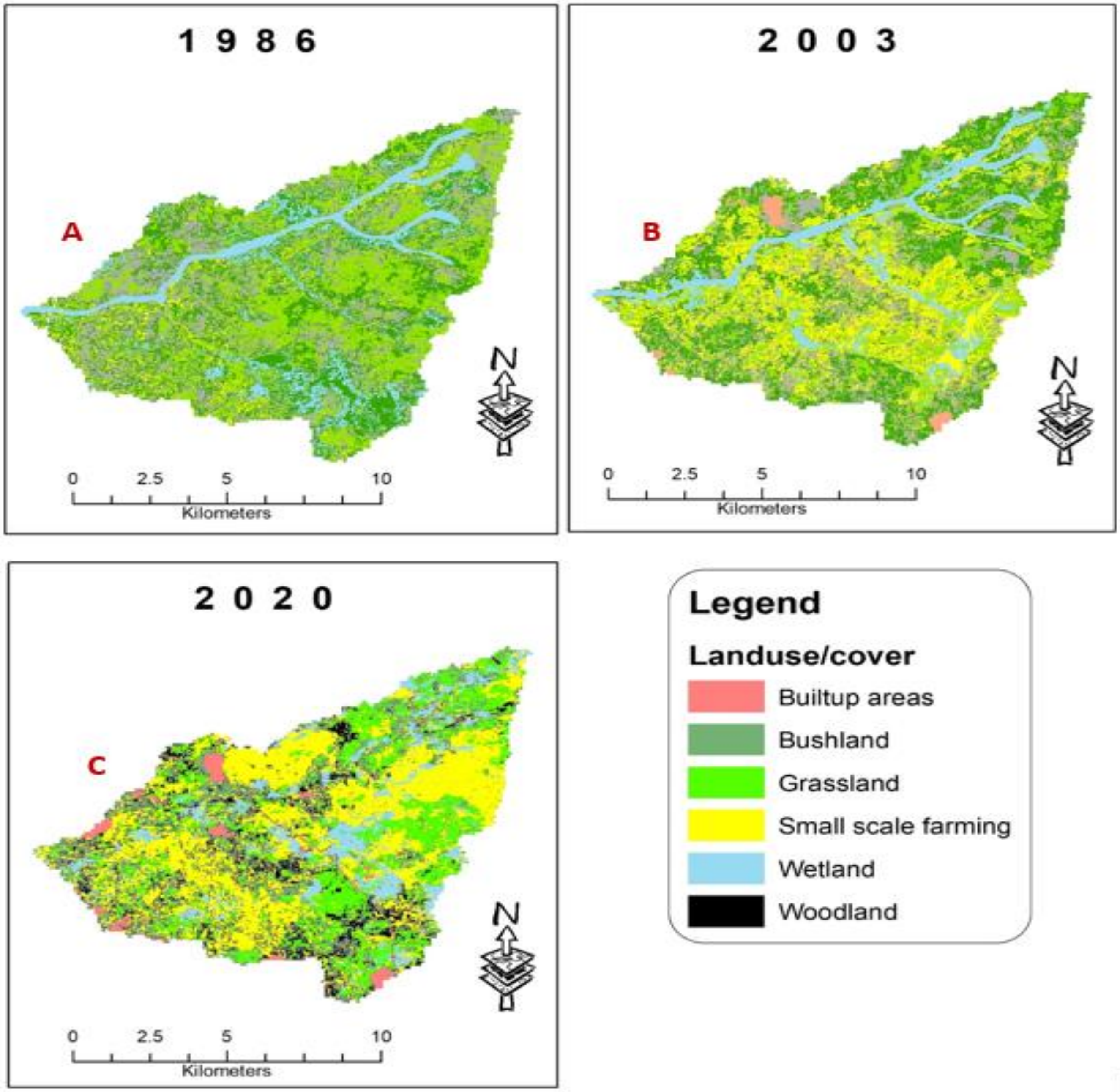

Figure 4:1: Land use/cover spatial distribution in Ogwapoke micro catchment from 1986-2020

4.1.2 Accuracy assessment

The results from accuracy assessment (Table 4.3) showed an overall accuracy of 86.6%, 83.8% and 82% for the classified images of 1986, 2003 and 2020 respectively (Table 4.3). In 1986, user's accuracy ranged from 81.1% to 94.7% while producer's accuracy ranged from 82.6% to 96.0%, while in 2003, user's accuracy ranged from 81.3% to 94.4% and producer's accuracy ranged from 81.5% to 85.1% (Table 4.3). In 2020, User's accuracy ranged from 79.5% to 92.2% while producer's accuracy ranged from 76.5% to 92.2%. Kappa statistics of 0.86, 0.81 and 0.78 was registered in 1986, 2003 and 2020 respectively (Table 4.3). Therefore, all years were considered to have more reliable user and producer accuracies greater than 75% as also agreed by a number of research studies like (Ayyanna et al., 2018; Priyadarshini et al., 2018; Garg et al., 2019).

Table 4.3: Accuracy assessment

1986							
Producer accuracy (%)	85.0	87.0	96.0	82.6		88.2	94.8
User accuracy (%)	81.3	81.1	91.1	94.7		90.1	84.9
Overall accuracy (OA) - (%)	88.6						
Kappa statistics	0.86						
2003							
Producer accuracy (%)	81.5	84.9	82.1	85.1		84.5	85.0
User accuracy (%)	81.3	81.6	82.1	88.1		84.5	94.4
Overall accuracy (OA) - (%)	83.8						
Kappa statistics	0.81						
2020							
Producer accuracy (%)	81.3	88.2	82.9		87.8	77.2	76.9
User accuracy (%)	81.3	82.2	90.0		80.0	92.2	79.5
Overall accuracy (OA) - (%)	82.0						
Kappa statistics	0.78						

4.1.3 Land use/cover prediction

The Markov model used in the research also revealed that after 20 years, small scale farming and built-up areas are likely to increase tremendously by 9.8% and 3.4% respectively from 2020 to 2040 (Table 4.4), leaving isolated pockets of wetland and bushlands.

Table 4.4: LULC change statistics for 2020-2040 and annual rate of change

	2020		**2040**		**change2020-2040**	
Land use/cover	**Area (Sq.km)**	**%**	**Area (Sq.km)**	**%**	**Area (Sq.km)**	**%**
Built-up areas	2.9	2.5	6.8	5.8	3.9	3.4

Bushlands	13.5	11.6	11.5	9.9	-2.0	-1.7
Grasslands	21.9	18.8	13.3	11.4	-8.7	-7.4
Small scale farming	47.4	40.7	58.8	50.4	11.4	9.8
Wetlands	12.1	10.3	8.0	6.9	-4.1	-3.5
Woodlands	18.8	16.2	18.2	15.6	-0.6	-0.5

The rest of the land covers were predicted to have reduced further compared to the values of 2020. Woodland had the least reduction followed by bushlands, wetlands and grasslands at 0.5%, 1.7%, 3.5% and 7.4% respectively. In 2040, only six LULC classes were predicted including small scale farming, built-up areas, grasslands, wetlands, bushlands, and woodlands (Figure 4.2).

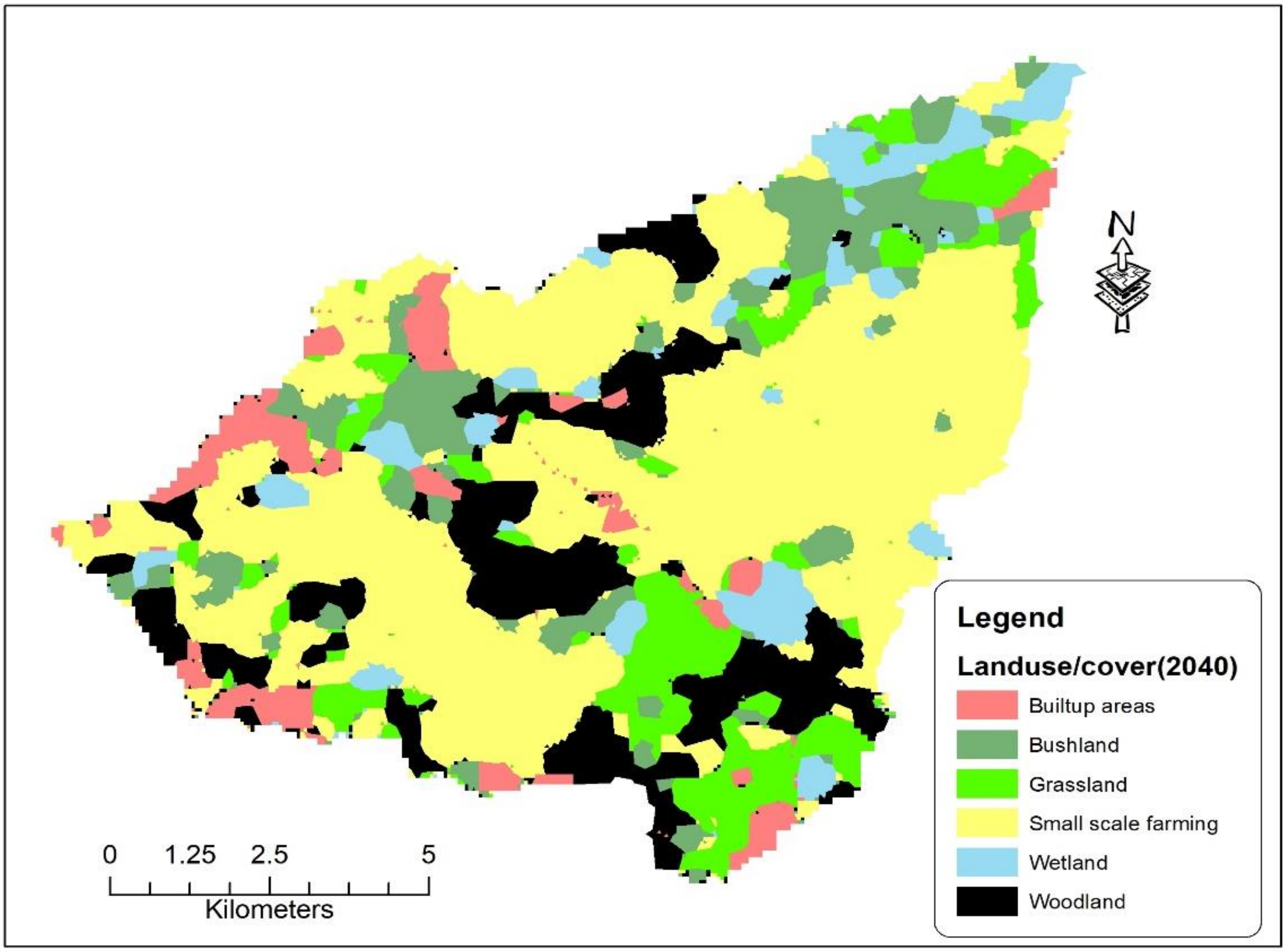

Figure 4:2: Spatial distribution of the predicted land use/cover (2040) in Ogwapoke micro catchment

The respondents also identified that in the last 34 years, animal grazing has been the biggest driver for changes in land use/cover change followed by bush burning (Figure 4.3). However, in the last 17 years, bush burning was considered to be the main driver of change in the Ogwapoke micro- catchment followed animal grazing (Figure 4.3)

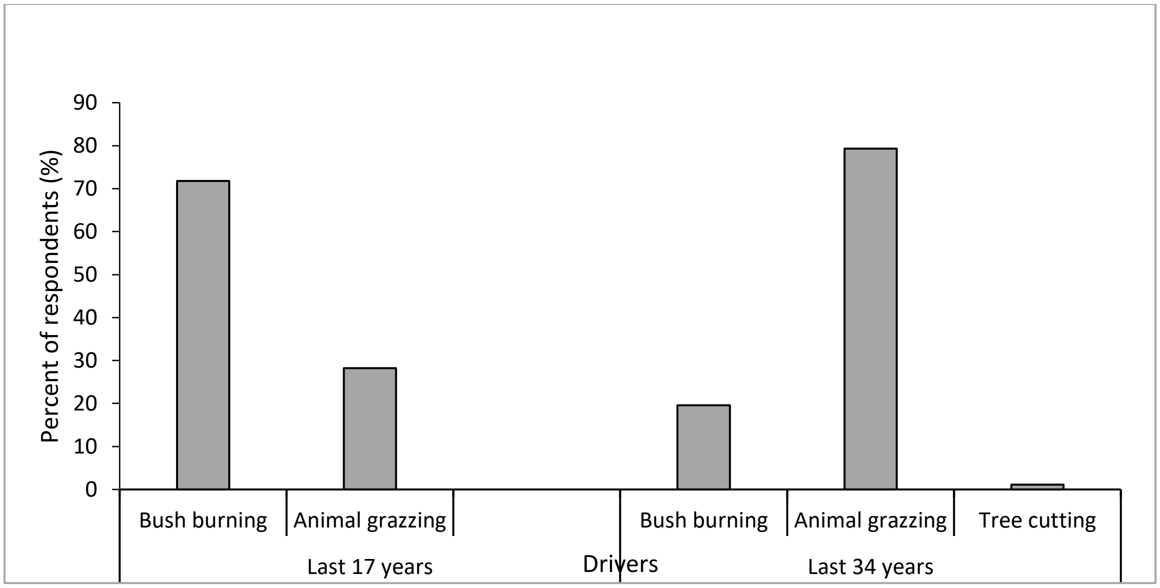

Figure 4:3: Drivers of land use/cover change in the last 17 and 34 years

4.2 Determining the effect of land use/cover change on soil erosion

Rainfall erosivity (R) factor estimation, the result of IDW interpolation using precipitation data showed that the mean annual rainfall of the micro catchment ranged from 1419.32 mm to 1453.85 mm with the highest value in the north eastern part of the micro catchment (Figure 4.4A). The R-factor value of micro catchment was between 227.6 and 231.4 MJ mm ha−1 year−1 (Figure 4.4B) with higher values occurring in the north eastern part of the micro catchment, and the potential of rainfall to erode soil gradually decreases toward the south and south eastern part of the micro catchment.

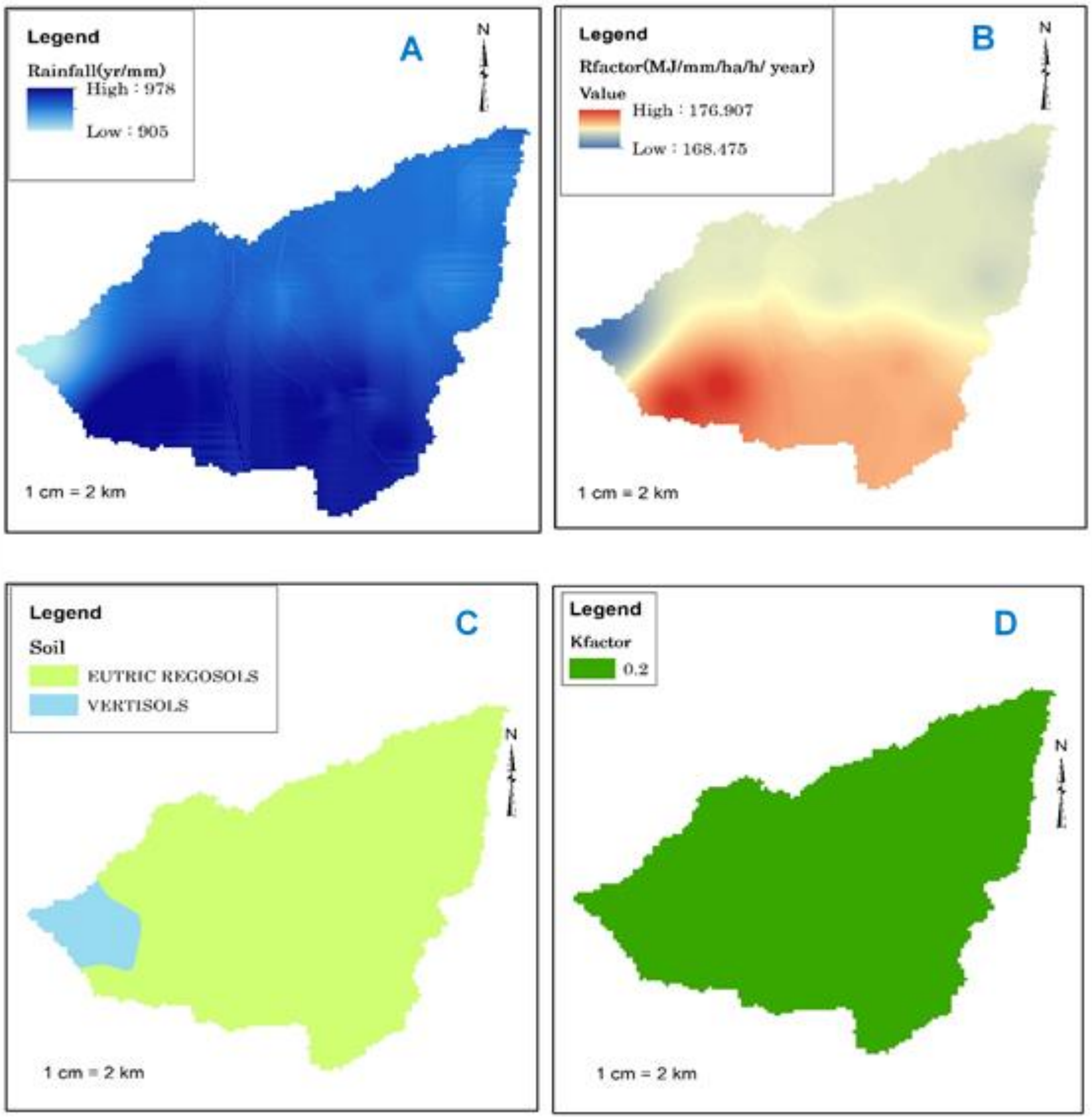

Figure 4:4: Spatial distribution of Rainfall in mm (A), Rainfall erosivity-Rfactor (B), Soil types(C), soil erodibility –Kfactor (D)

Soil erodibility (K) factor estimation.

The major soil types in the micro catchment are Eutric Regosols, Vertisols, with Eutric Regosols covering the largest part of the micro catchment (Figure 4.4C). However, the soil erodibility (K) factor value of the micro catchment was constant with 0.2 ha−1 MJ−1 mm−1 in all the soil types within the micro catchment (Figure 4.4D). Therefore, result indicated that about 100% of the micro catchment area has a K-value of 0.20 t/ha−1 MJ−1 mm−1.

LS factor estimation.

The slope steepness map (Figure 4.5E) was directly generated from the STRM DEM (30-m spatial resolution) map and results revealed that Ogwapoke micro catchment is generally flat with a slope ranging between 0.01-5.73 degrees. The slope length and slope steepness factor result in figure 4.5F indicated that the slope length and slope steepness (LS) factor value in the micro catchment varies from 0 in flat areas to 0.016 in stream bank or slightly hilly areas. The C-factor value of the watershed ranged from 0 to 0.38 (Figure 4.5H) with the lowest value in wetland areas and highest in crop land areas.

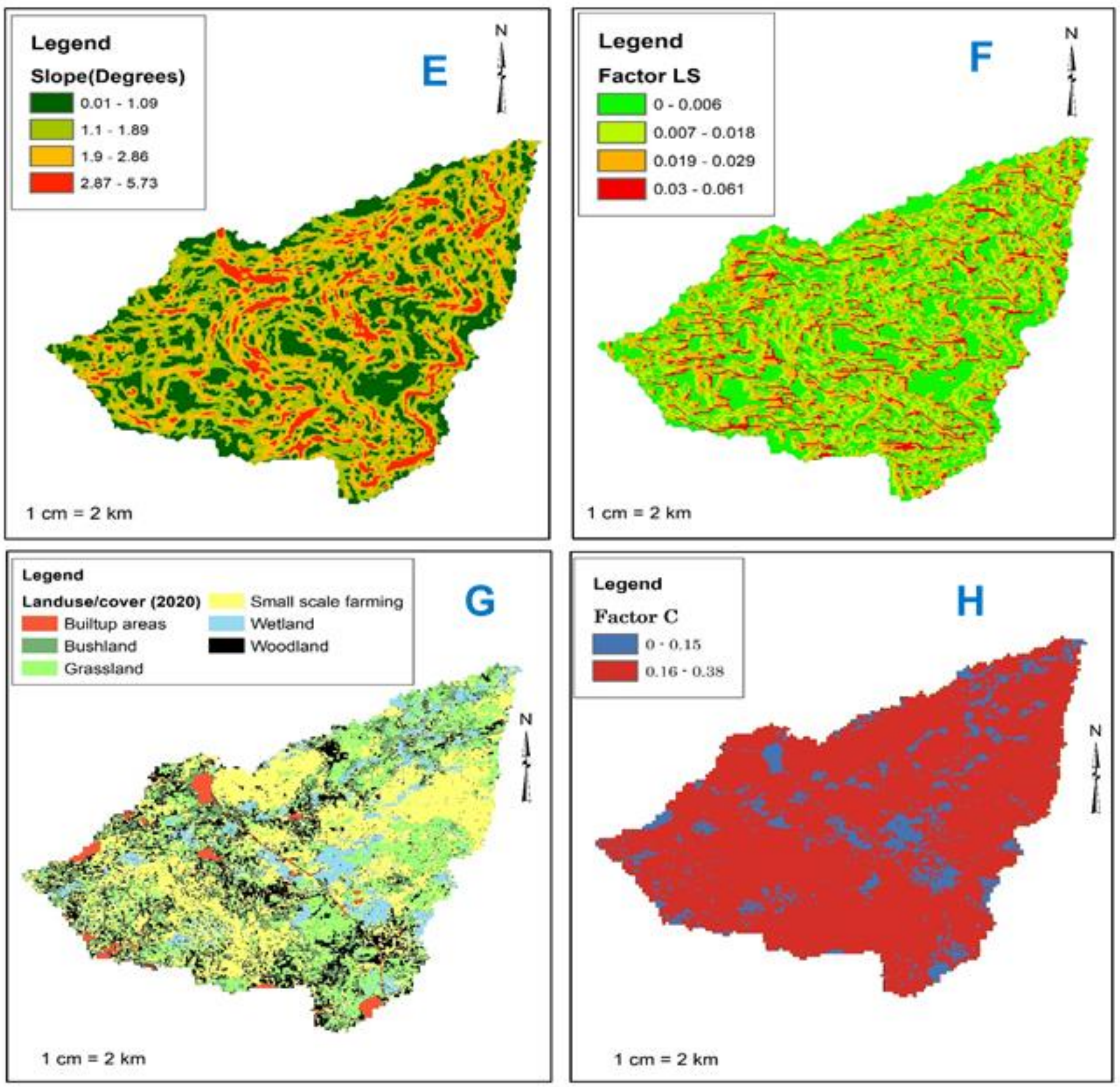

Figure 4:5: Spatial distribution of Slope in degrees (E), Slope length-gradient factor-LS factor (F), Land use/cover types (G), cover-management – Factor C (H)

Table 4.5 summarizes land use/cover classes effects on the annual soil loss in Ogwapoke micro catchment. The findings showed that most of the built-up areas and wetlands in Ogwapoke micro catchment experience low soil erosion (4% and 17.5% respectively). Most of the bushlands, grasslands and woodlands experience moderate soil erosion (17.1%, 31.1% and 21.7% respectively) whereas most of the small-scale farmlands have a very high of soil erosion (79.9%). Generally, Ogwapoke micro catchment showed a low soil erosion (56.7 sq.km), compared to moderate soil erosion (39.7 sq.km), high soil erosion (13.9 sq.km) and very high soil erosion (6.2 sq.km) (Table 4.5).

Table 4.5: Soil erosion coverage in the different land use/cover types in Ogwapoke micro catchment

	Low soil erosion		**Moderate soil erosion**		**High soil erosion**		**Very High soil erosion**	
Land use/cover	**Area (sq.km)**	**%**	**Area (sq.km)**	**%**	**Area (sq.km)**	**%**	**Area (sq.km)**	**%**
Built-Up Areas	9.94	17.54	1.09	2.76	0.46	3.27	0.20	3.29
Bushlands	5.24	9.24	6.79	17.11	0.79	5.70	0.27	4.39
Grasslands	9.58	16.89	12.36	31.14	1.10	7.86	0.28	4.54
Small Scale Farming	18.74	33.05	10.62	26.78	10.16	72.87	4.96	79.99
Wetlands	2.27	4.01	0.21	0.52	0.07	0.52	0.02	0.38
Woodlands	10.92	19.27	8.61	21.69	1.36	9.79	0.46	7.42
Total	***56.7***		***39.7***		***13.9***		***6.2***	

The respondents revealed that croplands/small scale farming is the most prone land use to soil erosion followed by built-up areas and bushlands, since the land surface is always bare and thus, exposed to high runoff resulting into surface soil movement downslope (Figure 4.6).

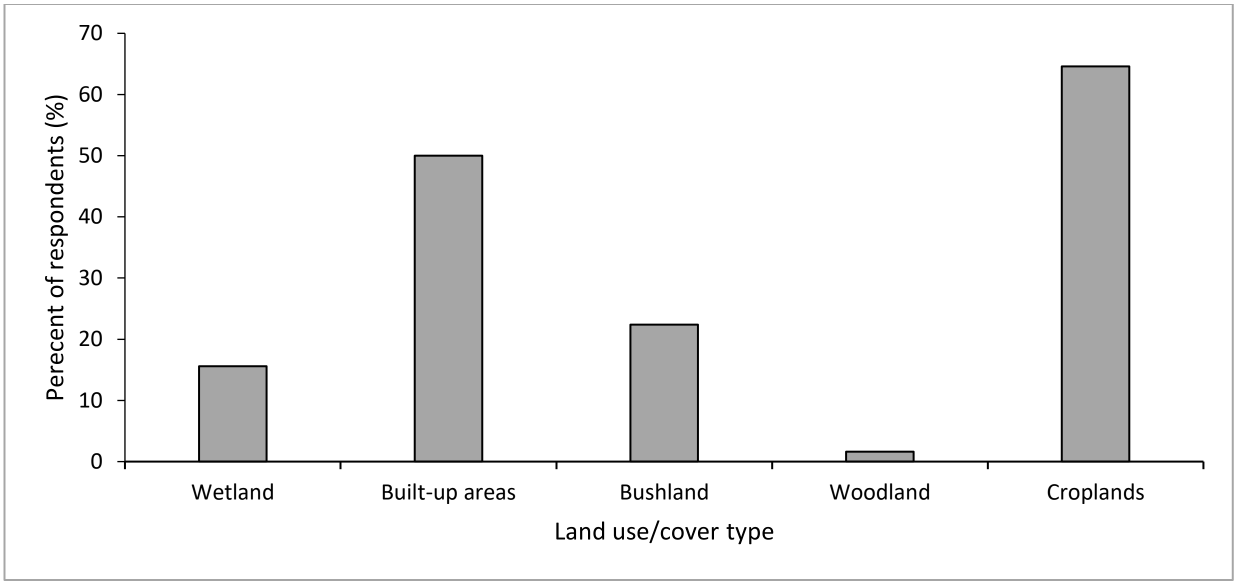

Figure 4:6: Land use/cover types perceived to be prone to soil erosion in the catchment

Figure 4.7 shows the categorization of soil erosion in Ogwapoke micro catchment. Generally, Ogwapoke micro catchment has a low soil erosion.

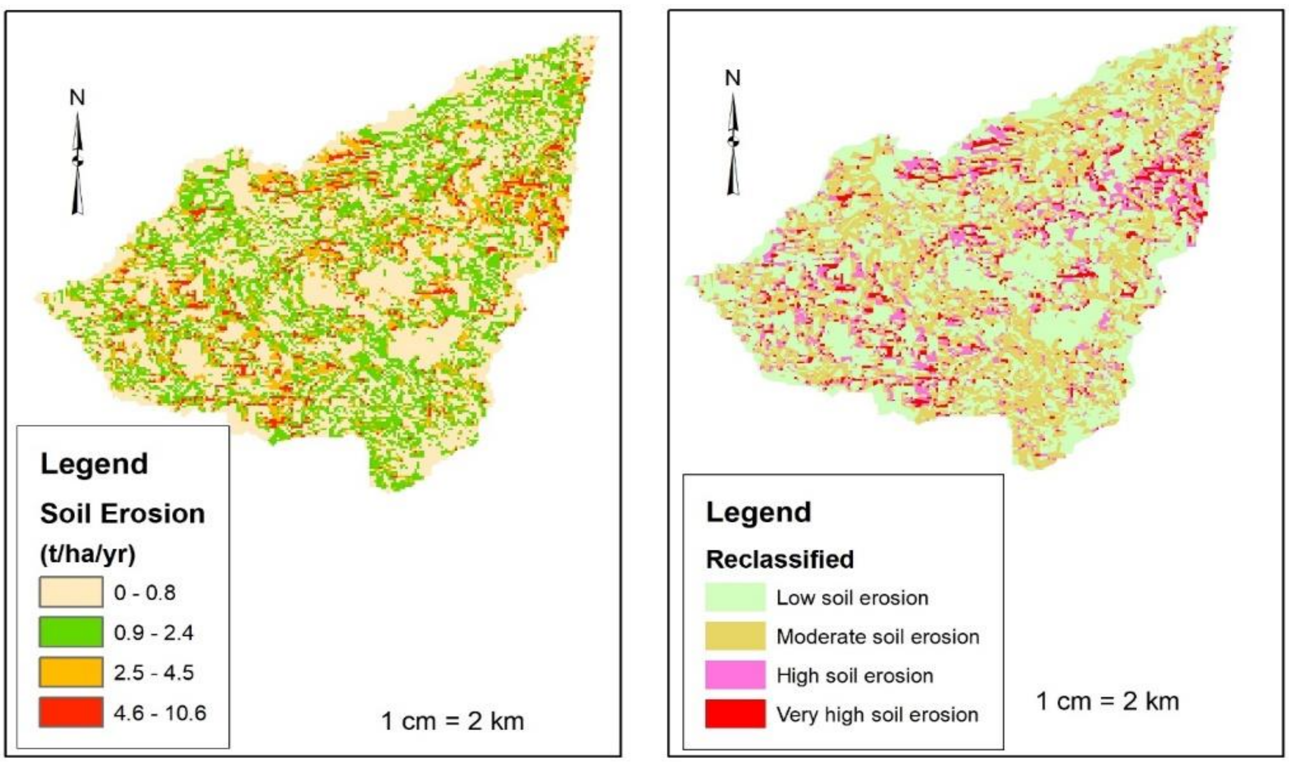

Figure 4:7: Soil Erosion rate (Left) and soil erosion ranking maps according to severity (right)

In an effort to reduce the effect of soil erosion, catchment management interventions are conducted in the study area and the main interventions according to the respondents include tree planting through reforestation (41%), mulching (26%) and vegetated strips/grass bunds (17%) (Table 4.6).

Table 4.6: Existing soil and water conservation practices at the farms (n=200)

Soil and Water Conservation Practices	**Frequency**	**Percent**
Reforestation	82	41
Vegetated strips	33	17
Contour plowing	5	3
Stone lining	7	4
Fallowing	9	5
Mulching	52	26
Live hedges	12	6
TOTAL	**200**	**100**

4.3 Assessing the impact of land use/cover change on the catchment hydrological flow

The effects of land use/cover changes scenarios (from 2003 to 2040) are shown in Table 4.7 for the annual water balance components. Surface runoff is highly affected by changes in land use/cover change in the micro-catchment. In the year 2020 (scenario 2), it increased by 120% and it's projected to increase by 188% under the projected land use/cover in the year 2040 from the reference land use/cover scenario (LULC 1986) (Figure 4.7).

Table 4.7: Annual water balance components (mm/yr) with regard to land use scenarios

Water balance components	**Baseline**	**Scenario 1 (2003)**	**Scenario 2 (2020)**	**Scenario 3 (2040)**
Total water yield	422.1	422.3	424.3	421.2
Base flow	375.2	371.03	363.1	352.1
Surface runoff	12.53	17.3	27.56	36.3
Lateral flow	12.63	12.49	12.54	12.29
Deep aquifer recharge	44.09	43.8	43	42.8
Actual evapotranspiration	531.78	531.8	530.6	533.9

Similarly, actual evapotranspiration and total water yield is observed to increase for both land use scenarios and these changes will have impacts on the micro-catchment ecosystem services and functioning.

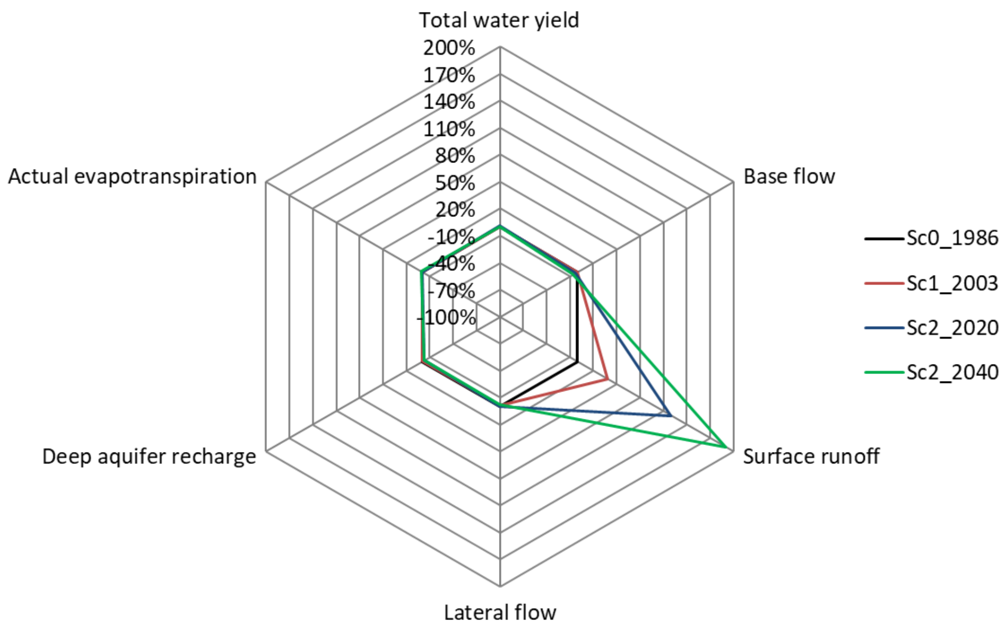

Figure 4:8: Change in annual water balance components due to land use/cover change in the micro-catchment

Figure 4.9 shows the spatial changes in the annual evapotranspiration (ET), surface runoff and total water yield within the micro-catchment due to the effect of land use scenarios. Between LULC 1986 and LULC 2003, a decrease (-1.9%) in ET occurred in the most parts of the micro-catchment with an increase in ET observed in the lower micro-catchment with the highest increase of 2.5% from the reference land use/cover situation of the year 1986. For the land use/cover scenario of 2020, a decrease in ET occurred in most parts of the micro-catchment, however, unlike to the land use/cover scenario of the year 2003, ET increased in the upper micro-catchment. According to the projected land use/cover scenario of the year 2040, annual ET will have a mixed change spatially in the micro-catchment with the large part of the micro-catchment experiencing a decrease in annual ET (Figure 4.9). Surface runoff spatially increased across the micro-catchment for all the land use/cover scenarios. The highest increase was experienced in the middle part of the micro-catchment between the period of 1986-2003 and the increase in surface runoff spatially expanded to the upper micro-catchment between the periods of 1986-2020, indicating an increase in micro-catchment degradation in the upper micro-catchment (Figure 4.9). According to the projected land use/cover for the year 2040, surface runoff is projected to increase up to 100% although slightly lower compared to the land use scenarios of the year 2020 and 2003 (Figure 4.10).

Total water yield increased (up to 3.5%) in most of the sub-basins of the micro-catchment due to land use/cover scenarios for the years of 2003 and 2020 from the reference land use scenario of the year 1986 (Figure 4.10), indicating availability of water for production in the micro-catchment. However, the decrease in total water yield also occurred in the two scenarios although it was observed that under land use scenario for the year 2020, decrease in total water yield spatially increased in the micro-catchment compared to the one of the years 2003. Further, the effect of the projected land use/cover situation in the micro-catchment indicates that the micro-catchment experiences a decrease in the total water yield (up to 8.6%) in most parts of the micro-catchment although some parts experience an increase in total water yield (Figure 4.9). Therefore, there was a projected mixed change in total water yield across the catchment by the year 2040 due to the effect of land use/cover.

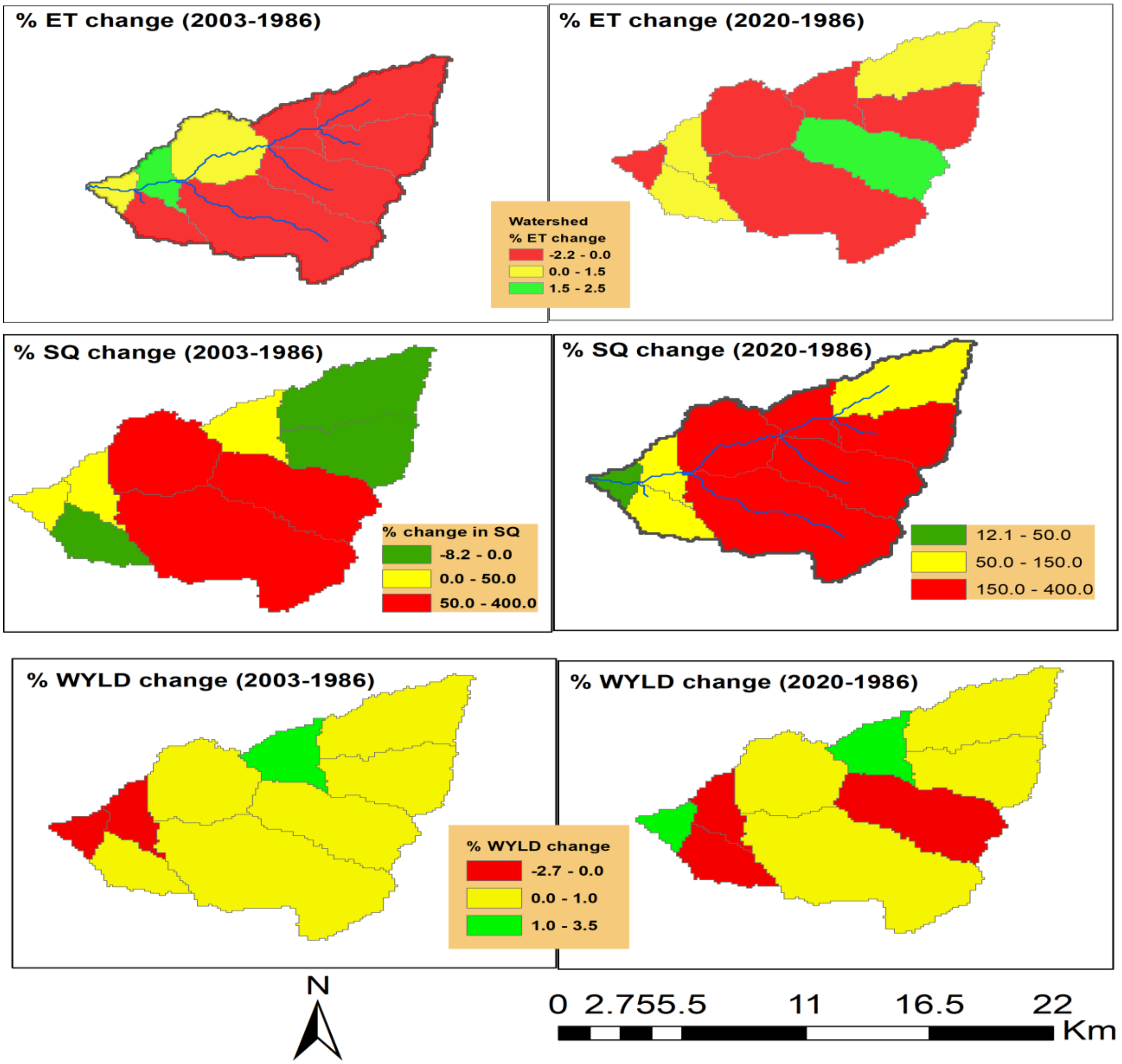

Figure 4:9: Annual change in water balance components with respective to land use scenarios from the baseline land use of 1986. ET refers to Actual evapotranspiration; SQ is surface runoff; and WYLD is Total water yield

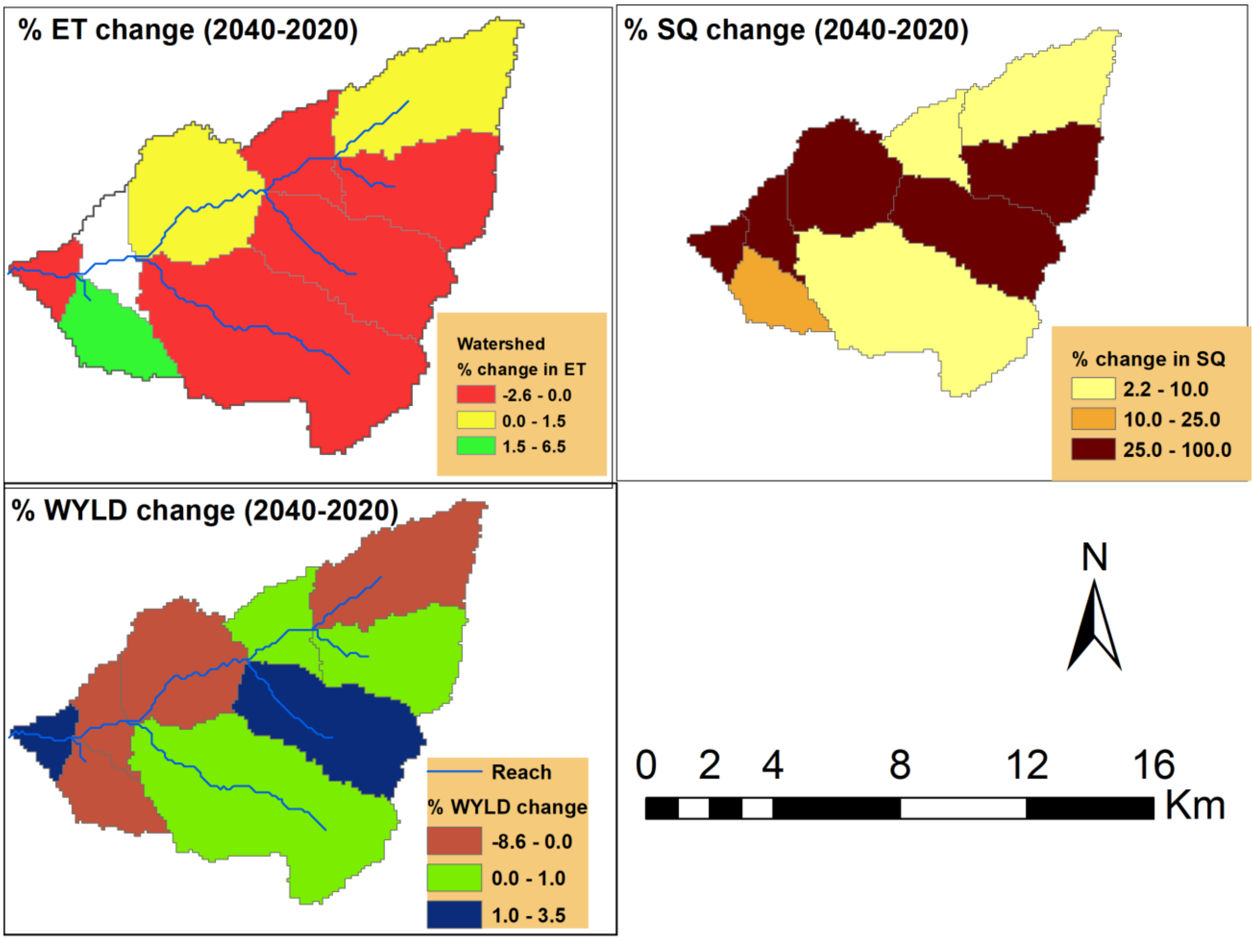

Figure 4:10: Annual water balance components change with respect to projected land use/cover scenario from the baseline land use of 2020. ET refers to Actual evapotranspiration; SQ is surface runoff; and WYLD is Total water yield.

Figure 4.11 depicts the intra-annual variability in the selected annual water balance components (surface runoff, base flow; GW_Q and evapotranspiration; ET) under the different land use scenarios in comparison with the reference land use scenario of the year 1986. Accordingly, Figure 4.11a, shows that in the land use scenario for the year 2002, an increase in ET occurred in the rainy season (April; May, September, October and November) and the month of December while for the land use scenario for the year 2020, monthly ET increased across all the seasons in the year. Therefore, monthly ET was seasonally affected by the changes in land use/cover within the micro-catchment. Figure 4.11b shows that surface runoff increased across all the seasons (rainy and dry seasons) with the highest increase in the month of March for both land use scenarios. Surprising is that during the well-known documented dry season (JJA) in Uganda, there was relatively high surface runoff which could be attributed to the recent shifts in seasonal precipitation due to the effect of climate change across the country. Figure 4.11c shows that base flow/groundwater flow increased throughout the months between the land use scenario of 2020 and reference land use of 1986, with the highest in the months of July and August. While between the land use scenarios for the year 2003 and reference 1986, base flow decreased throughout the months. Figure 4.11 b shows that the total water yield increased throughout of the year with the highest in the months of March and July using a land use scenario 2020 and the reference of 1986 regardless of the season.

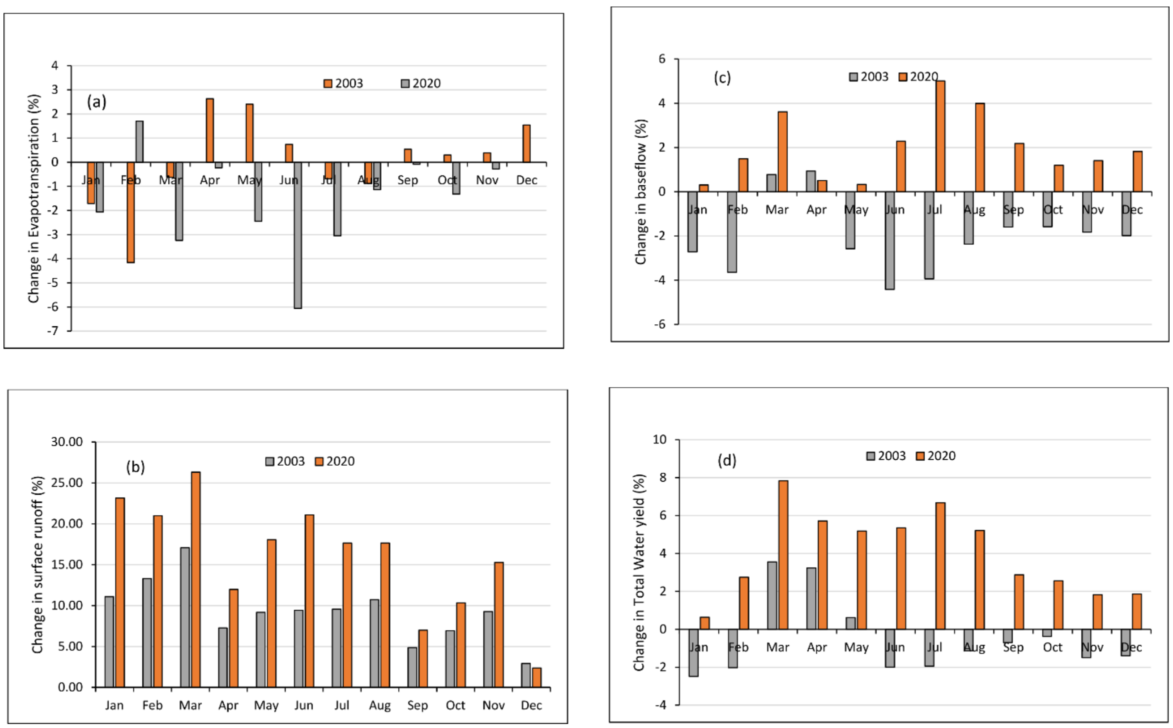

Figure 4:11: Change in monthly water balance components for land use/cover change scenarios compared to the reference scenario of the year 1986.

Figure 4.12 indicates the change in monthly water balance parameters between projected land use/cover scenarios for the year 2040 to the reference land use/cover scenario of 2020 for the micro-catchment. In the future, surface runoff is projected to increase throughout all the seasons/months. Evapotranspiration will generally decrease except for the rainy periods of April and May. Base flow (GW-Q) is also projected to decrease except in the rainy months of March and April which indicate an increase in base flow. In general, total water yield increases except in the month of January.

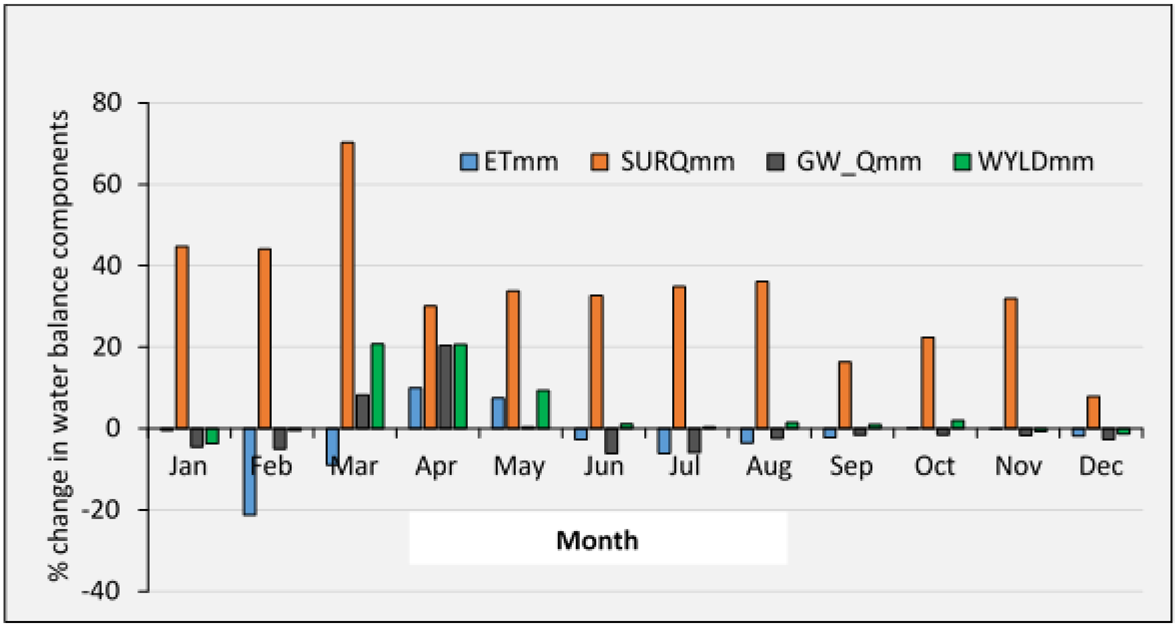

Figure 4:12: Monthly changes in water balance components between projected land use/cover scenario for the year 2040 to the reference land use/cover scenario of 2020 for the micro-catchment .Where: ET is Evapotranspiration, SURQ is Surface run off , GW_Q Ground water runoff and WYLD is Total water yield, all in in millimeters(mm)

The effects of major land use/cover types on the water balance components was carried out by fitting the percentage of LULC classes (small scale farming and grassland) to the corresponding simulated annual surface runoff, base flow and actual evapotranspiration through a linear regression shows the different trends on the effect of these LULC classes on these water balance parameters. Figure 4.13a indicates that surface runoff is positively correlated to the area of small-scale farming (R^2 =0.97) while base flow also positively correlated to the area of grasslands (R^2 =0.99; Figure 4.13e), indicating that changes in surface runoff and base flow can be directly attributed to the changes of small-scale farming and grassland areas, respectively. Figure 4.13d shows that surface runoff and percentage of grassland areas are negatively correlated and Figure 4.13b indicates that base flow and percentage of small-scale farming areas are negatively correlated. Therefore, increase in surface runoff can be explained by the interplay between grassland depletion and cropland expansion.

The trend in the mean annual ET shows a parabolic relationship with the percentage of small-scale farming and grassland areas. Figure 4.13c shows a parabolic increase in ET with an increase in small scale farming areas while a parabolic decrease in ET is observed with an increase in grassland areas.

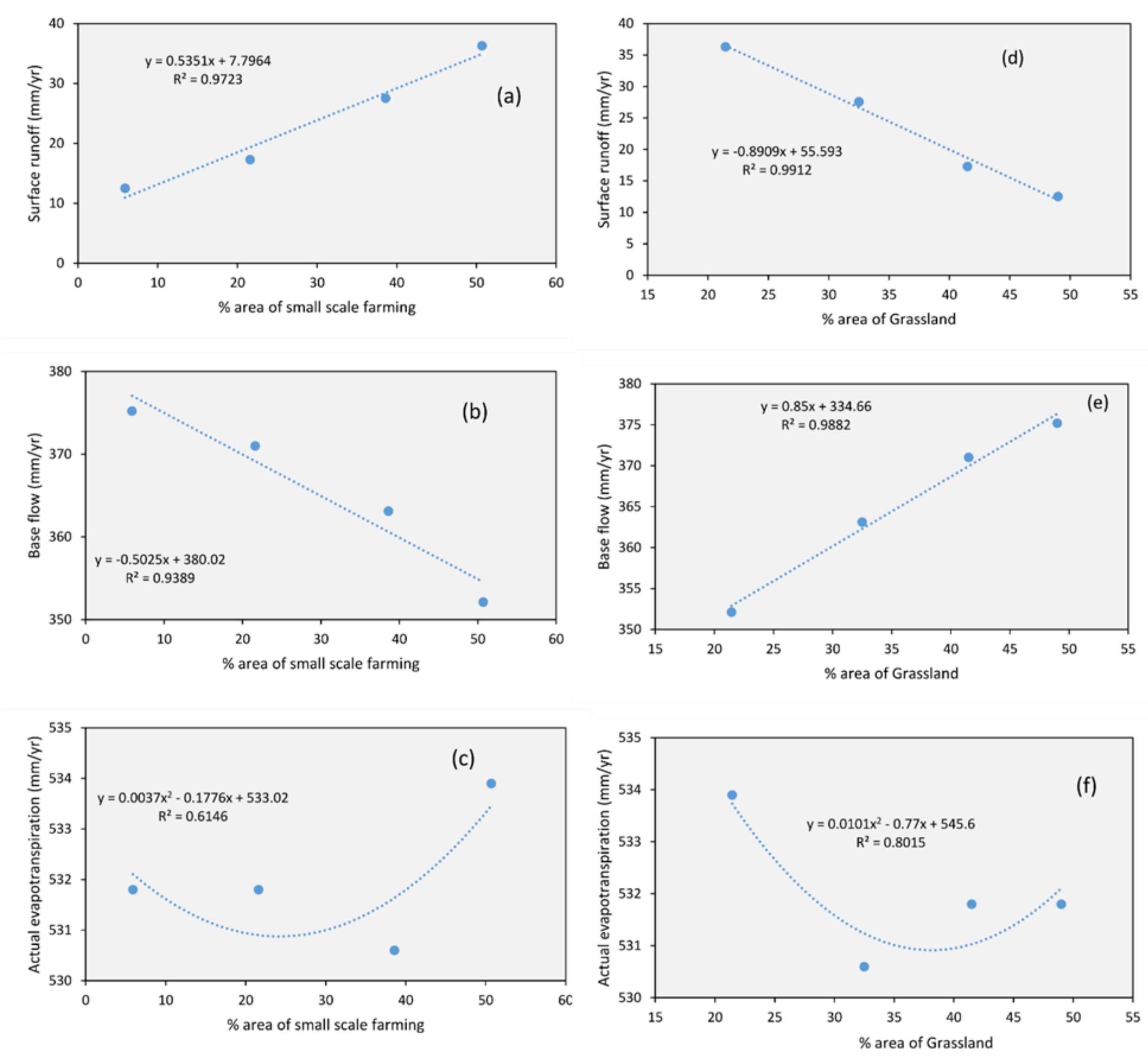

Figure 4:13: Change in surface runoff, base flow, and actual evapotranspiration explained by the percentage of small scale farming and grassland in the catchment

CHAPTER FIVE: DISCUSSION

5.1 Spatial-temporal changes in land use/cover in Ogwapoke micro catchment

The main land use/cover changes in the micro catchment for the period of 1986 and 2020 were conversions from grasslands, woodlands, wetlands and bushlands to small scale farming and settlements/built up areas in the micro catchment. Some portion of grassland area, woodland area, wetlands and bushlands area in the micro-catchment were converted into small scale farming and built-up by the year 2020. The same results obtained in the field survey also showed the same pattern human activities like bush burning and over grazing were key drivers of land use/cover changes. This was attributed to the increase in the demand for food, settlements and other natural resources such as firewood due to the increase in population in the catchment. In fact, according to UBOS (2016), the population growth rate in the country is 3.3% and Northern Uganda accounts for 22% of the total population.

Therefore, the growth in population density in the region has increasingly led to the exploitation of the natural resources in most of the catchments including Ogwapoke catchment (Kilama Luwa et al., 2020). Over the period of 34 years (1986-2020), grasslands, bushlands, woodlands and wetlands have been undergoing clearance to small scale farming, settlements and charcoal burning for livelihoods according to the stakeholders interviewed in the catchment. Therefore, LULC changes and the variations in magnitude captured during the study period, confirms that there has been land use and land cover changes in the sub catchment, with the land cover types being converted into small scaling farming and settlements as land use types. These changes affect the catchments stream flow regimes and other ecosystem services and functioning of the catchment. Land use and land cover changes to small scale farming and settlements without any carefully thought of conservation interventions results into increased water stress for the crops in the uplands, flood risks and soil erosion and thus, increased catchment degradation.

The decrease in land cover types (woodlands, grasslands, woodlands and bushlands) which have occurred in the catchment over the period of 1986 to 2020 have also been reported by Nyeko (2012) and Mwanjalolo et al (2018) as an ongoing trend in the Aswa catchment where Ogwapoke micro catchment is part of its sub catchment. The authors reported that deforestation of woodlands and grasslands for firewood and construction materials including small scale farming is occurring. The change in LULC is also in line with the findings of Egeru & Majaliwa (2009) who reported non-uniform LULC changes in northern Uganda specifically Karamoja sub region due to the increasing population and poverty rates (UBOS, 2019). In addition, Kiggundu et al (2018) reports a twofold increase in built up area in the Murchison Bay watershed of Lake Victoria Basin due to population increase. LULC changes into small scale farming and settlements are the driving forces in the sub Saharan African catchments (Chavula et al., 2011; Gashaw et al., 2018). If the situation remains as it is in terms of land use/cover change, the projection for land use/cover change from 2020 to 2040 from this study indicates that small scale farming and built-up areas has increased at the expense of land cover types. This is likely to increase micro-catchment degradation in terms of water resources and soil loss if no interventions for catchment management are put in place.

5.2 Effect of land use/cover change on soil erosion in Ogwapoke micro catchment

The rate of soil erosion in the micro catchment is still low although the highest rate of erosion is not surprising that it is observed in small scale farming. The high rate of erosion in small scale farming is due to the decrease in the vegetative cover due to loss of grasslands and woodlands. The loss of vegetative cover escalates the increase in the hortanian surface runoff which is directly related to soil erosion. An increase in soil erosion in the low vegetation cover such as farming and built-up areas is induced by the low tree cover, as a result, interception losses increase resulting in a higher net precipitation that reaches the surface and thus, higher soil erosion. Similar findings in the middle and upper reaches of the Heihe River Basin in north western China have been confirmed by Li et al (2015), who related an increase in soil erosion to the loss of vegetation cover while assessing the influence of changes in land use on the water resources. Further, Nugroho et al (2013) reported an increase in soil erosion due to reduced forest vegetation land cover which reduced soil infiltration and interception of through fall. In addition, Azanga et al (2016) attributed the increase in sediments and runoff in the Lake Tanganyika basin to the increase in cultivated land and built-up areas.

Furthermore, although soil and water conservation practices are being implemented in the catchment (MWE, 2020b), the increasing rate of anthropogenic activities such as bush clearing, deforestation, and agriculture among others versus the protection in the sub catchment attribute to the increased soil erosion along slopes and the croplands. The study findings concur with results from Hayicho et al (2019) in the Melka Wakena Catchment of Sub-Upper Wabe-Shebelle Watershed in south Eastern Ethiopia and Mbungu (2016) in the Upper Ruvu Watershed of Tanzania who found high soil erosion along hilly parts of the watershed and farmlands. The increased soil eroding in the catchment farmlands and slopes including the bare lands will affect the sub catchment health and stream flow through sedimentation thus, increasing risks of stream overflow causing flooding in the lower catchment. Therefore, the increased change in land use/cover will result into water shortage, flood risk and severe soil erosion and thus, leading to decline in the ecosystem services and functioning in the watershed.

5.3 Impact of land use/cover change on the hydrological flow in Ogwapoke micro catchment

Increases in specific water balance parameters (water yield and surface runoff) simulated under all the land use scenarios is due to the highly increasing changes in land covers to small-scale farming and built-up areas. The increase in water yield and surface runoff comes with benefits and challenges in the catchment. The benefits include increased water availability and challenges include flood risks which hinder the water quality and other ecosystem services and functioning of the catchment. The decrease in evapotranspiration is due to the decline in the vegetation coverage. The projected increase in surface runoff and water yield for both the rainy and dry seasons by the year 2040 from the reference year of 2020 is attributed to the highly projected decrease in grasslands, woodlands, bushlands and wetlands with an increase in small scale farming and built-up areas. These land use type cause an increase in surface runoff into the river network.

The increase in surface runoff following the conversion of land cover types to small scale farming is generally ascribed to the increase in the Hortanian surface runoff, where the canopy cover is reduced and infiltration rate of water into the soil is also reduced. This is in line with Sullivan et al (2019) who observed an increase in surface runoff and water yield after removing woodland riparian vegetation in the Kings Creek watershed on Konza Prairie in northeastern Kansas, USA. Giertz et al (2006) discovered that increasing the share of agricultural land increases surface runoff. They discovered that infiltration rates in grasslands were much higher than in croplands, and that a catchment dominated by cornfield yielded significantly higher surface runoff than a catchment dominated by grassland. Donohue et al (2007) demonstrated the important explanatory function of vegetation in catchment hydrology. They showed how dynamics of LAI and rooting depth of vegetation affect vegetation water use and therefore water flow and for catchments experiencing net vegetation change.

The reduction of the interception capacity also explains the increase in interflow and base flow as through fall increases. Several studies for example (Yira et al., 2016; Siswanto & Francés, 2019) confirm this claim, attributing the increase in catchment water production and surface runoff caused by agricultural land expansion to a decrease in LAI, root depth, vegetation height, and stomata conductance. As a consequence, less water is evaporated by interception, through fall increases and more water can infiltrate into the soil or flow as infiltration excess runoff. Therefore, for this study, the observed increase in surface runoff and a reduction in Evapotranspiration for all the agricultural seasons would in the long-time lead to catchment degradation and thus, adversely affect the biodiversity functions and other services such as flood control, especially in wetlands of the micro-catchment. If poor management practices continue in the catchment coupled with increase in population and climate change, the micro catchment is most likely to lose its integrity in the near future.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The study aimed to identify conservation measures and drivers that lead to continuous changes in land use/cover so as to combat the long-term effects of soil erosion on hydrological flow in Ogwapoke micro catchment. To achieve this, the study utilized questionnaires, Landsat satellite images, the Revised Universal Soil Loss Equation (RUSLE) and the Soil and Water Assessment Tool (SWAT) models.

The findings showed that several land use/cover changes have happened in Ogwapoke micro catchment between 1986 and 2020. The most significant changes were observed in small-scale farmlands, woodlands and bushlands. This change is further predicted to become more intense in the next 20 years. These changes in land use/cover are mostly driven by animal grazing, bush burning and deforestation.

The changes in land use/cover have had an impact on soil erosion in the micro catchment. Most of the very high soil erosion was experienced by small-scale farmlands. Still, land use/cover changes had a significant effect on hydrological response in Ogwapoke micro catchment. Between 1986 and 2020, surface runoff and total water yield increased whereas base flow, lateral flow, deep aquifer recharge and actual evapotranspiration decreased. The future land use/cover changes are expected to have mixed implications on the hydrological components of Ogwapoke micro catchment.

6.2 Recommendations

Due to increased changes in land use/cover, the government should encourage planting of trees in the micro catchment and encourage climate smart practices such as agroforestry, sustainable land management etc.

To control the rate of soil erosion, the study recommends sensitization of locals on land degradation and encourage proper farming methods and/ or conservation agricultural practices (such as vegetation cover restoration, the creation of slope terraces, and mulch-based cropping systems) and sustainable harvesting of trees, reforestation and afforestation.

For hydrological flow, there is a need for the decision makers to establish a hydro-meteorological network in the micro-catchment for future research and sensitize the local communities about land degradation.

Above all, the study suggests that the government should dialogue with communities to come up with community-based micro catchment management plans to sustainably manage and conserve this area.

Further research in line with this study should focus on the effect of land use/cover changes on water availability to communities, sediment yield, and soil properties (like soil moisture, soil organic carbon and soil pH etc.).

REFERENCES

Abbaspour, K. (2015). SWAT-CUP: SWAT Calibration and Uncertainty Programs - A User Manual. *Neprashtechnology.Ca*. https://doi.org/10.1007/s00402-009-1032-4

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E., & Rasmussen, J. (1986). An introduction to the European Hydrological System-Systeme Hydrologique Europeen, "SHE", 1: History and philosophy of a physically-based, distributed modelling system. *Journal of Hydrology, 87,* 45–59.

Aithal, B. H., Vinay, S., & Ramachandra, T. V. (2014). Landscape dynamics modeling through integrated Markov, Fuzzy-AHP and cellular automata. *International Geoscience and Remote Sensing Symposium (IGARSS)*. https://doi.org/10.1109/IGARSS.2014.6947148

Albright, T. P., Moorhouse, T. G., & McNabb, T. J. (2004). The rise and fall of water hyacinth in Lake Victoria and the Kagera River basin, 1989-2001. *Journal of Aquatic Plant Management*, *42*(JUL.), 73–84.

Alewell, C., Borrelli, P., Meusburger, K., & Panagos, P. (2019). Using the USLE: Chances, challenges and limitations of soil erosion modelling. In *International Soil and Water Conservation Research*. https://doi.org/10.1016/j.iswcr.2019.05.004

Amini Parsa, V., Yavari, A., & Nejadi, A. (2016). Spatio-temporal analysis of land use/land cover pattern changes in Arasbaran Biosphere Reserve: Iran. *Modeling Earth Systems and Environment*. https://doi.org/10.1007/s40808-016-0227-2

Anache, J. A. A., Bacchi, C. G. V., Panachuki, E., & Alves Sobrinho, T. (2015). Assessment of methods for predicting soil erodibility in soil loss modeling. *Geociencias*, *34*(1).

Arbuckle, J. (2012). IBM SPSS Amos 21 user's guide. *Crawfordville, FL: Amos Development …*. http://www.research.swinburne.edu.au/research-students/documents/IBM_amos_Users_guide.pdf

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., & Neitsch, S. L. (2013). Soil & Water Assessment Tool: Input/output documentation. version 2012. *Texas Water Resources Institute, TR-439,* 650.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Griensven, a. Van, VanLiew, M. W., Kannan, N., & Jha, M. K. (2012). Swat: Model Use, Calibration, and Validation. *Asabe*, *55*(4), 1491–1508.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). Large area hydrologic modeling and assessment part 1: Model development. *Journal of the American Water Resources Association*, *34*(1), 73–89.

Ayyanna, Polisgowdar, B. S., Ayyanagowdar, M. S., T. Dandekar, A., Yadahalli, G. S., & Bellakki, M. A. (2018). Accuracy Assessment of Supervised and Unsupervised Classification using Landsat-8 Imagery of D-7 Shahapur Branch Canal of UKP Command Area Karnataka, India. *International Journal of Current Microbiology and Applied Sciences*, *7*(07), 205–216. https://doi.org/10.20546/ijcmas.2018.707.025

Azanga, E., Majaliwa, M., Kansiime, F., Mushagalusa, N., Karume, K., & Tenywa, M. (2016). Land-use and land cover, sediment and nutrient hotspot areas changes in Lake Tanganyika Basin. *African Journal of Rural Development*, *1*(1978-2017–2066), 75–90.

Barasa, B., Kakembo, V., Mwololo Waema, T., & Laban, M. (2017). Effects of Heterogeneous Land Use/Cover Types on River Channel Morphology in the Solo River Catchment, Eastern Uganda. In *Geocarto International*. https://doi.org/10.1080/10106049.2015.1132480

Bastiaanssen, W. G. M., Allen, R. G., Droogers, P., D'Urso, G., & Steduto, P. (2007). Twenty-five years modeling irrigated and drained soils: State of the art. *Agricultural Water Management*, *92*(3), 111–125. https://doi.org/https://doi.org/10.1016/j.agwat.2007.05.013

Behera, M. D., Borate, S. N., Panda, S. N., Behera, P. R., & Roy, P. S. (2012). Modelling and analyzing the watershed dynamics using Cellular Automata (CA)-Markov model - A geo-information based approach. *Journal of Earth System Science*. https://doi.org/10.1007/s12040-012-0207-5

Benavidez, R., Jackson, B., Maxwell, D., & Norton, K. (2018). A review of the (Revised) Universal Soil Loss Equation ((R)USLE): With a view to increasing its global applicability and improving soil loss estimates. *Hydrology and Earth System Sciences*. https://doi.org/10.5194/hess-22-6059-2018

Bergström, S. (1976). *Development and application of a conceptual runoff model for Scandinavian catchments*. *7*, 1–162.

Biswas, S. S., & Pani, P. (2015). Estimation of soil erosion using RUSLE and GIS techniques: a case study of Barakar River basin, Jharkhand, India. *Modeling Earth Systems and Environment*, *1*(4), 1–13. https://doi.org/10.1007/s40808-015-0040-3

Boers, P. C. M. (1996). Nutrient emissions from agriculture in the Netherlands, causes and remedies. *Water Science and Technology*. https://doi.org/10.1016/0273-1223(96)00229-6

Bogale, A. (2020). Review, impact of land use/cover change on soil erosion in the Lake Tana Basin, Upper Blue Nile, Ethiopia. *Applied Water Science*, *10*(12), 1–6. https://doi.org/10.1007/s13201-020-01325-w

Bonilla, C. A., & Johnson, O. I. (2012). Soil erodibility mapping and its correlation with soil properties in Central Chile. *Geoderma*, *189*, 116–123. https://doi.org/https://doi.org/10.1016/j.geoderma.2012.05.005

Borrelli, P., Paustian, K., Panagos, P., Jones, A., Schütt, B., & Lugato, E. (2016). Effect of Good Agricultural and Environmental Conditions on erosion and soil organic carbon balance: A national case study. *Land Use Policy*, *50*, 408–421. https://doi.org/10.1016/j.landusepol.2015.09.033

Borrelli, P., Robinson, D. A., Fleischer, L. R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K. Van, Montanarella, L., & Panagos, P. (2017). An assessment of the global impact of 21st century land use change on soil erosion. *Nature Communications*. https://doi.org/10.1038/s41467-017-02142-7

Brandolini, P., Pepe, G., Capolongo, D., Cappadonia, C., Cevasco, A., Conoscenti, C., Marsico, A., Vergari, F., & Del Monte, M. (2018). Hillslope degradation in representative Italian areas: Just soil erosion risk or opportunity for development? *Land Degradation and Development*. https://doi.org/10.1002/ldr.2999

Breuer, L., Huisman, J. A., Willems, P., Bormann, H., Bronstert, A., Croke, B. F. W., Frede, H. G., Gräff, T., Hubrechts, L., Jakeman, A. J., Kite, G., Lanini, J., Leavesley, G., Lettenmaier, D. P., Lindström, G., Seibert, J., Sivapalan, M., & Viney, N. R. (2009). Assessing the impact of land use change on hydrology by ensemble modeling (LUCHEM). I: Model intercomparison with current land use. *Advances in Water Resources*. https://doi.org/10.1016/j.advwatres.2008.10.003

Bunyangha, J., Majaliwa, M. J. G., Muthumbi, A. W., Gichuki, N. N., & Egeru, A. (2021). Past and future land use/land cover changes from multi-temporal Landsat imagery in Mpologoma catchment, eastern Uganda. *Egyptian Journal of Remote Sensing and Space Science*. https://doi.org/10.1016/j.ejrs.2021.02.003

Caprioli, M., & Tarantino, E. (2003). A hybrid land cover classification of Landsat 7 etm+ data for an efficient vegetation mapping. *Local Resources and Global Trades: Environments and Agriculture in the Mediterranean Region*, *460*.

Cassol, E. A., da Silva, T. S., Eltz, F. L. F., & Levien, R. (2018). Soil erodibility under natural rainfall conditions as the K factor of the universal soil loss equation and application of the nomograph for a subtropical Ultisol. *Revista Brasileira de Ciencia Do Solo*. https://doi.org/10.1590/18069657rbcs20170262

Chandramohan, T., Venkatesh, B., & Balchand, A. N. (2015). Evaluation of Three Soil Erosion Models for Small Watersheds. *Aquatic Procedia*. https://doi.org/10.1016/j.aqpro.2015.02.156

Chavula, G., Brezonik, P., & Bauer, M. (2011). *Land Use and Land Cover Change (LULC) in the Lake Malawi Drainage Basin , 1982-2005*. *2011*(May), 172–178. https://doi.org/10.4236/ijg.2011.22018

Chen, K., Zhang, D., Yao, L., Guo, B., Yu, Z., & Liu, Y. (2021). Deep Learning for Sensor-Based Human Activity Recognition: Overview, Challenges, and Opportunities. *ACM Computing Surveys (CSUR)*, *54*(4), 1–40. https://doi.org/10.1145/3447744

Coe, M. T., Costa, M. H., & Soares-Filho, B. S. (2009). The influence of historical and potential future deforestation on the stream flow of the Amazon River - Land surface processes and atmospheric feedbacks. *Journal of Hydrology*. https://doi.org/10.1016/j.jhydrol.2009.02.043

Comber, A. J. (2013). Geographically weighted methods for estimating local surfaces of overall, user and producer accuracies. *Remote Sensing Letters*, *4*(4). https://doi.org/10.1080/2150704X.2012.736694

CORDAID, & MWE. (2017). *Catchment management plan: Lokok catchment support to Integrated Water Resources Management in Karamoja for Increased Community Resilience Programme*. *March*, 1–217.

Costa, M. H., Botta, A., & Cardille, J. A. (2003). Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia. *Journal of Hydrology*. https://doi.org/10.1016/S0022-1694(03)00267-1

de Koff, J. P., Moore, P. A., Formica, S. J., Van Eps, M., & DeLaune, P. B. (2011). Effects of Pasture Renovation on Hydrology, Nutrient Runoff, and Forage Yield. *Journal of Environmental Quality*. https://doi.org/10.2134/jeq2010.0158er

De Mello, C. R., Norton, L. D., Pinto, L. C., Beskow, S., & Curi, N. (2016). Agricultural watershed modeling: A review for hydrology and soil erosion processes. In *Ciencia e Agrotecnologia*. https://doi.org/10.1590/S1413-70542016000100001

Defersha, M. B., Melesse, A. M., & McClain, M. E. (2012). Watershed scale application of WEPP and EROSION 3D models for assessment of potential sediment source areas and runoff flux in the Mara River Basin, Kenya. *Catena*. https://doi.org/10.1016/j.catena.2012.03.004

Devia, G. K., Ganasri, B. P., & Dwarakish, G. S. (2015). A Review on Hydrological Models. *Aquatic Procedia*, *4*(Icwrcoe), 1001–1007. https://doi.org/10.1016/j.aqpro.2015.02.126

Dezhkam, S., Jabbarian Amiri, B., Darvishsefat, A. A., & Sakieh, Y. (2017). Performance evaluation of land change simulation models using landscape metrics. *Geocarto International*. https://doi.org/10.1080/10106049.2016.1167967

Donohue, R. J., Roderick, M. L., & McVicar, T. R. (2007). On the importance of including vegetation dynamics in Budyko's hydrological model. *Hydrology and Earth System Sciences*, *11*(2), 983–995. https://doi.org/10.5194/hess-11-983-2007

Egeru, A., & Majaliwa, M. (2009). Landuse / Cover Change Trend in Soroti District Eastern Uganda. *Journal of Applied Sciences and Environmental Management*, *13*(4), 77–79.

Ehlman, S. M., Martinez, D., & Sih, A. (2018). Male guppies compensate for lost time when mating in turbid water. *Behavioral Ecology and Sociobiology*, *72*(3), 46. https://doi.org/10.1007/s00265-018-2468-8

El Kateb, H., Zhang, H., Zhang, P., & Mosandl, R. (2013). Soil erosion and surface runoff on different vegetation covers and slope gradients: A field experiment in Southern Shaanxi Province, China. *Catena*. https://doi.org/10.1016/j.catena.2012.12.012

Favis-Mortlock, D., & Boardman, J. (1995). Nonlinear responses of soil erosion to climate change: a modelling study on the UK South Downs. *Catena*. https://doi.org/10.1016/0341-8162(95)00018-N

Fenta, A. A., Tsunekawa, A., Haregeweyn, N., Poesen, J., Tsubo, M., Borrelli, P., Panagos, P., Vanmaercke, M., Broeckx, J., Yasuda, H., Kawai, T., & Kurosaki, Y. (2020). Land susceptibility to water and wind erosion risks in the East Africa region. *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2019.135016

Foody, G. M. (2002). Status of land cover classification accuracy assessment. In *Remote Sensing of Environment*. https://doi.org/10.1016/S0034-4257(01)00295-4

Gabiri, G., Diekkrüger, B., Näschen, K., Leemhuis, C., van der Linden, R., Mwanjalolo Majaliwa, J. G., & Obando, J. A. (2020). Impact of climate and land use/land cover change on thewater resources of a tropical inland valley catchment in Uganda, East Africa. *Climate*. https://doi.org/10.3390/CLI8070083

Ganasri, B. P., & Ramesh, H. (2016). Assessment of soil erosion by RUSLE model using remote sensing and GIS - A case study of Nethravathi Basin. *Geoscience Frontiers*. https://doi.org/10.1016/j.gsf.2015.10.007

Garcia-Estringana, P., Alonso-Blázquez, N., Marques, M. J., Bienes, R., González-Andrés, F., & Alegre, J. (2013). Use of Mediterranean legume shrubs to control soil erosion and runoff in central Spain. A large-plot assessment under natural rainfall conducted during the stages of shrub establishment and subsequent colonisation. *Catena*. https://doi.org/10.1016/j.catena.2011.09.003

Garg, V., Nikam, B. R., Thakur, P. K., Aggarwal, S. P., Gupta, P. K., & Srivastav, S. K. (2019). Human-induced land use land cover change and its impact on hydrology. *HydroResearch*. https://doi.org/10.1016/j.hydres.2019.06.001

Gashaw, T., Tulu, T., Argaw, M., & Worqlul, A. W. (2018). Science of the Total Environment Modeling the hydrological impacts of land use / land cover changes in the Andassa watershed , Blue Nile Basin , Ethiopia. *Science of the Total Environment*, *619–620*, 1394–1408. https://doi.org/10.1016/j.scitotenv.2017.11.191

Geissen, V., Sánchez-Hernández, R., Kampichler, C., Ramos-Reyes, R., Sepulveda-Lozada, A., Ochoa-Goana, S., de Jong, B. H. J., Huerta-Lwanga, E., & Hernández-Daumas, S. (2009). Effects of land-use change on some properties of tropical soils - An example from Southeast Mexico. *Geoderma*. https://doi.org/10.1016/j.geoderma.2009.03.011

Geist, H. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and the Resources*.

Gemitzi, A. (2021). Predicting land cover changes using a CA Markov model under different shared socioeconomic pathways in Greece. *GIScience and Remote Sensing*. https://doi.org/10.1080/15481603.2021.1885235

Getahun, S., & Van, L. H. (2015). Assessing the Impacts of Land Use-Cover Change on Hydrology of Melka Kuntrie Subbasin in Ethiopia, Using a Conceptual Hydrological Model. *Hydrology: Current Research*, *6*(3), 1. https://doi.org/10.4172/2157-7587.1000210

Getu Engida, T., Nigussie, T. A., Aneseyee, A. B., & Barnabas, J. (2021). Land Use/Land Cover Change Impact on Hydrological Process in the Upper Baro Basin, Ethiopia. *Applied and*

Environmental Soil Science. https://doi.org/10.1155/2021/6617541

Ghosal, K., & Das Bhattacharya, S. (2020). A Review of RUSLE Model. *Journal of the Indian Society of Remote Sensing*, *48*(4), 689–707. https://doi.org/10.1007/s12524-019-01097-0

Giertz, S., Diekkrüger, B., & Steup, G. (2006). Physically-based modelling of hydrological processes in a tropical headwater catchment (West Africa) – process representation and multi-criteria validation. *Hydrology and Earth System Sciences*, *10*(6), 829–847. https://doi.org/10.5194/hess-10-829-2006

Girma, R., Fürst, C., & Moges, A. (2022). Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift. *Environmental Challenges*, *6*(December), 100419. https://doi.org/10.1016/j.envc.2021.100419

Godar, J., Gardner, T. A., Jorge Tizado, E., & Pacheco, P. (2014). Actor-specific contributions to the deforestation slowdown in the Brazilian Amazon. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.1322825111

Grimm, P. (2010). Pretesting a Questionnaire. In *Wiley International Encyclopedia of Marketing*. https://doi.org/https://doi.org/10.1002/9781444316568.wiem02051

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering*, *4*(2), 135–143. https://doi.org/10.1061/(ASCE)1084-0699(1999)4

Guzha, A. C., Rufino, M. C., Okoth, S., Jacobs, S., & Nóbrega, R. L. B. (2018). Impacts of land use and land cover change on surface runoff, discharge and low flows: Evidence from East Africa. In *Journal of Hydrology: Regional Studies*. https://doi.org/10.1016/j.ejrh.2017.11.005

Hamad, R., Balzter, H., & Kolo, K. (2018). Predicting land use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability (Switzerland)*. https://doi.org/10.3390/su10103421

Hasan, S., Shi, W., & Zhu, X. (2020). Impact of land use land cover changes on ecosystem service value - A case study of Guangdong, Hong Kong, and Macao in South China. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0231259

Hayicho, H., Alemu, M., & Kedir, H. (2019). *Assessment of Land-Use and Land Cover Change Effect on Melka Wakena Hydropower Dam in Melka Wakena Catchment of Sub-Upper*

Wabe-Shebelle Watershed , South Eastern. 819–840. https://doi.org/10.4236/as.2019.106063

He, M., & Hogue, T. S. (2012). Integrating hydrologic modeling and land use projections for evaluation of hydrologic response and regional water supply impacts in semi-arid environments. *Environmental Earth Sciences*. https://doi.org/10.1007/s12665-011-1144-3

Holz, D. J., Williard, K. W. J., Edwards, P. J., & Schoonover, J. E. (2015). Soil Erosion in Humid Regions: A Review. *Journal of Contemporary Water Research & Education*. https://doi.org/10.1111/j.1936-704x.2015.03187.x

Hyandye, C., & Martz, L. W. (2017). A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431161.2016.1259675

Jordan, G., Van Rompaey, A., Szilassi, P., Csillag, G., Mannaerts, C., & Woldai, T. (2005). Historical land use changes and their impact on sediment fluxes in the Balaton basin (Hungary). *Agriculture, Ecosystems and Environment*. https://doi.org/10.1016/j.agee.2005.01.013

Julien, P. (1995). Erosion and Sedimentation. *Environmental & Engineering Geoscience*, *1*(4), 532–533.

Kang, J., Fang, L., Li, S., & Wang, X. (2019). Parallel cellular automata markov model for land use change prediction over MapReduce framework. *ISPRS International Journal of Geo-Information*, *8*(10). https://doi.org/10.3390/ijgi8100454

Kansiime, F., Saunders, M. J., & Loiselle, S. A. (2007). Functioning and dynamics of wetland vegetation of Lake Victoria: an overview. *Wetlands Ecology and Management*, *15*(6), 443–451. https://doi.org/10.1007/s11273-007-9043-9

Karakus, C. B., Cerit, O., & Kavak, K. S. (2015). Determination of Land Use/Cover Changes and Land Use Potentials of Sivas City and its Surroundings Using Geographical Information Systems (GIS) and Remote Sensing (RS). *Procedia Earth and Planetary Science*. https://doi.org/10.1016/j.proeps.2015.08.040

Kauffeldt, A., Wetterhall, F., Pappenberger, F., Salamon, P., & Thielen, J. (2016). Technical review of large-scale hydrological models for implementation in operational flood forecasting schemes on continental level. *Environmental Modelling and Software*, *75*, 68–76. https://doi.org/10.1016/j.envsoft.2015.09.009

Kelderman, P., Kansiime, F., Tola, M. A., & van Dam, A. (2007). The role of sediments for phosphorus retention in the Kirinya wetland (Uganda). *Wetlands Ecology and Management*, *15*(6), 481–488. https://doi.org/10.1007/s11273-007-9048-4

Kemp, P., Sear, D., Collins, A., Naden, P., & Jones, I. (2011). The impacts of fine sediment on riverine fish. *Hydrological Processes*. https://doi.org/10.1002/hyp.7940

Kiggundu, N., Anaba, L. A., Banadda, N., Wanyama, J., & Kabenge, I. (2018). Assessing Land Use and Land Cover Changes in the Murchison Bay Catchment of Lake Victoria Basin in Uganda. *Journal of Sustainable Development*, *11*(1), 44. https://doi.org/10.5539/jsd.v11n1p44

Kilama Luwa, J., Bamutaze, Y., Majaliwa Mwanjalolo, J. G., Waiswa, D., Pilesjö, P., & Mukengere, E. B. (2020). Impacts of land use and land cover change in response to different driving forces in Uganda: evidence from a review. *African Geographical Review*. https://doi.org/10.1080/19376812.2020.1832547

Kogo, B. K., Kumar, L., & Koech, R. (2020). Impact of Land Use/Cover Changes on Soil Erosion in Western Kenya. In *Sustainability* (Vol. 12, Issue 22, p. 9740). https://doi.org/10.3390/su12229740

Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences*, *5*, 89–97. https://doi.org/10.5194/adgeo-5-89-2005

Krejcie, R., & Morgan, D. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607–610. https://doi.org/10.1891/9780826138446.0006

Kusuma, S. (2015). Application of Land Change Modeler for Prediction of Future Application of Land Change Modeler for Prediction of Future Land Use Land Cover a Case Study of Vijayawada City. *International Journal of Advanced Technology in Engineering and Science*.

Kyambadde, J., Kansiime, F., Gumaelius, L., & Dalhammar, G. (2004). A comparative study of Cyperus papyrus and Miscanthidium violaceum-based constructed wetlands for wastewater treatment in a tropical climate. *Water Research*, *38*(2), 475–485. https://doi.org/https://doi.org/10.1016/j.watres.2003.10.008

Lal, R. (2003). Soil erosion and the global carbon budget. In *Environment International*.

https://doi.org/10.1016/S0160-4120(02)00192-7

Lamek, N., Lanhai, L., Alphonse, K., Fidele, K., Christophe, M., Felix, N., & Enan, M. N. (2016). Agricultural impact on environment and counter measures in Rwanda. *African Journal of Agricultural Research*, *11*(25), 2205–2212. https://doi.org/10.5897/ajar2016.10899

Li, Yujin, Jiao, J., Wang, Z., Cao, B., Wei, Y., & Hu, S. (2016). Effects of Revegetation on Soil Organic Carbon Storage and Erosion-Induced Carbon Loss under Extreme Rainstorms in the Hill and Gully Region of the Loess Plateau. In *International Journal of Environmental Research and Public Health* (Vol. 13, Issue 5, p. 456). https://doi.org/10.3390/ijerph13050456

Li, Yunyun, Chang, J., Luo, L., Wang, Y., Guo, A., Ma, F., & Fan, J. (2019). Spatiotemporal impacts of land use land cover changes on hydrology from the mechanism perspective using SWAT model with time-varying parameters. *Hydrology Research*. https://doi.org/10.2166/nh.2018.006

Li, Z., Deng, X., Wu, F., & Hasan, S. S. (2015). Scenario Analysis for Water Resources in Response to Land Use Change in the Middle and Upper Reaches of the Heihe River Basin. In *Sustainability* (Vol. 7, Issue 3, pp. 3086–3108). https://doi.org/10.3390/su7033086

Liang, X., Lettenmaier, D. P., Wood, E. F., & Burges, J. (1994). A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*, *99*(7), 14415–14428.

Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0200493

Lu, Q., Chang, N. Bin, Joyce, J., Chen, A. S., Savic, D. A., Djordjevic, S., & Fu, G. (2018). Exploring the potential climate change impact on urban growth in London by a cellular automata-based Markov chain model. *Computers, Environment and Urban Systems*. https://doi.org/10.1016/j.compenvurbsys.2017.11.006

Mahmood, R., Pielke, R. A., Hubbard, K. G., Niyogi, D., Bonan, G., Lawrence, P., McNider, R., McAlpine, C., Etter, A., Gameda, S., Qian, B., Carleton, A., Beltran-Przekurat, A., Chase, T., Quintanar, A. I., Adegoke, J. O., Vezhapparambu, S., Conner, G., Asefi, S., … Syktus, J. (2010). Impacts of land use/land cover change on climate and future research priorities. In

Bulletin of the American Meteorological Society (Vol. 91, Issue 1, pp. 37–46). https://doi.org/10.1175/2009BAMS2769.1

Marie Mireille, N., M. Mwangi, H., K. Mwangi, J., & Mwangi Gathenya, J. (2019). Analysis of Land Use Change and Its Impact on the Hydrology of Kakia and Esamburmbur Sub-Watersheds of Narok County, Kenya. *Hydrology*. https://doi.org/10.3390/hydrology6040086

Martínez-Retureta, R., Aguayo, M., Stehr, A., Sauvage, S., Echeverría, C., & Sánchez-Pérez, J.-M. (2020). Effect of land use/cover change on the hydrological response of a southern center basin of Chile. In *Water* (Vol. 12, Issue 1, p. 302). https://doi.org/10.3390/w12010302

Mati, B. M., Mutie, S., Gadain, H., Home, P., & Mtalo, F. (2008). Impacts of land-use/cover changes on the hydrology of the transboundary Mara River, Kenya/Tanzania. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use*, *13*(2), 169–177. https://doi.org/https://doi.org/10.1111/j.1440-1770.2008.00367.x

Mbungu, W. (2016). Impacts of Land Use and Land Cover Changes , and Climate Variability on Hydrology and Soil Erosion in the Upper Ruvu Watershed , Tanzania. In *Virginia Polytechnic Institute and State University*.

Meshesha, T. W., Tripathi, S. K., & Khare, D. (2016). Analyses of land use and land cover change dynamics using GIS and remote sensing during 1984 and 2015 in the Beressa Watershed Northern Central Highland of Ethiopia. *Modeling Earth Systems and Environment*. https://doi.org/10.1007/s40808-016-0233-4

Moore, T. R. (1979). Rainfall Erosivity in East Africa. *Geografiska Annaler. Series A, Physical Geography*. https://doi.org/10.2307/520909

Moriasi, D., Gitau, M., Pai, N., & Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/https://doi.org/10.13031/trans.58.10715

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. *American Society of Agricultural and Biological Engineers*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Moriasi, N., Arnold, G., Liew, V., Bingner, L., D Harmel, & Veith, L. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations.

Transactions of the ASABE, *50*(3), 885–900. https://doi.org/https://doi.org/10.13031/2013.23153

Mugonola, B., Vranken, L., Macrtens, M., Deckers, J., Taylor, D. B., Bonabana-Wabi, J., & Mathijs, E. (2013). Soil and water conservation technologies and technical efficiency in banana production in upper Rwizi micro-catchment , Uganda. *African Journal of Agricultural and Resource Economics*.

Mukisa, G. (2021). Effect of land use/cover changes on soil erosion risk in Mitano catchment, south western Uganda. In *Kyambogo University, Uganda*.

Munthali, M. G., Davis, N., Adeola, A. M., Botai, J. O., Kamwi, J. M., Chisale, H. L. W., & Orimoogunje, O. O. I. (2019). Local perception of drivers of Land-Use and Land- Cover change dynamics across Dedza district, Central Malawi region. *Sustainability (Switzerland)*. https://doi.org/10.3390/su11030832

Mwanjalolo, M. G. J., Bernard, B., Paul, M. I., Joshua, W., Sophie, K., Cotilda, N., Bob, N., John, D., Edward, S., & Barbara, N. (2018). Assessing the extent of historical, current, and future land use systems in Uganda. *Land*. https://doi.org/10.3390/land7040132

MWE. (2013). Aswa Catment management Plan. *Aswa Catchment Management Plan*, *1*, 1–104. https://www.mwe.go.ug/sites/default/files/library/Aswa CMP Popular Version_0.pdf

MWE. (2016). *Aswa Catchment Management Plan*. https://www.mwe.go.ug/sites/default/files/library/Aswa CMP Popular Version.pdf

MWE. (2020a). *Joint Technical Review 2020 Detail of Undertaking no . 6* (Issue 6). https://mwe.go.ug/sites/default/files/library/6-Progress of Undertaking No-6 .pdf

MWE. (2020b). *Situational Diagnosis Report for Development of Ogwapoke Micro-catchment Management Plan*.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I - A discussion of principles. *Journal of Hydrology*, *10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Nath, C. D., Pélissier, R., & Garcia, C. (2010). Comparative efficiency and accuracy of variable area transects versus square plots for sampling tree diversity and density. *Agroforestry Systems*, *79*(2), 223–236. https://doi.org/10.1007/s10457-009-9255-5

Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.;Williams, J. . (2011). *Soil & Water Assessment Tool Theoretical Documentation Version 2009*.

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K., Alhusseini, T., … Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*. https://doi.org/10.1038/nature14324

Nugroho, P., Marsono, D., Sudira, P., & Suryatmojo, H. (2013). Impact of Land-use Changes on Water Balance. *Procedia Environmental Sciences*, *17*, 256–262. https://doi.org/https://doi.org/10.1016/j.proenv.2013.02.036

Nwaogu, C., Benc, A., & Pechanec, V. (2018). *Prediction Models for Landscape Development in GIS BT - Dynamics in GIscience* (I. Ivan, J. Horák, & T. Inspektor (eds.); pp. 289–304). Springer International Publishing.

Nyeko, M. (2012). GIS and Multi-Criteria Decision Analysis for Land Use Resource Planning. *Journal of Geographic Information System*, *04*(04), 341–348. https://doi.org/10.4236/jgis.2012.44039

Ochoa, P. A., Fries, A., Mejía, D., Burneo, J. I., Ruíz-Sinoga, J. D., & Cerdà, A. (2016). Effects of climate, land cover and topography on soil erosion risk in a semiarid basin of the Andes. *Catena*. https://doi.org/10.1016/j.catena.2016.01.011

Olson, K. R., Al-Kaisi, M., Lal, R., & Cihacek, L. (2016). Impact of soil erosion on soil organic carbon stocks. *Journal of Soil and Water Conservation*. https://doi.org/10.2489/jswc.71.3.61A

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

Ozturk, D. (2015). Urban growth simulation of Atakum (Samsun, Turkey) using cellular automata-Markov chain and Multi-layer Perceptron-Markov chain models. *Remote Sensing*. https://doi.org/10.3390/rs70505918

P.U., I., A.A., O., O.C., C., I.I., E., & M.M., M. (2017). Soil Erosion: A Review of Models and Applications. *International Journal of Advanced Engineering Research and Science*. https://doi.org/10.22161/ijaers.4.12.22

Pan, S., Liu, D., Wang, Z., Zhao, Q., Zou, H., Hou, Y., Liu, P., & Xiong, L. (2017). Runoff responses to climate and land use/cover changes under future scenarios. *Water (Switzerland)*. https://doi.org/10.3390/w9070475

Panagos, P., Borrelli, P., Meusburger, K., Alewell, C., Lugato, E., & Montanarella, L. (2015). Estimating the soil erosion cover-management factor at the European scale. *Land Use Policy*, *48*, 38–50. https://doi.org/10.1016/j.landusepol.2015.05.021

Parsaie, A. (2016). Analyzing the distribution of momentum and energy coefficients in compound open channel. *Modeling Earth Systems and Environment*, *2*(1), 1–5. https://doi.org/10.1007/s40808-015-0054-x

Peng, T., & Wang, S. (2012). Effects of land use, land cover and rainfall regimes on the surface runoff and soil loss on karst slopes in southwest China. *CATENA*, *90*, 53–62. https://doi.org/https://doi.org/10.1016/j.catena.2011.11.001

Polyakov, V. O., & Lal, R. (2008). Soil organic matter and CO2 emission as affected by water erosion on field runoff plots. *Geoderma*, *143*(1–2), 216–222. https://doi.org/10.1016/j.geoderma.2007.11.005

Pontius Jr., R. G., & Chen, H. (2006). GEOMOD Modeling. *Clark Labs*, 1–44.

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., … Vuuren, D. P. va. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*. https://doi.org/10.1016/j.gloenvcha.2016.10.002

Priyadarshini, K., Kumar, M., Rahaman, S., & Nitheshnirmal, S. (2018). A comparative study of advanced land use/land cover classification algorithms using Sentinel-2 data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*(5), 20–23. https://doi.org/10.5194/isprs-archives-xlii-5-665-2018

Pulley, S., & Collins, A. L. (2019). Field-based determination of controls on runoff and fine sediment generation from lowland grazing livestock fields. *Journal of Environmental Management*. https://doi.org/10.1016/j.jenvman.2019.109365

Rao, K. S., & Pant, R. (2001). Land use dynamics and landscape change pattern in a typical micro watershed in the mid elevation zone of central Himalaya, India. *Agriculture, Ecosystems and Environment*, *86*(2), 113–124. https://doi.org/10.1016/S0167-8809(00)00274-7

Rathjens, H., & Oppelt, N. (2012). SWAT model calibration of a grid-based setup. *Advances in Geosciences*, *32*, 55–61. https://doi.org/10.5194/adgeo-32-55-2012

Raytheon, T., Moorhouse, T., & McNabb, T. (2002). The abundance and distribution of water hyacinth in Lake Victoria and the Kagera River Basin, 1989-2001. *USGS/EROS Data Center and Clean Lakes. Inc*, 42.

Reed, B. C., Schwartz, M. D., & Xiao, X. (2009). *Remote Sensing Phenology BT - Phenology of Ecosystem Processes: Applications in Global Change Research* (A. Noormets (ed.); pp. 231–246). Springer New York. https://doi.org/10.1007/978-1-4419-0026-5_10

Regmi, R. R., Saha, S. K., & Subedi, D. S. (2017). Geospatial Analysis of Land Use Land Cover Change Modeling in Phewa Lake Watershed of Nepal by Using GEOMOD Model. *Himalayan Physics*. https://doi.org/10.3126/hj.v6i0.18363

Reid, R. S., Kruska, R. L., Muthui, N., Taye, A., Wotton, S., Wilson, C. J., & Mulatu, W. (2000). Land-use and land-cover dynamics in response to changes in climatic, biological and socio-political forces: The case of southwestern Ethiopia. *Landscape Ecology*, *15*(4), 339–355. https://doi.org/10.1023/A:1008177712995

Reis, S. (2008). Analyzing land use/land cover changes using remote sensing and GIS in Rize, North-East Turkey. *Sensors*. https://doi.org/10.3390/s8106188

Rimal, B., Zhang, L., Keshtkar, H., Wang, N., & Lin, Y. (2017). Monitoring and modeling of spatiotemporal urban expansion and land-use/land-cover change using integrated Markov chain cellular automata model. *ISPRS International Journal of Geo-Information*, *6*(9). https://doi.org/10.3390/ijgi6090288

Rowlands, L. (2019). Erosion and sediment control—WSUD during the construction phase of land development. *Approaches to Water Sensitive Urban Design*, 163–176. https://doi.org/https://doi.org/10.1016/B978-0-12-812843-5.00008-3

Sambou, S. (2015). Land Use-Land Cover Change and Drivers of Deforestation in the Patako Protected Area (Center-West of Senegal). *American Journal of Environmental Protection*. https://doi.org/10.11648/j.ajep.20150406.17

Samndong, R. A., Bush, G., Vatn, A., & Chapman, M. (2018). Institutional analysis of causes of deforestation in REDD+ pilot sites in the Equateur province: Implication for REDD+ in the Democratic Republic of Congo. *Land Use Policy*. https://doi.org/10.1016/j.landusepol.2018.02.048

Sampaio, G., Nobre, C., Costa, M. H., Satyamurty, P., Soares-Filho, B. S., & Cardoso, M. (2007). Regional climate change over eastern Amazonia caused by pasture and soybean cropland expansion. *Geophysical Research Letters*, *34*(17). https://doi.org/https://doi.org/10.1029/2007GL030612

Sang-Arun, J., Mihara, M., Horaguchi, Y., & Yamaji, E. (2006). Soil erosion and participatory remediation strategy for bench terraces in northern Thailand. *Catena*. https://doi.org/10.1016/j.catena.2005.11.010

Santhi, C., Arnold, J., Williams, J., Dugas, W., Srinivasan, R., & Hauck, L. (2001). Validation of the SWAT model on a large river basin with point and non point sources. *Journal of the American Water Resources Association*, *37*(5), 1169–1188.

Sasal, M. C., Castiglioni, M. G., & Wilson, M. G. (2010). Effect of crop sequences on soil properties and runoff on natural-rainfall erosion plots under no tillage. *Soil and Tillage Research*. https://doi.org/10.1016/j.still.2010.03.010

Schroeder, S. B., Dupont, C., Boyer, L., Juanes, F., & Costa, M. (2019). Passive remote sensing technology for mapping bull kelp (Nereocystis luetkeana): A review of techniques and regional case study. In *Global Ecology and Conservation*. https://doi.org/10.1016/j.gecco.2019.e00683

Seehausen, O., Van Alphen, J. J. M., & Witte, F. (1997). Cichlid fish diversity threatened by eutrophication that curbs sexual selection. *Science*. https://doi.org/10.1126/science.277.5333.1808

Seibert, J., & McDonnell, J. J. (2010). Land-cover impacts on streamflow: a change-detection modelling approach that incorporates parameter uncertainty. *Hydrological Sciences Journal*, *55*(3), 316–332. https://doi.org/10.1080/02626661003683264

Sharma, A., Tiwari, K. N., & Bhadoria, P. B. S. (2011). Effect of land use land cover change on soil erosion potential in an agricultural watershed. *Environmental Monitoring and Assessment*, *173*(1–4), 789–801. https://doi.org/10.1007/s10661-010-1423-6

Shen, Z. Y., Chen, L., & Chen, T. (2012). Analysis of parameter uncertainty in hydrological and sediment modeling using GLUE method: a case study of SWAT model applied to Three Gorges Reservoir Region, China. *Hydrology and Earth System Sciences*, *16*(1), 121–132. https://doi.org/10.5194/hess-16-121-2012

Singh, S. K., Mustak, S., Srivastava, P. K., Szabó, S., & Islam, T. (2015). Predicting Spatial and

Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. *Environmental Processes*. https://doi.org/10.1007/s40710-015-0062-x

Siswanto, S. Y., & Francés, F. (2019). How land use/land cover changes can affect water, flooding and sedimentation in a tropical watershed: a case study using distributed modeling in the Upper Citarum watershed, Indonesia. *Environmental Earth Sciences*, *78*(17), 1–15. https://doi.org/10.1007/s12665-019-8561-0

Specht, M. J., Pinto, S. R. R., Albuqueque, U. P., Tabarelli, M., & Melo, F. P. L. (2015). Burning biodiversity: Fuelwood harvesting causes forest degradation in human-dominated tropical landscapes. *Global Ecology and Conservation*. https://doi.org/10.1016/j.gecco.2014.12.002

Srinivasan, R., Singh, S. K., Nayak, D. C., Hegde, R., & Ramesh, M. (2019). Estimation of soil loss by USLE model using remote sensing and GIS Techniques - A case study of Coastal Odisha, India. *Eurasian Journal of Soil Science*, *8*(4). https://doi.org/10.18393/ejss.598120

Stromberg, J. C., Lite, S. J., & Dixon, M. D. (2010). Effects of stream flow patterns on riparian vegetation of a semiarid river: Implications for a changing climate. *River Research and Applications*, *26*(6), 712–729. https://doi.org/https://doi.org/10.1002/rra.1272

Stuart, G. W., & Edwards, P. J. (2006). Concepts about forests and water. In *Northern Journal of Applied Forestry*. https://doi.org/10.1093/njaf/23.1.11

Sullivan, P. L., Stops, M. W., Macpherson, G. L., Li, L., Hirmas, D. R., & Dodds, W. K. (2019). How landscape heterogeneity governs stream water concentration-discharge behavior in carbonate terrains (Konza Prairie, USA). *Chemical Geology*, *527*, 118989. https://doi.org/https://doi.org/10.1016/j.chemgeo.2018.12.002

Taabu-Munyaho, A., Marshall, B. E., Tomasson, T., & Marteinsdottir, G. (2016). Nile perch and the transformation of Lake Victoria. In *African Journal of Aquatic Science*. https://doi.org/10.2989/16085914.2016.1157058

Tang, L., Yang, D., Hu, H., & Gao, B. (2011). Detecting the effect of land-use change on streamflow, sediment and nutrient losses by distributed hydrological simulation. *Journal of Hydrology*. https://doi.org/10.1016/j.jhydrol.2011.08.015

Terefe, H. (2020). Effect of integrated land management, slope position and land-use type on soil physicochemical properties, discharge, species richness and carbon stock in Geda watershed, north Shewa Ethiopia. In *Center for Environmental Science, Addis Ababa*

University.

Trambauer, P., Maskey, S., Winsemius, H., Werner, M., & Uhlenbrook, S. (2013). A review of continental scale hydrological models and their suitability for drought forecasting in (sub-Saharan) Africa. *Physics and Chemistry of the Earth*, *66*, 16–26. https://doi.org/10.1016/j.pce.2013.07.003

Turner, B. L. 2nd, Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(52), 20666–20671. https://doi.org/10.1073/pnas.0704119104

Twesige, J. (2019). Hydrological Response to Land use and Land Cover Change in Katonga River Basin, Uganda. In *Pan-African University Institute for Water and Energy Sciences (Including Climate Change)*.

UBOS. (2016). The National Population and Housing Census 2014 - Main Report, kampala. Uganda. *Uganda Bureau of Statistics*, 1–105.

UBOS. (2019). The State of Uganda Population Report. In *United Nations Population Fund* (Vol. 53, Issue 9).

van Oost, K., van Rompaey, A., Poesen, J., Govers, G., & Verstraeten, G. (2002). Evaluating an integrated approach to catchment management to reduce soil loss and sediment pollution through modelling. *Soil Use and Management*. https://doi.org/10.1079/sum2002150

Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: Current practice and research priorities. *GeoJournal*, *61*(4), 309–324. https://doi.org/10.1007/s10708-004-4946-y

Wairiu, M. (2017). Land degradation and sustainable land management practices in Pacific Island Countries. In *Regional Environmental Change*. https://doi.org/10.1007/s10113-016-1041-0

Wang, J., Sammis, T. W., Gutschick, V. P., Gebremichael, M., Dennis, S. O., & Harrison, R. E. (2010). Review of Satellite Remote Sensing Use in Forest Health Studies~!2010-01-27~!2010-04-05~!2010-06-29~! *The Open Geography Journal*. https://doi.org/10.2174/1874923201003010028

Wang, Q., Xu, Y., Wang, Y., Zhang, Y., Xiang, J., Xu, Y., & Wang, J. (2020). Individual and combined impacts of future land-use and climate conditions on extreme hydrological events in a representative basin of the Yangtze River Delta, China. *Atmospheric Research*, *236*, 104805. https://doi.org/https://doi.org/10.1016/j.atmosres.2019.104805

Wantzen, K. M., & Mol, J. H. (2013). Soil erosion from agriculture and mining: A threat to tropical stream ecosystems. *Agriculture (Switzerland)*. https://doi.org/10.3390/agriculture3040660

Wasige, J. E., Groen, T. A., Smaling, E., & Jetten, V. (2013). International Journal of Applied Earth Observation and Geoinformation Monitoring basin-scale land cover changes in Kagera Basin of Lake Victoria using ancillary data and remote sensing. *International Journal of Applied Earth Observations and Geoinformation*, *21*, 32–42. https://doi.org/10.1016/j.jag.2012.08.005

Welde, K., & Gebremariam, B. (2017). Effect of land use land cover dynamics on hydrological response of watershed: Case study of Tekeze Dam watershed, northern Ethiopia. *International Soil and Water Conservation Research*. https://doi.org/10.1016/j.iswcr.2017.03.002

Wu, Q., Li, H. qing, Wang, R. song, Paulussen, J., He, Y., Wang, M., Wang, B. hui, & Wang, Z. (2006). Monitoring and predicting land use change in Beijing using remote sensing and GIS. *Landscape and Urban Planning*. https://doi.org/10.1016/j.landurbplan.2005.10.002

Wubie, M. A., Assen, M., & Nicolau, M. D. (2016). Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia. *Environmental Systems Research*. https://doi.org/10.1186/s40068-016-0058-1

Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2012). Opening the archive: How free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, *122*, 2–10. https://doi.org/https://doi.org/10.1016/j.rse.2012.01.010

Wynants, M., Solomon, H., Ndakidemi, P., & Blake, W. H. (2018). Pinpointing areas of increased soil erosion risk following land cover change in the Lake Manyara catchment, Tanzania. *International Journal of Applied Earth Observation and Geoinformation*. https://doi.org/10.1016/j.jag.2018.05.008

Xu, M., Han, H., & Kang, S. (2017). Modeling Glacier Mass Balance and Runoff in the Koxkar River Basin on the South Slope of the Tianshan Mountains, China, from 1959 to 2009. In *Water* (Vol. 9, Issue 2, p. 100). https://doi.org/10.3390/w9020100

Yang, H., Li, S., Chen, J., Zhang, X., & Xu, S. (2017). The Standardization and harmonization of land cover classification systems towards harmonized datasets: A review. In *ISPRS International Journal of Geo-Information*. https://doi.org/10.3390/ijgi6050154

Yang, L., Xian, G., Klaver, J. M., & Deal, B. (2003). Urban land-cover change detection through sub-pixel imperviousness mapping using remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, *69*(9), 1003–1010. https://doi.org/10.14358/PERS.69.9.1003

Yira, Y., Diekkrüger, B., Steup, G., & Bossa, A. Y. (2016). Modeling land use change impacts on water resources in a tropical West African catchment (Dano, Burkina Faso). *Journal of Hydrology*, *537*, 187–199. https://doi.org/https://doi.org/10.1016/j.jhydrol.2016.03.052

Yirsaw, E., Wu, W., Shi, X., Temesgen, H., & Bekele, B. (2017). Land Use/Land Cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the Su-Xi-Chang region. *Sustainability (Switzerland)*, *9*(7), 1–17. https://doi.org/10.3390/su9071204

Yu, S., Wang, F., Qu, M., Yu, B., & Zhao, Z. (2021). The Effect of Land Use/Cover Change on Soil Erosion Change by Spatial Regression in Changwu County on the Loess Plateau in China. In *Forests* (Vol. 12, Issue 9, p. 1209). https://doi.org/10.3390/f12091209

Yue, Y., Keli, Z., Liang, L., Qianhong, M., & Jianyong, L. (2019). Estimating long-term erosion and sedimentation rate on farmland using magnetic susceptibility in northeast China. *Soil and Tillage Research*. https://doi.org/10.1016/j.still.2018.11.011

Zhang, Q., Ban, Y., Liu, J., & Hu, Y. (2011). Simulation and analysis of urban growth scenarios for the Greater Shanghai Area, China. *Computers, Environment and Urban Systems*. https://doi.org/10.1016/j.compenvurbsys.2010.12.002

Zhou, W., Huang, G., Troy, A., & Cadenasso, M. L. (2009). Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study. *Remote Sensing of Environment*. https://doi.org/10.1016/j.rse.2009.04.007

Zohrabi, M. (2013). Mixed method research: Instruments, validity, reliability and reporting findings. *Theory and Practice in Language Studies*. https://doi.org/10.4304/tpls.3.2.254-262

APPENDICES

Appendix 1: Sample field survey Questionnaire

QUESTIONNAIRE FOR STUDY LEADING TO MASTER OF SCIENCE IN CONSERVATION AND NATURAL RESOURCE MANAGEMENT –KYAMBOGO, KAMPALA

I……………………………………….a student of Kyambogo University, I kindly request you to provide me information on Landcover, soil and hydrological trends and all your views will be treated with utmost confidentiality.

The information provided will be key in attaining my Master's degree as indicated above under the Topic "**impact of land use/cover change on soil erosion potential in Ogwapoke sub-catchment, northern Uganda**". The researcher therefore requests your consent to participation in this study. Your cooperation will be highly appreciated. Thank you.

RESPONDENT'S BIODATA

Household location

X: ………………………………. Y: ……………………………..

Name of respondent: ………………………………………………………………

Sex:

Female ☐ Male ☐

Age:

18year ☐ 18-25years ☐

25-30years ☐ <30 years ☐

District……………………………… Sub county………………………

Parish/Ward: ……………………………

A: LAND USE/COVER

1. Identify the main land use/cover (LULC) in Ogwapoke micro catchment

…………………………………………………………………………………………………

…………………………………………………………………………………………………

2. When did you start occupying this land (Year)?

…………………………………………………………………………………………………

3. Before occupying this land, which land covers were present?

X:	
Y:	
X:	
Y:	
X:	
Y:	

4. Identify the main land covers that have occurred in the last 17years and 34 years ***(tick where appropriate)***

Years	Grassland	Bushland	woodland	wetlands	crops	Built-up areas
Last 17 years						
Last 34 years						

4b). Which of the above land use/cover has been main replacement of other land covers at least in the last 17years? (Tick where appropriate)

Grassland	Bushland	woodland	wetlands	crops	Built-up areas

5. Briefly describe the main drivers of land use change in the previous years stated in the table above

……………………………………………………………………………………………………

……………………………………..………………………………………………………………..

B: SOIL EROSION

1. What types of crops do you grow?

....

2. Where do you grow them?

Flat land ☐ Slightly Hilly ☐ Hilly land ☐

3. Do you experience soil erosion in the micro catchment?

Yes ☐ No ☐

3b). If yes, identify the main soil erosion agents in Ogwapoke micro catchment

Wind ☐ Water ☐

3c). How do you rate the amount of soil erosion that occurs in the micro catchment?

Very high (75-100%) ☐ High (50-75%) ☐

Moderate (25-50%) ☐ Low (0-25%) ☐

4. What are main drivers of soil erosion in Ogwapoke micro catchment?

Topography ☐ Poor soils ☐ Poor road construction ☐

High rainfall ☐ Poor farming methods ☐ None ☐

5. Identify the major land cover that are more prone to soil erosion loss

Grassland ☐ Wetland ☐ Built-up areas ☐

Bush ☐ Woodland ☐ Croplands ☐