IMPACT OF LAND USE/COVER AND CLIMATE CHANGE ON SURFACE WATER RESOURCES IN SEMI-ARID LOKOK AND LOKERE CATCHMENTS, UGANDA

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DEDICATION

To my parents, Mr. and Mrs. Oketcho; my wife, Mrs. Joyce Nandudu Osaliya; sons, Raphael Afuoyo Osaliya and Enoch Nissi Rieko Osaliya; daughter Jemimah Upendo Bero Osaliya; Spiritual mentor, Mami Scovia Odeke as well as academic mentors, Prof. Majaliwa and Prof. Adipala Ekwamu – for inspiration, encouragement and prayers.

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ABBREVIATION AND ACRONYMS

AgMIP	Agricultural Model Intercomparison and Improvement Project
AOGCMs	Atmosphere-Ocean General Circulation Models
ASALs	Arid and Semi-Arid Lands
CORDEX	Coordinated Regional Downscaling Experiment
CUSUM	Cumulative Sum
DJF	December-January-February
EMICs	Earth system Models of Intermediate Complexity
ET	Evapotranspiration
GCM	General Circulation Model
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for the Conservation of Nature
JJA	June-July-August
LCSS	Land use/cover Classifications System
LULC	Land Use Land over
MAM	March-April-May
MERRA	Modern-Era Retrospective Analysis for Research and Application
MLP	Multi Perceptron neural network
NBS	National Biomass Study
NFA	National Forestry Authority
NGOs	Non-Governmental Organisations
OLS	Ordinary Least Squares
RCP	Representative Concentration Pathway
SON	September-October-November
SRA	Standard Rainfall Anomaly
STI	Standard Temperature Index
SWAT	Soil and Water Assessment Tool

GENERAL ABSTRACT

Globally, the need to conserve and sustainably manage freshwater resources has become a major goal due to concern over the increasing impact of land use and land cover (LULC) and climate change on water resources especially in arid and semi-arid areas of eastern Africa. In Lokok and Lokere Catchments of the semi-arid Karamoja subregion, Uganda, stream flow has been highly fluctuating, with prolonged hydrological drought. However little is known about the contribution of each of these factors on the stream behavior. To assess the historical and plausible future impacts of land use/cover and climate change on water resources in the Catchments, LULC for 1984, 1994, 2003, and 2013 were established through unsupervised and supervised classification of satellite images. Qualitative information was used to obtain a historical account of LULC in order to identify its drivers. By cross comparing 1994 and 2003 LULC, the automatic multi-perceptron neural network built on Markov chain modeling method along with multi-criteria evaluation strategies, all embedded in the IDRISI Land Change Modeler (LCM) software, was applied to develop three plausible LULC scenarios for the Catchments, for 2030 and 2050, namely Business as Usual (BAU), pro-farming policy scenario (PFP) and pro-livestock policy scenario (PLP). The Model was validated with the 2013 LULC. In addition, spatio-temporal trends and variability in temperature and rainfall time series (1980-2009) were assessed using the ordinary least square (OLS) regression and Cumulative Sum (CUSUM). The standard temperature index (STI) and standard rainfall anomaly (SRA) were used to detect hot and dry years respectively. Furthermore, an ensemble of the four locations (stations) future temperature and rainfall scenarios for three periods (2010–2039, 2040–2069, and 2070-2099 or early, mid and end-century respectively) downscaled using the delta method from twenty of the latest International Panel on Climate Change (IPCC) climate models embedded in the Agricultural Model Intercomparison and Improvement Project (AgMIP). These were compared with 1980-2009 as the baseline period. Using the Soil and Water Assessment Tool (SWAT), the water balance of Lokok and Lokere Catchments was simulated using 2003 LULC and 1980-2009 MERRA climate data for the baseline period. Simulations were also made using 2030 and 2050 LULC, with early-century and mid-century ensemble of climate data respectively, under RCP 4.5 and 8.5. These simulation results were compared with the baseline to obtain a change in water balance components.

Results showed a change in LULC, especially in the conversion of woodlands and bushlands into small-scale croplands, with degradation of woodland and bushlands increasing grassland area. The area under grasslands, and the largest, increased from 43.64 in 1984 to 60.05 percent in 2013. Small-scale farming (SSF) steadily rose from 9.67 percent in 1984 to 15.69 percent in 2013, at an annual rate of 2.1 percent. The long agro-pastoralism tradition of the inhabitants is expected to continue in the years 2030 and 2050 as SSF would increase in all LULC scenarios. And increase in crop cultivation would persist to the year 2050 even if policy shifts to promote livestock rearing, pro-farming policies would, in both the 2030 and 2050 modeling periods, result in the reduction of grassland as SSF substantially increases – doubling the 2003 land area in 2050.

Catchments' temperature significantly increased ($p < 0.05$) in the 1980-2009 period. Minimum temperature (Tmin) increased faster than maximum temperature (Tmax), especially during the rainy seasons. During the dry season, Tmax significantly increased and was more variable than Tmin. The increase in rainfall was lowest in Amuria Station which received the highest rainfall. Total annual rainfall significantly increased only in Kotido and Moroto stations during 1980-2009 period. Variability of both temperature and rainfall was higher in the first decade of analysis than in the third; and positive shifts in temperature trends occurred after 2000.

Compared to the baseline, temperature was projected to increase, and change in Tmin would be higher than the change in Tmax. Tmax in the Catchments would change by 0.7^{o}C and 0.8^{o}C in the early century, 1.3 ^{o}C and 1.9 ^{o}C in the mid-century, and 1.7 ^{o}C and 3.3 ^{o}C in the end-centuries – for RCP 4.5 and RCP 8.5 scenarios. Tmin would change by 0.9 ^{o}C and 1.0 ^{o}C, 1.6 ^{o}C and 2.1 ^{o}C, and 2.0 ^{o}C and 3.8 ^{o}C – for RCP 4.5 and RCP 8.5 in the early, mid, and end-centuries respectively. Future increase in temperature would be higher in the cooler and wetter months and seasons (March-April-Mary, MAM; June-July-August, JJA) than in the warmer season (December-January-February, DJF) – which shows a temporal variation in change. And while rainfall in the catchments is projected to increase by 10 and 8 percent in early-century, 15 and 16 percent in mid-century, and 20 and 30 percent in end-centuries – for RCP 4.5 and RCP 8.5 respectively – the increase would be higher in the drier periods than in the wetter ones.

The simulated water balance of the catchments showed that evapotranspiration (ET) is the major component of the hydrological budget in the catchments, as over 97 percent of the precipitation received is lost through ET. As a result, the values of the other components (surface runoff, lateral flow, return flow, and groundwater recharge) are so small, and their changes in percentage terms would be too large. Under future climate scenarios, the percentage increase in water yield would range from 79.5 percent under early-century RCP 8.5 to 204.7 percent under mid-century RCP 4.5M. However, an increase in water yield would be marginal under change in LULC, ranging from 5.7 percent to 18.4 percent under BAU2030 and 2050 pro-farming scenario where SSF is expected to increase. Water yield is expected to be relatively high under combined future scenario of LULC and climate change. It would range from 193.7 percent under the 2050 pro-livestock LULC and RCP 8.5 mid-century climate to 223.2 percent under the 2050 pro-farming LULC and RCP 8.5 mid-century climate.

The study demonstrates that the current changes in small holder farming in the catchments would continue into the mid-century (2050). However, grassland would still be more dominant but could be less supportive to livestock herding due to fragmentation by cropland and restriction to sharing of grazing grounds. The results also show that the present increase in rainfall and temperature could continue. And while change in LULC would result in relative increase in water yield, change in climate would have more substantial increase in the water balance of the Catchments. Whereas the projected change in water yield appears minimal, it could have positive ecosystem, social and economic impacts. Given that mobile herding is more adaptive to climate variability, policies and strategies that improve both crop and livestock production could be more beneficial to the population.

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Background

There is a global call to conserve and sustainably manage freshwater and particularly surface water resources, as water scarcity becomes a major concern (Bigas, 2012). Human activities, whether through direct abstraction for use or exploitation of freshwater ecosystems are undermining the ability of surface water resources to support people and ecosystems. Water scarcity is associated with, among others, a rapidly growing population and competition between sectors, such as industrial, agriculture, and energy for the critical land and water resources (Penning de Vries *et al.*, 2003). The use of land and water resources to meet human needs such as food is one of the major drivers of landscape change including conversion of forests and grasslands into agricultural land, with a negative impact on surface water (Penning de Vries *et al.*, 2003 and Majaliwa, 2004).

In East Africa, land use/land cover changes such as loss of forest and natural vegetation cover have been reported to impact flows in catchments through reduced rainfall interception/evapotranspiration and infiltration, and increase surface runoff in watersheds (Baker and Miller, 2013 and Guzha et al., 2018); thus altering water availability. For example, land-use changes have been associated with the increasing frequency of drying of Kenya's Ewaso Ng'iro River and its tributaries (Few et al., 2015). This situation, coupled with climate change, contributes to water scarcity in arid and semi-arid areas, therefore threatening peoples' livelihoods in these regions (Bigas, 2012).

In arid and semi-arid regions of Eastern Africa, less than 250 mm rainfall is received in some areas of Djibouti, Eritrea, Ethiopia, Kenya, Somalia, and Sudan, (GWP, 2015) and is highly variable (Few *et al*., 2015). The region, particularly Djibouti, Eritrea, Ethiopia, Somalia, and parts of Kenya, belongs to one of the world's most vulnerable drought-prone regions (GWP, 2015). For example, the 2010–2011 drought in the region affected approximately 12 million people (Dutra *et al*., 2012), and its end in the latter half of 2011 resulted in flood conditions (Nicholson, 2014). And yet trends in global warming observed over the past centuries and decades have been predicted to increase over the 21st Century.

Global surface temperature changes for the end of the 21st century, 2100, will likely exceed 1.5°C relative to 1850 to 1900 (IPCC, 2013). This trend in global warming is predicted to likely increase during the 21st century under all the Representative Concentration Pathways (RCPs). However, like the observed, the predicted warming will continue to exhibit interannual-to-decadal variability as well as spatial variability as it will not be regionally uniform. Changes in the global water cycle will also occur in response to global warming, and like temperature, spatial and temporal variations will occur with respect to rainfall. It is projected that the contrast in precipitation between wet and dry regions and between wet and dry seasons will increase, although there may be regional exceptions (IPCC, 2013).

Recent studies show that future rainfall and temperature in Eastern Africa will vary or depart from present or historical baselines. ICPAC (2016) reported projected changes in annual and seasonal rainfall and temperature in the 2020s, 2030s, 2050s, and 2070s under three different socio-economic scenarios compared to the 1971-2000 baseline. Based on estimates from general circulation models (GCMs), Shongwe *et al*. (2011) reported a positive shift of rainfall distribution in East Africa during the wet seasons, projected increase in mean precipitation rates, and intensity of high rainfall events but for less severe droughts.

These recent studies however have tended to focus on larger regions and to overlook the effect of local features such as East Africa's varied topography (Shongwe *et al*., 2011). Understanding the likely water catchments' response of climate parameters to global warming is critical in informing development planning and disaster preparedness, especially in a region prone to drought and its consequences such as water scarcity and famine.

Lokere and Lokok catchments are found in Uganda's Karamoja sub-region which is a semi-arid rangeland with low and highly variable rainfall, ranging from 500 to 800 mm a year (Mubiru, 2010). The communities in these areas are mainly involved in pastoral and agro pastoral production. The catchments play a key role in these livelihood strategies by providing dry season grazing refuge and water reserves along the moist river banks. Both catchments face water scarcity and their per capita quantity of water was estimated to be 406 m^3/per/year in 2011 (IUCN-Uganda Office, 2011). Frequent and severe droughts in these areas, which are attributed to climate change (Mubiru, 2010 and Stark, 2011) is making water scarcity more acute in the catchments thus affecting food and forage availability.

The upstream seasonal streams and swamps of Lokere and Lokok catchments are cultivated for crop production. Cultivation along the streams and swamps alters hydrological processes in the catchment (Lastoria, 2008). The sedentarisation of pastoralists in efforts to address conflict among the Karimojong community in Uganda and the Pokot in Kenya fueled by cattle rustling (Stark, 2011) and degazettement of protected areas (Majaliwa *et al*., 2012) has also contributed to the increasing adoption of crop cultivation alongside livestock rearing in the sub-region. This study, therefore, assessed the impacts of land use/cover change, and climate change scenarios on water resources in Lokere and Lokok catchments.

1.2 Theoretical and conceptual framework

The study is based on the theory that land use and land cover change (LULCC) occurs in a dynamic, coupled human-natural system with complex and non-linear feedback effects (Munroe and Muller, 2007). The biophysical attributes such as soil, drainage, and climate influence human actions that result in socio-economic characteristics of a given population which in turn modify the biophysical attributes of the landscape.

The hydrological response of a catchment is a function of soil, topography, land use/cover, and climate. Soil and topography are quasi-constant within a climate period. However, land use/cover and climate can change. In this study, land use/cover change is conceptualized as a result of the non-linear interaction among biophysical and socio-economic factors in the study area (Figure 2.1). These factors are assumed to be the predictor of the future land use/cover in this study. These studies considered only two periods among the different scenarios of climate change that exist: the near future and the mid-century periods; and two concentration pathways (RCP 4.5 and 8.5). The study assumes that the main effect of climate and land use/cover change can be separated through hydrological modeling.

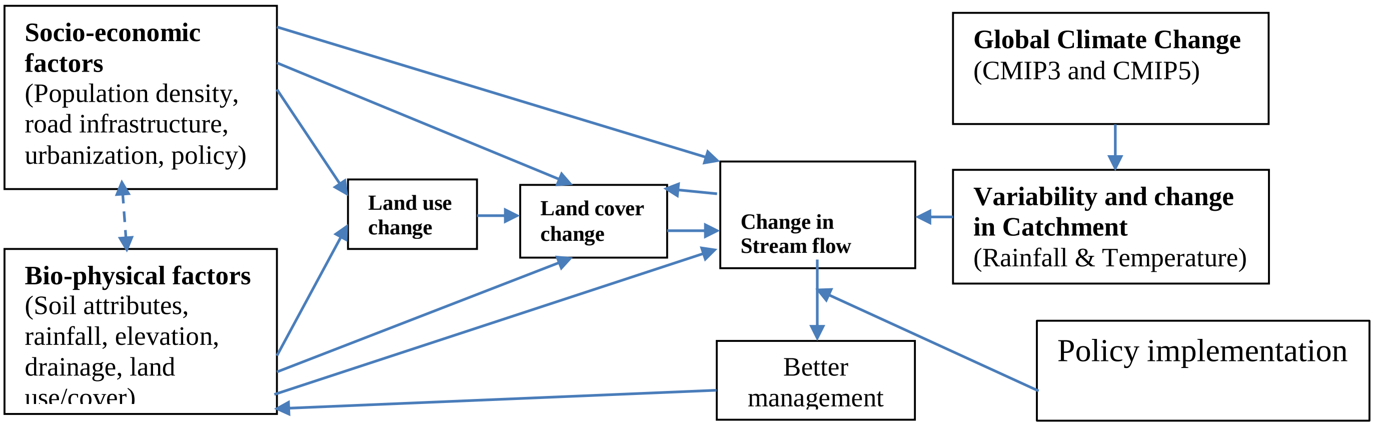


Figure 2.1: Conceptualization of the human-environment interaction, its influence on land use/cover (LULC) change, hydrological responses to LULC and climate change, and impact of the application of information on the catchments

1.3 Statement of the problem

Land use/cover change is occurring in the arid and semi-arid pastoral areas of Eastern Africa, with climate variability and change, and community and government responses to mitigate and (or) adapt being among the driving factors (Tsegaye *et al.*, 2010; Rufino *et al.*, 2013). In Ethiopia, for example, Tsegaye *et al.* (2010) reported a rapid reduction in woodland from 8.35 percent to 0.28 percent and an eightfold increase in cultivated land in the Northern Afar rangelands between 1972 and 2007. Among the Maasai community of Kenya, there is an integration of agriculture into traditional pastoralism aimed at diversifying livelihoods as a way of reducing climate risks and is also viewed as changing cultural and social norms that has been influenced by power differentials among the different age sets (population structure) and by government policies (McCabe *et al.*, 2010). The present trends of land use and cover change have led to concerns over its potential to negatively alter surface water availability, particularly stream flow regime in the already water-scarce semi-arid regions of Eastern Africa (Choto and Aramde Fetene, 2019).

Like Land use/cover, change in climate and associated impacts are a concern for drylands; the IPCC report shows that the (global) annual area of drylands in drought increased on average by slightly more than 1 percent over the 1961-2013 period (IPCC, 2019). While reported climate projections indicate a substantial increase in runoff in eastern Africa and parts of semi-arid Sub-Saharan Africa (Bates *et al.*, 2008), increasing frequency and intensity of drought and floods linked to increasing climate variability (Ongoma *et al.*, 2015) have also been projected, and the situation is expected to worsen due to climate change (Degefu, 2018). In the Afar region of Ethiopia, the frequency of drought is reported to increase from an average interval of about 10 years to nearly yearly in some areas (UNDP, 2014). As land use/ cover and climate are major drivers of surface water availability (Lastoria, 2008; Dwarakish and Ganasri 2015 and Anaba *et al.*, 2017), the impact of their change, particularly in semi-arid regions, is of increasing concern (Bigas, 2012). In arid and semi-arid regions of Eastern Africa, the 2010–2011 drought-affected approximately 12 million people (Dutra *et al*., 2012), and a swift change to flood conditions in the second half of 2011 also affected the people (Nicholson, 2014).

Uganda's semi-arid Karamoja region, including the Lokere and Lokok catchments, was endowed with good coverage of woodland and healthy grasslands in the 1960s (Rugadya and Kamusiime, 2013 and Nakalembe *et al.*, 2017). However, for the last five decades, woodland cover has drastically declined. While most of the pastoral land in the region was converted to national parks and game reserves in the 1950s, conservation areas dropped from 94.6 percent in 1965 to 40.8 percent in 2002, due to encroachment of crop cultivation between 1972 and the early 1990s (Rugadya and Kamusiime, 2013 and Nakalembe *et al.*, 2017). In 2002, 50 percent (14,904 km^2) of the protected area were gazetted to allow expansion of crop farming and mining (Krätli, 2010 and Nakalembe *et al.*, 2017). Between 1986 and 2013, 98.7 percent of woodland was converted to other land use/cover types (Egeru, 2014). Therefore, the land is majorly bare, particularly during the dry periods. Reduction in pastoral land has been pushing the Karamojong pastoralists to look elsewhere for forage and water during the dry season, therefore leading to conflict with the neighboring communities (Stark, 2011, Vidal, 2011 and Egeru 2014).

In addressing these challenges, NGOs and the government have focused on policies aimed at pastoralist sedentarization and the introduction of alternative livelihoods. These are further driving land-use conversion to cropland, leading to reduction of grazing and conservation land which scientists consider more ecologically rational land uses in rangelands (Davies *et al*., 2012 and Majaliwa *et al*., 2012). For example, a 299 percent increase (from 706 ha to 23,328 ha) in cropland area between 2000 and 2011, mostly in Moroto station was reported (Nakalembe *et al.*, 2017).

The streamflow for both catchments has been highly fluctuating, with a prolonged period of hydrological drought. As indicated by Mubiru (2010); Stark (2011) and Majaliwa *et al.* (2012), both land use/cover and climate change contribute to streamflow fluctuations. However little is known about the contribution of each of these factors (LULC and climate change) in the stream behavior. This information is key for planning for restoration and sustainable use of both Catchments. This study used remotely sensed data and hydrological modeling to determine the past, current and plausible contribution of land use/cover and climate change to streamflow in Lokere and Lokok Catchments.

1.4 Justification

This study characterized the current land use/cover and the climate. It projected future land use/cover and climate and assessed their contribution to streamflow in Lokere and Lokok catchments. The study was necessary because the semi-arid catchments are experiencing land use/cover (LULC) change-driven, among others, by policies and actions aimed at pastoralist sedentarisation (Stark, 2011), and the change could impact water availability. At the same time, the semi-arid area is experiencing an increase in temperatures, increased frequency of droughts, and unpredictable rainfall patterns associated with climate change that are making water scarcity more acute, and affecting food and forage availability (e.g Stark, 2011; Egeru *et al*., 2014; Bukenya *et al*., 2014; Nimusiima *et al.*, 2014). Increased water scarcity could jeopardize efforts to improve food security, reduce poverty and reduce the vulnerability of communities to water stress, and in turn affect the attainment of the sustainable development goals (SDGs), particularly to end poverty (SDG 1) and end hunger (SDG 2).

Concerns of increased water scarcity are increased, by climate model predictions that are showing a significant rise in temperature and minimal increase in precipitation (Egeru *et al*., 2019), as well as by the unknown outlook of land use change in the medium and long term. However little is known about the contribution of each of these factors in the stream behavior of the catchments. In this regard, updating of trends in temperature and rainfall is crucial in not only assessing the contribution of climate to the catchments' water balance but also developing adaptation strategies (Hadgu *et al.,* 2013) for building the resilience of the ecosystem and community to climate variability and change. Likewise, it is important to understand the likely overall future direction of

LULC to aid in the assessment of impacts as well as planning for sustainable livelihood strategies and catchment management. If unregulated or not well managed, land use/cover change can result in degradation, drying or receding, and pollution of water resources (Darghouth *et al*., 2008).

Understanding the impacts of land use/cover and climate change on water resources is useful to the decision makers for better planning of human activities for the sustainable utilization and management of natural resources and the Catchments. It can also be used to design better climate change adaptation and for building the resilience of communities and ecosystems, and awareness creation. Datasets generated such as on plausible land use/cover scenarios are also useful for validation of models. This is especially important for Lokere and Lokok catchments because they are important for the Ramsar sites at Lakes Opeta and Bisina, and are vital for the availability of pasture and water supply during dry periods in Karamoja, one of east Africa's semi-arid areas and an important cattle region in Uganda.

1.5 Objectives

1.5.1 Overall objectives

The overall objective of this study was to analyze the impact of land /cover and climate change on stream flow in Lokere and Lokok catchments, Northeastern Uganda, in order to support the development of management strategies for adaptation and reducing the ecosystems' and communities' vulnerability to climate extreme events.

1.5.2 Specific objectives

The specific objectives of this study were to:

a) Analyse change in land use/cover in Lokere and Lokok Catchments between 1984 and 2013.
b) Determine plausible scenarios of future land use/cover change in Lokere and Lokok catchments.
c) Analyze the trend of current and future scenarios of rainfall and temperature in Lokere and Lokok catchments.
d) Determine streamflow under present and future land use/cover and climate scenarios in Lokere and Lokok catchments.

1.6 Research questions

a) How has land use/cover changed between 1984 and 2013 in Lokere and Lokok catchments?

b) What is the plausible land use and land cover in Lokere and Lokok catchments by the years 2030 and 2050 if current trends continue, under pro-farming policies or pro-livestock policies?

c) What is the trend of current and future scenarios of rainfall and temperature to the year 2099 in Lokere and Lokok catchments?

d) How do present and plausible future scenarios of land use/cover and climate impact on stream flow in Lokere and Lokok catchments?

1.7 Limitations of the Study

The study utilized Landsat images available for free from their Earth Explorer (http://earthexplorer.usgs.gov/) and Global Visualization (GLOVIS) (http://glovis.usgs.gov/) websites. These datasets are of a relatively low spatial resolution of 30 m and are affected by cloud cover. However, for land use/cover classification, this resolution has been deemed suitable and only images of under 20 percent cloud cover were considered. Ground truthing, participatory mapping as well as visual analysis, and comparison with topographic maps were used to aid in image classification.

There were also challenges with streamflow data which had several gaps. The data (1984-2010) obtained from the Directorate of Water Resources Management (Entebbe, Uganda) for one gauged location (Akokorio) in the studied catchments had many gaps. Two periods with fewer gaps were selected for validation and calibration, and gap-filling was performed to obtain daily streamflow.

Needless to mention, is the limitation of modeling, as models cannot accurately simulate nonlinear patterns and processes in human-environment relationships. However, with calibration, models can fit these processes reasonably well (Irwin and Geoghegan, 2001 and Agarwal *et al*., 2000). And though only some of the several plausible futures were studied, scenarios are a powerful tool that aids decision making and critical thinking about possible futures in the face of uncertainty (Mietzner and Reger, 2005), particularly presented by anthropogenic climate change. Therefore, this study is particularly applicable to semi-arid areas with similar socio-ecological conditions as the Karamoja subregion of Uganda – Eastern Africa.

CHAPTER TWO

REVIEW OF LITERATURE

2.1 **Land use/cover change in East Africa and Uganda**

There are various definitions of land use and land cover; Meyer (1995) defined land use as how, and the purpose for which, human beings use the land and its resources, and land cover as "the physical state of the land surface". Dale *et al.* (2000) define land use as "the purpose to which land is put by humans" and land cover as "the ecological state and physical appearance of the land surface". Mohamed (2017) referred to land use as man's activities and the varied uses carried on land; and land cover as the assemblage of biotic and abiotic components on the earth's surface. Land cover is also referred to as "the biophysical state of the earth's surface and immediate subsurface"(Elaalem *et al*. 2013). Ellis and Pontius (2007) distinguish how natural scientists and social scientists define land use as: "syndromes of human activities" that "alter land surface processes", and "social and economic purposes and contexts for and within which lands are managed", respectively. Ellis and Pontius (2007) then defined land cover as "the physical and biological cover over the surface of land".

From the aforementioned definitions "land use" and "land cover" are not synonymous terms (Parveen *et al*., 2018) but are interrelated and may influence each other. The definitions show that land use is the activity on a given portion of land, while the land cover is the physical cover observed on the earth's surface of the land. Land use may determine or influence land cover because human activities alter land processes (Ellis and Pontius, 2007) through use, they modify land cover (Mohamed, 2017). Conversely, land cover type, for example, grassland, may also facilitate a particular land use, like grazing. Therefore, a land cover type may reflect a particular land use as in the case of cropland and farming/crop cultivation. However, land cover can be natural or anthropogenic and land use occurs in both natural and anthropogenic land cover.

Land use/cover of a given area is usually classified into different types or categories often to fit the intended purpose (Briassoulis, 2000). The classification provides a predefined list of categories that are an abstract representation of the real world based on a well-defined diagnostic criterion (Di Gregorio *et al.,* 2016). And while there are several land use/cover classifications systems (LCSS) across the globe, none has been recognized as a universal standard (Latham *et al*., 2002). This is because the various LCSS are developed to suit certain land cover types, data collection methods and geographic locations. Therefore, the choice of LCSS should show the environmental and socio-economic features required for the study or management decision.

Anderson *et al.* (1976) developed a land use/cover classification system for the needs of the United States agencies based on a uniform categorization at a more generalised first and second levels and that would also accommodate satellite and aircraft remote sensors. For each of the nine broader level 1 classes (e.g wetland), several more detailed (Level II) classes were provided (e.g forested wetland and non-forested wetland). This detailing allows a given location to bear only one class of land use/cover. For Africa, the level is the Africover classification system which was developed by the Food and Agriculture Organisation of the United Nations (FAO) to provide a digital geo-referenced database on land cover data for the whole Continent (FAO, 1997).

The Africover LCCS is a three-level hierarchical system where land is initially dichotomously sub-divided into two categories, vegetated or non-vegetated areas. Based on these two categories, eight classes which form the second-level categories, are obtained. The third-level, and potentially lower levels, are developed based on a modular-hierarchical phase in such a manner that a set of pre-defined pure land cover classifiers for a given second-level land cover class is combined with the user-defined environmental and/or specific technical attributes (like vegetation type) to arrive at the desired land cover class. The innovative hierarchical LCCS methodology enables global harmonization of land cover classes while at the same time, with the “modular-hierarchical” phase, providing flexibility for designing the project’s outputs to suit the users’ requirements (Latham, 2006). The LCCS was applied in the east African module of the Africover mapping project, which was completed in 2004.

In Uganda, the then Forest Department (1992) prepared a non-hierarchical classification scheme for Phase I of the National Biodiversity Study (NBS) which was implemented in peri-urban nine areas, from 1989-1992, based on a combination of twelve land cover and land use. A new scheme with 13 main classes was developed for Phase III of the NBS when existing schemes were found unsuitable for biomass inventory (Forest Department, 2002). Seven of the 13 main classes were further sub-stratified into very low, low, high, and very high (only the plantations and woodlots class had all these subdivisions). The combined land use/cover system, and the classification score was determined in accordance with the overall dominating class and were also useful for non-biomass spatial and non-spatial needs. In this regard, classification systems are distinguished in terms of the spatial scale of analysis and their intended purpose which determine the level of detail and particular attributes of the land use/cover types (Mugisha, 2002). It is also important to note that the available technology for data collection, types of models to be used and techniques of data analysis also determine the choice of land use/cover classification used in studies. And, classification schemes typically combine land use and land cover, thereby allowing both a high level of mappability of cover and use description (Di Gregorio and Jansen, 1998 and LaGro, 2005).

Studies have applied similar but relatively varying classifications to suit their purposes, and show that land use/cover in east Africa is spatially heterogeneous. Land cover in the region ranges from vast savannas (mixed woodland-grassland ecosystems) to dense forest and riparian wetlands, while land use comprises a variety of human activities, from intense agriculture, cattle grazing to ecotourism and conservation (Torbick *et al*., 2006). The heterogeneity is shaped by variations in landscapes, climate, culture, and political and livelihood systems (Olson, 2006).

The heterogeneity has been observed across the countries. For example, in Kenya where approximately 80 percent of the total land area is arid and semi-arid lands (ASALs), savannah/grassland/shrubs vegetation is reported to occupy most of the northern, the upper eastern, and a few areas of the southwestern, while agricultural activities, forests, and water bodies are concentrated within the western and Rift Valley parts of the country (Otieno and Anyah, 2012). The drylands of Ethiopia, which cover over 65 percent of the country's landmass are associated with tropical dry forests (Alemu *et al*., 2015). Haile *et al*. (2010) reported that grassland and woody vegetation are the dominant land use/cover types in the Borana rangelands of Southern Ethiopia, among five categories that included cultivated land, settlement, and bare land. Azanga *et al.*, (2016) showed that cultivated land is the dominant land use/cover type in Kalimabenge micro-catchment of the Lake Tanganyika Basin, followed by forest/tree plantations, grassland, and built-up area. In the Kagera Basin that stradstraddles parts of Burundi, Rwanda, Tanzania, and Uganda, Berakhi *et al*. (2014) reported that among five land use/cover types, agriculture and woodland savannas cover approximately 90 percent of the land, with the other types being forest, water bodies, and wetlands. The transboundary Basin is characterized by humid, sub-humid, and semiarid climates.

In Uganda, Majaliwa *et al*. (2018) identified 29 classes of land use/cover systems and broadly categorized them as agricultural, bushland, forest, grasslands, impediments (Bare rocks and land), wetlands, woodland, open water, and urban settlement. Of these nine categories, croplands, followed by grassland, woodland, and open water were the most dominant land uses. Grasslands dominate the semi-arid sub-regions of the Country, as the land use/cover type covers over 66 percent of the land in Karamoja subregion (Egeru, 2014). Egeru and Majaliwa (2009) also reported small scale farming and grasslands as the dominant land use/cover type in Soroti District, eastern Uganda.

2.2 **Trends in land use land cover change in East Africa and Uganda**

Like elsewhere in the world where grasslands, forests, bushlands and woodlands are being converted into croplands (Tsegaye *et al*., 2010, Baldi *et al*. 2013 and OECD, 2018), East Africa has in the last five decades, experienced a spatial pattern of land use/cover change that is characterized by increasing intensive conversion of grazing land and another marginal land into cropping land, particularly in the semi-arid and sub-humid areas (Olson, 2006). Several studies in eastern African countries are consistent with Olson (2006) study (e.g Tsegaye *et al*., 2010; Haile *et al*., 2010; Gebrelibanos and Assen, 2013). In the Northern Afar rangelands of Ethiopia, a rapid reduction in woodland from 8.35 percent to 0.28 percent and an eightfold increase in cultivated land occurred between 1972 and 2007 (Tsegaye *et al*., 2010). Conversion of grasslands and shrublands also resulted in a 24.6 percent increase of land under cultivation and rural settlement in the Hirmi watershed between 1964 and 2006 (Gebrelibanos and Assen, 2013), and a 15.49 percent expansion of cultivated land during 1976-2008 period in the Gilgel Tekeze catchment (Tesfaye *et al*., 2014), all in Northern Ethiopia. South of the Country, Haile *et al*. (2010) also reported a similar trend, as cultivated land, bare land, and settlement increased by 2, 5, and 3 percent and 6, 7, and 6 percent, in selected villages of Yabello and Areero Districts of the Borana rangelands, during the 1967 to 2002 period. However, unlike in a study conducted by Tsegaye *et al.* (2010) where woodlands declined, Haile *et al.* (2010) reported that woody vegetation cover increased by 9 and 15 percent in Yabello and Areero districts over the 35 years.

In the Kenya-Tanzania transboundary Mara Basin, Mati *et al*. (2005) showed that the combined encroachment of forest and savanna grassland led to an unprecedented increase (55 percent) of agricultural land in just 14 years (1986 -2000), with the former, in turn, reducing by 23 percent and 24 percent respectively. An even more unprecedented 203 percent increase in agricultural land over the basin was reported by Mati *et al*. (2008) from the 1973 to 2000 period, as savanna, grassland, and shrubs reduced by 52 percent and forest by 32 percent. Again in Tanzania's Kalimabenge micro-catchment, Azanga *et al*. (2016) reported a gradual decline in grassland/savannah over the 1973 to 2010 period, while cultivated land increased in the 1973 to 1986 period, but declined to below 1973 levels, by 2010. Forest/woodlot/tree plantations were reported to increase gradually over the same period.

In Uganda, recent studies have shown similar trends. The National Biodiversity Study (NBS) showed conversion of forest cover to agriculture or deterioration to shrubland, as 1.8 (2.27% outside protected areas) percent of forest cover was lost per year, during 1990-2005 period (NFA, 2009). And while small-scale farming increased by 2 percent, grassland reduced by 4 percent in the same period. Li and Ayana (2015) also reported that agricultural land increased by 14.78 percent while forest area reduced by 49.82 percent. Similarly, Majaliwa *et al.* (2018) showed that agriculture-related land-use systems (commercial, irrigated and subsistence) in the Country increased by 8.56 percent, while woodland reduced by 11.86 percent, in 2015 as compared to 1990.

In the rangeland of Kanungu district (Uganda), small-scale farming largely increased by 5 percent in the 1975 to 1999 period, while tropical high forests decreased by 16 percent between 1975 and 1987 before slightly increasing by 1 percent in 1999 (Barasa *et al*., 2010). Byenkya *et al*. (2014) showed that in 27 years (1986-2013), in Buliisa District (Uganda), grassland declined by 48.3 percent while woodland, wetland, small-scale farming, and forest area increased by 0.2, 62.2, 320.7 and 64.1 percent, respectively. Although the same study reported a similar change in grassland and small scale farming (96.1 and 26.8 percent decline and increase respectively) in

Nakasongola District, forest cover and bushland decreased by 17.2 and 25.6 percent respectively, as bare land increased by 210.9 percent. Egeru and Majaliwa (2009) reported a 5.3 percent decline in small-scale farming in Soroti District in Teso subregion between 1973 and 1986 as grasslands, wetlands, bushlands, and built-up areas gained, with respective percentage increases of 2.9, 2.18, 3.01, and 2.76. This was attributed to the prevailing insecurity during the insurgence that restricted access to the area. During the same period, small-scale farming increased between 1986 and 2001 by 13.6 percent, while woodlands, bushlands, forest, and wetlands declined. However, Ebanyat *et al*. (2010) reported that in three selected villages (Akadot, Agule and Chelekura) of Pallisa District, also in Teso subregion where mixed crop-livestock farming is practiced, cultivated land increased from 46 to 78 percent, while communal grazing lands greatly declined during 1960 to 2001 period. And while in Karamoja, grasslands remained the dominant land use/cover type over the 1986-2013 study period, it declined from 75.8, 74.2 to 66 percent in 1986, 2000 and 2013 respectively, as croplands increased ten-fold between 2000 and 2013, from 0.06 to 0.6 percent (Egeru 2014). Nakalembe *et al.* (2017) reported a 299 percent increase in cropland area in Karamoja, from 2000 to 2011.

As much as the general trend depicts a change, particularly from natural and/or modified land cover and associated land use to cropland and settlements, the above studies and others show some regional and local level reverse trends. For example, in Kenya, Musa and Odera (2015) showed a reduction in agricultural land over the 1984-2013 period from 39.7 percent to 15.8 percent in Kiambu County. Despite reporting increasing cropland, Musa and Odera (2015) findings are possibly because Kiambu County border Nairobi City as built-area/urban increased tremendously while grassland, forest, water body, and bare-land/rocky areas decreased. Yeshaneh *et al* (2013) showed that though woody vegetation in Koga Catchment, Ethiopia, decreased from 5,576 ha to 3,012 ha from the 1950s to 2010, most of the deforestation contributing to this 50-year long change took place between the 1970s and 1980s, after which is an increasing trend was observed.; Over the Karamoja subregion, land use/cover conversion is expected to continue given a wide range of efforts to popularize alternative livelihoods strategies to pastoralism such as g, aloe vera production, crop, and vegetable production (ACTED, 2010 and Majaliwa *et al*., 2012). The above reports show that local studies provide the required spatial and temporal resolution to understand specific cause-effect dynamics of land cover (Turner *et al.* 1994) for planning local and context-based policy and management interventions.

2.3 Modeling and projection of land use/cover

As seen in the aforementioned trends and studies, present land use/cover will continue to change, as driving forces combine in a dynamic complex and non-linear coupled human-nature system interactions to bring a change in the land use/cover (Munroe and Muller, 2007). Understanding drivers of past land use/cover changes is a prerequisite to studying potential future land use/cover change (Mugisha, 2002).

Authors (Meyer, 1995; Briassoulis, 2000; Serneels and Lambin, 2001; Veldkamp and Lambin, 2001; Agarwal *et al*., 2000; Eastman, 2009; and Sleeter *et al*., 2012) generally agree that drivers of land-use change are both biophysical and socio-economic, reflecting the complexity of land-use systems. The biophysical drivers are characteristics and processes of the natural environment such as climate variations, drainage, topography, while the socio-economic drivers are those linked to human behavior, actions, and processes such as population, politics, and related policies, markets, technology, and infrastructure (Briassoulis, 2000). While biophysical factors may influence land use/cover change alone, a combination of these often influence change, in space and time (Briassoulis, 2000 and Bürgi *et al.*, 2017). Therefore, biophysical and socio-economic drivers are the basic classification of land use/cover change drivers (Briassoulis, 2000).

Briassoulis (2000) establishes a further distinction of land use/cover change drivers into three; human driving forces, human mitigating forces, and proximate driving forces, based on "semantic" characterization of various factors and processes that in different ways contribute to land-use change and, through certain human actions, cause land cover and environmental change. On one hand, human driving forces are fundamental societal forces, such as population and technological change, that in a causal sense link human to nature and which bring about global environmental changes. On the other hand, human mitigating forces impede, alter or counteract human driving forces. Examples of these forces are local to international regulation, market adjustments, technological innovations, and informal social regulation through norms and values (Briassoulis, 2005).

Drivers are also distinguished as direct or proximate and indirect or underlying causes (Olson *et al*. 2004; Ostwald *et al*. 2009 and Bürgi *et al*. 2017). Ostwald *et al.* (2009) define proximate causes as human activities or immediate actions at the local level that have a direct impact on land cover and land use. Briassoulis (2000 & 2005) considers proximate drivers as the aggregate final activities that result from the interplay of human driving and mitigating forces to directly cause environmental transformations. Understanding proximate causes would require analyzing indirect drivers; defined as those that influence how individuals or groups of individuals interact with, and change, land cover (Karsidi, 2004). Therefore, the interactions with land are the proximate causes that in turn arise from underlying causes. Further, land-use change expresses, among others, changes in human and environmental dynamics and their interactions which themselves are regulated by land (Briassoulis, 2000). The resulting land-use/cover changes have negative or positive consequences or combinations of both to humans and the environment including water resources. Therefore, in land use/cover studies, divers also known as determinants of environment and socio-economic impacts of land use/cover change are considered (Briassoulis, 2000).

Because interactions between land use/cover and its drivers of change occur at different scales, in time and space (Olson *et al*., 2004), the subject of drivers of land use/ cover change has received quite a lot of attention from researchers. Drivers are often used to explain land use/cover change. Sleeter and Raumann (2006) highlighted that population growth, land ownership, and recreation opportunities drove land cover change (1972-2000) in the Mojave Basin, Southwestern United States. Varun *et al*. (2014) examined among others, distance from road networks and slope as drivers of land use/land cover in Muzaffarpur town, India. Agarwal *et al*. (2000) analyzed nineteen land-use models applied across the globe and identified the following human-driver variables: population returns to land use, job growth, costs of conversion, rent, collective rulemaking (zoning and tenure), relative geographical position to infrastructure (distance from road, distance from town/market, distance from village/settlement, presence of irrigation), generalized access variable, village size, silviculture, agriculture, technology level, affluence, human attitudes and values, and food security.

Various studies carried out in East Africa have revealed different drivers depending on the study area. Berakhi *et al*. (2014) identified population growth, settlement expansion, and local policies as key drivers of land use/cover change in the Kagera Basin. Elsewhere, Tsegaye *et al.* (2010) also cited policies that favor cropping, the influx of migrants (population), along unfavorable amount and distribution of rainfall as factors that resulted in the expansion of cultivation in the Afar region of Ethiopia between 1972 and 2007. Sewnet (2015) found out that decline in bushlands and wetlands, as well as fluctuation of forest cover in the Infraz watershed of Northwestern Ethiopia, from 1973 to 2011, was influenced by an increase in population, with the introduction Bahir Dar City as the regional capital, adding to the dynamics. But it was poverty, population pressure, and institutional and policy factors that were identified as underlying drivers of land use/cover change in Ethiopia's Hirmi watershed between 1964 and 2006 (2006 (Gebrelibanos and Assen, 2013). Tsegaye *et al*. (2010) identified natural elements; two severe drought of droughts in 1973/74 and 1984/85 that caused an influx of immigrants; and human factors, including land tenure policies that encouraged sedentarisation of pastoralist, as the underlying forces which led to conversion of grasslands into cropland, wood extraction for fuel and overgrazing in the Northern Afar Region (Ethiopia) between 1972 and 2007. Hyandye and Martz (2017) applied road distance, river distance, settlement distance, elevation, slope, annual precipitation, population density, and soil type as factors in a multi-criterion evaluation (MCE) of the suitability of land for land use/cover change and prediction, in the Usangu catchment of Tanzania. These are similar to the drivers (distances to the major town/Narok, roads, villages, and water; elevation, agro-climatic zone, soil suitability, land tenure, and population density) that were applied by Serneels and Lambin (2001) to explain land use/cover change in the southwestern Kenya rangelands of Narok District.

Like in the Afar region (Tsegaye *et al.,* 2010), the role of government programs in promoting sedentary agriculture against mobile herding was also reported as a key driver of the expanding cultivated land in Karamoja (Nakalembe *et al.,* 2017). The study also reported improved security following the disarmament of 2006, open access to cultivable land (tenure), and the increasing population, as key land use/cover drivers in Karamoja. A study by Barasa *et al*. (2010) showed that household size, weak land-use laws, type of crops grown, extension agents' visits, and customary land tenure were vital drivers of land use/cover change in Karima Sub-county of Kanungu District in Uganda while increasing livestock activities and education levels were reported as nonsignificant drivers. They noted that land use/cover change drivers are location specific. While the aforementioned studies in the country largely examined socio-economic drivers, Majaliwa *et al.* (2018) applied the digital terrain model (DEM), which represents slope and elevation, and the national road network, in the prediction of the future land use/cover over Uganda. However, a narrow selection of mainly distributed drivers/variables/factors which may not substantially incorporate the complex localized socio-economic factors could be considered as a limitation of their study. As Erle and Pontius (2007) observed, it is necessary to assess driving forces behind LULCC if past patterns are to be explained and used in forecasting future patterns.

Models provide tools for understanding causes and impacts of land use/cover change, climate change, and water resources or hydrological process dynamics (Koomen *et al.*, 2007). They combine biophysical and social science to help understand, manipulate and project plausible future scenarios of land use, climate, or water resource dynamics (Koomen *et al.*, 2007), which provides a framework for analysis of land systems as coupled human environments system (Schaldach *et al.*, 2008).

Gonzales (2009), in a literature synthesis, presented five distinguished model categories based on dominant model design feature, solution technique, and spatial and temporal levels of analysis to include: empirical-statistical models which in turn include multivariate techniques and regression models and are mainly exploratory tools; stochastic models represented by a Markov chain which are mainly transition probability models; and optimization models that comprise the linear programming models family that are prescriptive models also used as evaluation tools. The other two models are: the dynamic process-based simulation models, which emphasize the interactions among all components forming a system and attempt to imitate the run of these processes and follow their evolution, also condensing and aggregating complex ecosystems into a small number of differential equations in a stylized manner. In addition, there are the connectionist models that include the cellular automata and neural networks, which attempt to respond to the need to account for the important role of spatial detail in many real-world systems. Koomen *et al.,* (2007) distinguish models in a dichotomous manner, as either static or dynamic, transformation or allocation models, focusing on the land use/cover or the land user, deterministic as opposed to probabilistic models, and sector-specific or integrated models. Irwin and Geoghegan (2001) distinguish spatially explicit land use/cover change models into three categories: simulation, estimation, and a hybrid approach that integrates estimated parameters with simulation.

All models of land use/cover have strengths and weaknesses depending on their intended use (Wilson and Weng, 2011). Irwin and Geoghegan (2001) zanalyzed models in terms of their treatment of economic processes of land use/cover change and highlighted a concern that the models paid less attention to understanding the human behavioral component that underlies land-use change. However, they acknowledged that spatially explicit empirical models of land use/cover change that employ explanatory variables, often derived from remotely sensed data and using GIS, and sometimes along with socio-economic drivers, fit the spatial process and land use/cover change "reasonably well". Agarwal *et al.* (2000) also assessed nineteen selected land use/cover models on how well they incorporate space, time, and human decision-making. This includes the nonlinearities of human-environment relationships. To integrate the social, behavioral, and economic aspects of human ecosystems, Agarwal *et al*. (2000) proposed the inclusion of the following patterns and processes: Demography, technology, and economy, political and social institutions; culturally determined attitudes, beliefs, and behavior; and information and its flow.

Because the selected modeling approach should capture the most critical aspects of land use/cover, particularly heterogeneity, interactions, and dynamics (Plantinga *et al*., 2006), researchers have used a combination of models. To address the inability of the Markov model to determine spatial position or characteristics of spatial change and distribution, and to utilize its ability to predict change in quantity and the area proportion of each land use/cover type in the future, Yang *et al*. (2014) combined the Markov model with the cellular automata and AHP in a GIS to predict land use/cover change, with a 72 percent accuracy in land use/cover change of the Jinzhou New District. Hyandye and Martz (2017) used a hybrid Markov Chain and Cellular Automata Analysis (CA-Markov) model to utilize CA's capability to simulate spatial and temporal patterns of land use/cover. While CA models are capable of spatially allocating land use/cover and simulating complex natural phenomena, Markov model helped offset its inability to interpret complicated Spatio-temporal decision-making behaviours and human factors because of focusing on interactions of the local neighborhood of cells (Zenga *et al.*, 2008; Yang *et al*. 2014 and Hyandye and Martz 2017). By applying the hybrid CA-Markov model to Usangu catchment in Tanzania, Hyandye, and Martz (2017) obtained an overall prediction accuracy of 0.9125 and showed forestland and shrubs would decrease by 20.6 and 6.9 percent respectively, while about 10.3 percent of woodlands could be converted to agricultural land, by 2020, compared to 2013. Gashaw *et al*. (2017) also applied the CA-Markov model, in IDRISI module, to project that the 1985-2015 land use/cover change trends in Andassa watershed (Ethiopia) would continue to 2030 and 2045; and respectively result in a cultivated land increase to 83.3 and 85.8 percent compared to 76.8 percent in 2015. Using the Markov chain model built-in Idrisi software Alemayehu *et al*. (2019) predicted, based on 2005-2017 land use/cover, that in 2029, agriculture and forestland in Somodo Watershed of South-Western Ethiopia would increase by 19.6 and 4.9 percent, while grassland and home garden Agroforestry/settlement would decrease by 39.3 and 1.65 percent respectively.

Yalew *et al*. (2016) applied SITE, software for developing and applying land use/cover simulation models, to simulate a potential 1986-2009 to 2009-2025 trajectory for land use/cover for Abbay Basin in Ethiopia using a cellular- automata, and with land suitability rules based on a multi-criteria analysis of biophysical and socioeconomic drivers. After showing that model predicted 84 percent of validation land use/cover map, they (Yalew *et al*., 2016) simulated, among others, that agricultural land would expand at a declining rate, from 69.5 percent in 2009 to 77.5 percent in 2025; and plantation forest will also increase at a much higher rate and triple by 2025, mainly at the expense of natural vegetation, agricultural land, and grasslands.

In Uganda, Li and Oyana (2015) and Li *et al*. (2016) setup an agent-based modeling (ABM) using Agent extension toolkit on ArcGIS and correctly simulated 83 and 84 percent of the observed 2013 agricultural land in the Country, respectively, based on 1996 land use/cover map. Using the AMB, Li *et al*. (2016) simulated that agricultural land use/cover under the deforestation scenario would be higher than under the business as usual scenario. Despite being flexible to set and capable of modeling interactions between both human and natural systems (Valbuena *et al*., 2009) and subsequently able to simulate dynamic temporal and spatial changes of land use/cover, ABMs decision-making framework, and inspection and verification methods require further exploration to improve the reliability of simulations (Yang *et al.*, 2014).

As advances in Remote Sensing (RS) and Geographic Information System (GIS) techniques support numerous land use/cover modeling approaches, researchers and developers of modeling frameworks can combine different modeling methods (Verburg *et al*., 2010). Among these is the combination of methods (Pontius *et al*. 2004 and Bernetti and Marinelli, 2010) involving a multi perceptron neural network (MLP) for a spatial allocation of simulated land cover scores built on Markov chain modeling method, for time prediction, embedded in the IDRISI Land Change Modeler (LCM) software (Eastman, 2009). The MLP is capable of modeling complex nonlinear relationships between variables, is able to detect and model interaction effects among variables, and is robust for modeling the potential transitions (Eastman, 2009). Using these methods, Majaliwa *et al.* (2018) projected that by 2040, subsistence agricultural land is likely to increase by about 1 percent while tropical high forest with livestock activities is expected to decrease by 0.2 percent, and woodland/forest unprotected by 0.07 percent, compared to 2015.

2.4 **Impacts of land use/cover change on streamflow in East Africa and Uganda**

Land use/cover may result in changes in topography and morphology of the landscape which mainly affects the "blue water" or causes changes in vegetation and land use/cover that primarily affects the "green water" through alteration of processes of the hydrological cycle such as infiltration rate, evapotranspiration rates and their patterns (Lastoria, 2008). Runoff, infiltration, percolation, groundwater recharge, and discharge are affected by soil hydraulic properties which are modified by land use (Botsford *et al*., 2003). When altered, these mechanisms can result in an increase or reduction of water resources and can become channels for transporting, or increasing the concentration of pollutants in the water sources.

Over the last five decades, land use/land cover change in East Africa has been reported to cause variable impacts on surface water resources, particularly streamflow in catchments, including in semi-arid areas. Loss of forest and natural vegetation cover has been reported to reduce rainfall interception/evapotranspiration and infiltration, and increase surface runoff in watersheds (Mati *et al*. 2008: Baker and Miller, 2013: Guzha *et al*., 2018). In Tanzania, conversion of natural to agricultural land has increased surface run-off in the Ngerengere Catchment, and flooding in its mountainous areas (Natkhin *et al*., 2018). Using SWAT, Baker and Miller (2013) simulated — that conversion of land use/cover, especially from indigenous and plantation forest to smallholder agriculture between 1986 and 2003, in the River Njoro watershed, resulted in corresponding increases in surface runoff and decreases in infiltration/groundwater recharge. The authors underlined that Mau forested highlands were the most significantly affected, as surface runoff increased by up to 300 percent when deforestation increased – a significant alteration of catchment hydrology.

However, Guzha *et al.* (2018) reported that modeling studies in East Africa have shown that forest cover loss increased annual discharge and surface runoff approximately by 16 and 45 percent, while their percentages also decreased by 13 and 25 percent, respectively, when forest cover increased. In the Suluh Catchment, surface runoff increased by only 4.6 percent, and water yield reduced by 1.5 percent between 1972 and 2003, despite almost all the natural vegetation being lost through being transformed into cultivated land (Abebe, 2014).

In Uganda's Solo river catchment, Barasa *et al.* (2018) estimated an increase in channel planform size from 3.7 in 1986 to 4.2 km^2 in 2013 due to concentration of sediments, bed load materials, bank-instability, and stream-flow by increased rates of rainfall-runoff from agricultural land use/cover and catchment degradation. Further, Barasa *et al.* (2018) through field experiment and rainfall-runoff modeling, estimated that the highest agricultural land use/cover followed by bushlands and thickets land cover types generated the highest runoff over the Malaba river watershed in Uganda. Twesige (2019) also showed that the streamflow trend of the Katonga River Basin greatly increased by land conversion to agriculture.

Research also shows that land use/cover change particularly alters peak flow. In the Mara Basin, reduction in the 1973 forest and rangeland (savannah, grasslands, and shrublands), lost to agriculture by 2000, had resulted in sharp increases in flood peak flows by 7 percent, and an earlier occurrence of the peaks by 4 days (Mati *et al*., 2008). As the conversion of land use/cover reduces stream flow during the dry periods and low peak flow (Guzha *et al*., 2018), the negative effects are more serious in semi-arid and drier areas where rainfall is low and variable. Land use/cover change-induced reduction in dry season streamflow worsens water scarcity (Mango *et al*., 2011), especially in view of climate variability and change in semi-arid areas.

2.5 Impact of climate change on streamflow

Climate change refers to any change in climate over time, whether due to natural causes or as a result of human activity (IPCC, 2001a). Globally, there is a general consensus that climate change is a reality (Stern, 2006; IPCC, 2007 and Pueyo, 2012). Africa is 0.5^{o}C warmer now than a century ago, with interannual and multi-decadal rainfall variations in some regions over the last 100 years (Hulme, *et al*, 2001). By the end of the 21st Century, surface temperatures could increase by 3–4°C over much of Africa (Marshall *et al*., 2012). Yet the Continent could experience a 3 °C temperature rise earlier, as average temperatures in Africa are predicted to increase by 1.5 to 3 °C by the year 2050 and further upwards thereafter (IPCC, 2007).

Although precipitation modeling results face more uncertainty than temperature, the most plausible scenario given by the IPCC shows that the Sahel and East Africa will experience modest increases of approximately 5 percent by the end of the 21st century (Marshall *et al*., 2012). Goulden *et al.* (2009) reported that climate models show that mean annual and seasonal temperatures, and rainfall over east Africa will rise, respectively, by 3.2°C and by 3.1°C (DJF, SON) to +3.4°C (JJA), and rainfall by 7 percent between the 2000s and 2080s. Based on estimates from general circulation models (GCMs), Shongwe *et al*. (2011) reported a positive shift of rainfall distribution in East Africa during the wet seasons, projected increase in mean precipitation rates, and intensity of high rainfall events but for less severe droughts. Climate change is projected to increase temperature and precipitation variability in East Africa (Adhikari *et al.*, 2015).

Despite uncertainty in climate change models projections, a substantial increase in runoff in eastern Africa and parts of semi-arid sub-Saharan Africa could occur (Bates *et al*., 2008). An increase of 1 ^{o}C in temperature at a constant amount of rainfall could result in the reduction of continental-scale runoff by up to 10 percent between 2050 and 2100, climate change impact on streamflow could range from a decrease of 15 percent to a rise of up to 5 percent, above the 1961-1990 baseline (ACPC/UNECA, 2011). Musau *et al*. (2015) used SWAT to simulate that climate change would likely alter streamflow in four Mount Elgon Watersheds (Koitobos, Kimilili, Rongai, and Kuywa), however in different magnitudes and seasons of the year, despite them being closely located. The change in annual streamflow would range from: a decline of down to 59.3 percent under IPCC Special Report on Emissions Scenarios (SRES) B1 in Kuywa to a rise of 92.9

percent under SRES B1 in Rongai in the 2020s; a decline of up to 59.6 percent under SRES A2 in Kuywa to a rise of 135.6 percent under SRES A1B in Rongai in the 2050s; and a decline of up to 59.3 percent under SRES A1B in Kuywa to a rise of 189.6 percent under SRES A2 Rongai in the 2080s.

Based on simulations from 33 GCMs for RCP 4.5 and 8.5, Keith *et al.* (2014) using a Vensim model estimated that precipitation will increase the Blue Nile's stream flow by upto 20 to 25 percent in Ethiopia. The study reported an expected 13 to 18 percent rise in stream flow in the Atbara, Ethiopia, and in the White Nile (Uganda), but moderately constant flows in (approximately 8 percent increase) in Sudan, which is expected to cause a decline of up to 17 percent in Egypt, particularly after 2050, despite the increase in temperature.

In Uganda, human-induced climate change is likely to result in an unprecedented rise in average temperatures by up to 1.5 ºC in 2030 and by up to 4.3 ºC by the 2080s (Mubiru, 2010). The country is also expected to face changes in rainfall patterns and total annual rainfall amounts but these are less certain than changes in temperature (Uganda NAPA, 2007). Climate extreme events are also expected to lead to an increase in both frequency and intensity. Droughts have been reported as the most frequent climate change event occurring in the country with a frequency of occurrence increasing (up to seven droughts) in the period between 1991 and 2000 (Uganda NAPA, 2007 and Mubiru, 2010). The occurrence of heavy rains and associated floods had also been reported to have increased in Uganda (Uganda NAPA, 2007 and Mubiru, 2010).

As in the East African region, literature shows that change in climate in Uganda, and its hydrological impact, varies. Based on projections obtained using the Statistical Downscaling Model to obtain data for the Ssezibwa Catchment from the UK HadCM3 climate model, Nyenje and Batelaan (2009) reported that potential increase in wet season rainfall (March - Mary; October - December) would range from 30 percent in the 2020s to over 100 percent in the 2080s compared to 1961–1990 base period, with a corresponding temperature rise of 1 to 4 ºC. The study applied the WetSpa hydrological model and simulated a potential 20 - 80 percent increase in baseflow, between the 2020s and the 2080s. Using a suite of climate simulations from 30 GCMs (22 RCP4.5 and 30 RCP8.5), Mehdi *et al*. (2019) showed an increase in temperature for the Lake Bunyonyi catchment in 2071- 2100 compared to 1971-2000 would range from between 1 and over 3^{o}C under RCP4.5 scenarios, to between approximately 2.5 and 6^{o}C under RCP 8.4 scenario. The corresponding change in rainfall would range from 0 to over 50 percent, and a decrease of 25 to an increase of over 75 percent, under RCP4.5 and 8.5 respectively. Although simulation with the COSERO hydrological model showed the potential change could result in higher actual evapotranspiration and an overall trend of increasing runoff, Mehdi *et al.* (2019) noted the risk of water shortage in the Ruhezamyenda catchment, the lake's outlet river, would below.

However, in Uganda's rangeland ("cattle corridor") studies involving interviews with local people such as that by Stark (2011) indicate that increased temperatures, declining sources of water, and drying of wetlands, increased frequency of droughts, and unpredictable rainfall patterns are evident. Pastoralist and agro-pastoralist populations in Karamoja were reported to have faced four consecutive years of drought by 2010 (ACTED, 2010). The application of traditional knowledge to make decisions on the planting of crops and movement of animals in search of pasture and water became unreliable in the area (Stark, 2011). Further, perennial rivers and streams turned seasonal while riverbeds that traditionally were reliable dry season sources of water now yield no water (Stark, 2011). Moreover, future climate change is predicted to exacerbate water scarcity and pollution problems, especially in the semi-arid areas, urban centers, and rural communities (Uganda NAPA, 2007). The observed and projected changes in climate, as well as their variability in time and regions, call for studies at various temporal and spatial scales.

Models are useful for estimating trends and changes of climate to aid impacts assessment. On a global scale, Global Circulation Models (GCMs) have been used and they provide adequate simulations of atmospheric general circulation at the continental scale (Mtongori, 2016 and Randall *et al*., 2019). GCMs, try to represent the main components of the climate system in three dimensions by breaking the atmosphere and ocean into a grid distinguished by latitude, longitude, and height, making a rectangular "box" that provides a summary of climate in that particular location (grid) on the earth's surface (Mtongori, 2016 and Randall *et al*., 2019). These dimensions are typically between 250 and 600 km horizontal resolution, 10 to 20 vertical layers in the atmosphere, and sometimes as many as 30 layers in the oceans (IPCC, 2013).

GCMs are constantly being enhanced to incorporate a new understanding of the physical processes at work in the atmosphere, oceans, and the Earth's surface, for example, significant improvements have occurred since IPCC Third Assessment Report (Flato *et al*., 2013). Randall *et al*. (2007) presented three categories or areas of model improvement: the dynamical cores along with the horizontal and vertical resolutions; incorporation of more processes particularly in the modeling of aerosols, and of land surface and sea ice processes; and improved parametrization of physical processes.

According to Flato *et al*. (2013), climate models range from simple energy balance models to complex Earth System Models (ESMs) that require state-of-the-art high-performance computing. When atmospheric and ocean conditions are studied or simulated separately, Ocean or Atmosphere General Circulation Models (OGCM or AGCM) are used respectively (Beraki *et al*., 2013). A higher hierarchy is attained when these are coupled. Coupled Atmosphere-Ocean General Circulation Models (AOGCMs) are used to understand the dynamics of the physical components of the climate system (atmosphere, ocean, land, and sea ice), and for making projections based on future greenhouse gas (GHG) and aerosol forcing (Flato *et al*., 2013). The models are particularly useful in process studies or applications with a focus on a particular region. Up to 23 AOGCMs were widely used in the TAR (Meehl *et al*., 2007 and Randall *et al*., 2007).

ESMs are more advanced models as they "expand on AOGCMs to include representation of various biogeochemical cycles such as those involved in the carbon cycle, the sulfur cycle, or ozone." (Flato *et al.*, 2013). ESMs provide the most comprehensive tools available for simulating past and future response of the climate system to external forcing, in which biogeochemical feedbacks play an important role." Earth System Models of Intermediate Complexity (EMICs) are distinguished by their attempt to embed external components of the earth system to provide an understanding of climate feedback on a very long-term (millennial time) scale or exploring sensitivities in which long model integrations or large ensembles are required. EMICs are often more idealistic or with a low resolution than the AOGCMs and other ESMs.

There is confidence in models because they are founded on acceptable physical laws and principles; can simulate important aspects of the climate system (mean features such as large-scale distribution of atmospheric temperature, precipitation, etc.); and have been found to reproduce present and past climate change (Randall *et al*., 2007 and Flato *et al*., 2013). This gives confidence in the models' suitability for detection and attribution studies; and for quantitative future predictions and projections (Flato *et al.*, 2013). However, models have significant errors that are greater at a small scale (Randall *et al.*, 2007).

Models remain deficient in the simulation of tropical precipitation, the El Niño Southern Oscillation, and the Madden-Julian Oscillation (Wu *et al.*, 2007). Errors occur because many small-scale processes cannot be clearly represented in models but only approximated in large-scale climate processes they interact with as computational power and understanding of the climate system is limited and detailed observations are inadequate or unavailable. Owing to low confidence in global model outputs at smaller scales, other techniques, such as the use of regional climate models, or downscaling methods, have been specifically developed for the study of regional- and local-scale climate change (Laflamme *et al*., 2015; Alemseged and Tom, 2015; Kour *et al*., 2016; and Eyring *et al*., 2019). Nonetheless, models are continually improving as reflected in improved resolution, analysis of climate systems, physical processes, and interactions; increasing computational power is also improving regional to small scale representation (Grose *et al.*, 2014). Climate modelers and scientists have also engaged in comparing the performance of these models. For example, the Climate Model Intercomparison Project (CMIP) since 1995 (Meehl *et al*., 2005) and the Agricultural Model Intercomparison and Improvement Project (AgMIP, Ruane *et al*., 2015).

Climate Model Intercomparison Project (CMIP) results, form part of and inform the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports, where the most notable two are the projections from CMIP phase 3 (CMIP3) that informed the IPCC Fourth Assessment and CMIP phase 5 (CMIP5), which in turn informed the Fifth Assessment Report (Taylor *et al*., 2011; Brekke *et al.*, 2013). While CMIP3 was based on SRES scenarios developed using AOGCMs (Meehl *et al*., 2007), CMIP5 projections were generated using representative concentration pathways (RCP) that use more improved ESMs. Climate Model Intercomparison Project (CMIP) outputs provide data from which scientists, through their analysis, can gain more insights. With more than 20 modeling groups that perform CMIP5 simulations using more than 50 models, CMIP5 generated projections have informed other scientific works, for example, the generation of high-resolution downscaled climate data by the Coordinated Regional Downscaling Experiment (CORDEX, Taylor *et al*., 2011). Like CORDEX, AgMIP supports downscaling of the latest CMIP GCM model outputs using the statistical delta method using a script provided in the AgMIP protocol (Rosenzweig *et al*. 2013 and Hudson and Ruane, 2015).

AgMIP simulations follow a set of Representative Agricultural Pathways (RAPs) developed for consistency with climate modeling, based on the set of SRES emissions scenarios and RCPs used in the IPCC AR4 and AR5, respectively. Representative Concentration Pathways (RCPs), which supersede Special Report on Emissions Scenarios (SRES) projections published in 2000, are four greenhouse gas concentration trajectories adopted by the IPCC for its fifth Assessment Report (AR5) in 2014. The Representative Concentration Pathways include RCP 2.6; RCP 4.5, RCP 6.0, and RCP 8.5. The four RCPs are based on multi-gas concentration scenarios (Meinshausen *et al.*, 2011) and provide a quantitative description of concentrations of the climate change pollutants in the atmosphere over time, as well as their radiative forcing in 2100, spanning from 2.6 to 8.5 W/m2, selected from a wide range of literature (van Vuuren *et al*. 2011). The RCPs have been used to drive climate model simulations planned as part of the World Climate Research Programme's CMIP5. The naming represents radiative forcing target level for 2100, with RCP 8.5 representing a high emissions scenario, while RCP 4.5 denoting a medium mitigation scenario. To assess the potential impact of simulated climate change, hydrological models are used, particularly at the basin level.

Hydrological models are simplified systems to quantify the processes of the hydrological cycle in an entire river basin or parts of it (Lastoria, 2008). This can be achieved based on a set of interrelated equations that try to convert the physical laws, which govern extremely complex natural phenomena, to abstract mathematical forms (Lastoria, 2008). Hydrological models include those that describe water flows, water quality, water ecology, and water economy (Refsgaard, 2007). Authors take different approaches to classify models (Pechlivanidis *et al*., 2011). These classifications are generally based on the model representation of physical processes (their structure), their spatial and temporal description or application (Lastoria, 2008; Pechlivanidis *et al*., 2011 and Refsgaard, 2007).

Like the aforementioned climate models, hydrological models have been classified in different ways. Based on process description, hydrological models may be deterministic or stochastic models, but also a hybrid of joint stochastic-deterministic (Refsgaard, 2007). Pechlivanidis *et al*. (2011) describe deterministic models as those where the results are uniquely determined through known relationships between the states and data such that a given input will always produce the same output if the parameter values are kept constant. Stochastic models, on the other hand, are described as those that use random variables to represent process uncertainty and generate different results from one set of input data and parameter values when they run under "externally seen" identical conditions.

Lastoria (2008) distinguishes models as data-driven models and knowledge-driven models respectively, based on the different ways of using a priori knowledge. The author also distinguished the models into three main categories based on spatial description: lumped models, semi-distributed models, and distributed models. In lumped models, the whole catchment is considered as a single entity (computational unit) with ignored or averaged spatial variations and basin response is evaluated only at the outlet. The SCS curve number method is one example and has been widely used to assess surface runoff in catchments because of its simplicity and a limited number of parameters needed to estimate runoff (Kour *et al*., 2016). A semi-distributed model is an intermediate approach that uses some kind of distribution, either in catchments or in hydrological response units, where areas with the same key characteristics are aggregated to sub-units without considering their actual locations within the catchment (Arnold *et al*., 2011 and Refsgaard, 2007). In distributed models, catchment processes are described at geo-referenced computational grid points within a catchment. Based on temporal description, hydrological models may be event-driven models which can simulate short-term events such as a single storm lasting a few hours to a few days; or continuous-processes models that are capable of simulating continuous events over a longer period and can predict watershed response both during and between precipitation events (Lastoira, 2008).

As various hydrological models have been developed and applied to study the impact of land use/cover and/or climate change, the researcher's choice depends on the purpose of the study and model availability (Ng and Marsalek, 1992). Among hydrological models that are based on one or a combination of the aforementioned characteristics are the Hydrologiska Byran's Vattenbalansavdelning (HBV), the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS), the Soil Water Assessment Tool (SWAT), MIKE BASIN, MIKE SHE, the Distributed Hydrology Soil Vegetation Model (DHSVM), the Precipitation-Runoff Modeling System (PRMS), the Geospatial Stream Flow Model (GeoSFM); the Natural Resource Conservation Service – Curve Number model (NRCS-CN), the Water Balance simulation Model – WaSim (Devi *et al.*, 2015; Kour *et al*., 2016; Guzha *et al*., 2018). Whereas HEC-HMS, Curve Number method (USDA Soil Conservation Service), HBV model, and GeoSFM model are among those that have been used in east Africa, SWAT is the most commonly used in the region (Guzha *et al*., 2018). Examples of studies applying the models to study the impact of land use/cover and climate change in catchments include the HEC-HMS mode in the Kilombero River basin, Tanzania (Yawson *et al.*, 2005); GeoSFM in the Mara Basin, Kenya/Tanzania (Mati *et al*., 2008); the NRCS-CN on the Nyando River Basin, Kenya (Kundu and Olang (2011); and the HBV model in Katonga River basin, Uganda (Twesige (2019). While the HBV, SWAT, GeoSFM, and HEC-HMS are semi-distributed models, which are capable of capturing the spatial distribution of input variable and subsequently a better simulation, the CN method is an empirical lumped model for estimating direct runoff from a landscape (Mati *et al*., 2008; Guzha *et al.*, 2018). Examples, where SWAT has been successfully applied, the semi-arid upper Ewaso Ngiro North basi, Kenya (Mutiga *et al*., 2011) and Gilgel Abay River, Ethiopia (Dile *et al*., 2013).

The SWAT modeling can be done using its ArcGIS interface, ArcGIS-SWAT (ArcSWAT), which allows users to leverage the efficient spatial data analysis and application of remote-sensing data that GIS provides (Olivera *et al*., 2006 and Khatami and Khazaei, 2014). It is capable of simulating hydrological, sediment, and agricultural yields impacts of land-use change and management practices in large and complex watersheds with varying soil, land use, and management conditions over a long time (Nejadhashemi *et al*. 2011). The model can also use readily available data such as climate and LULU in government agencies, and is computationally efficient, and is capable of studying long-term impacts. A little direct calibration is sufficient for the SWAT model to obtain good hydrologic predictions (Devi *et al*., 2015).

CHAPTER THREE

LAND CONVERSION IS CHANGING THE LANDSCAPE IN THE SEMI-ARID LOKERE AND LOKOK CATCHMENTS, NORTHEASTERN UGANDA

Abstract

The Lokere and Lokok catchments, which form the main watershed in the semiarid Karamoja sub-region of Uganda, are experiencing land use and land cover (LULC) change from extensive livestock production to crop agriculture. This paper assessed the change in LULC in the catchments during the period 1984-2013 through unsupervised and supervised classification of satellite images using Idrisi Selva and ArcGIS 10.3 tools and ground-truthing. In addition, perceptions of the local communities were used to obtain a historical account of LULC and to determine the drivers of land use and land cover change. The classified LULC was cross-compared for change detection. Results showed a change in LULC driven by sedentarisation and diversification of livelihoods, as pastoralist communities adopt crop cultivation following promotion by government and non-state development agencies. Key changes include conversion of woodlands and bushlands into small-scale croplands, with degradation of woodland and bushlands increasing grassland area. Grasslands, which covered the largest land area, from 43.64 percent in 1984 to 60.05 percent in 2013, was the most dominant. Small-scale farming was steadily rising from 9.67 percent area coverage in 1984 to 15.69 percent in 2013. The annual rate of increase of farmland during this period was 2.1 percent, however, the highest rate of the increase was experienced between 1994 and 2003 at 4.2 percent when 514.2 km2 (37.53 percent) was converted to farmland. Loss of woodland, bushland, and degradation contributes significantly to the inherent water shortage in the Lokere and Lokok catchments and Karamoja area in general. This has adverse impacts on communities' livelihoods. Central and local governments and non-state actors in the catchments should regulate LULC change through the formulation of land use policies; participatory land-use planning; and involvement of the communities in sustainable land management practices.

Key words: Karamoja, land use and land cover change, land degradation, livelihoods, small-scale farming, Uganda.

3.1 Introduction

Globally, grasslands, forests, bushlands, and woodlands are being converted into croplands (Tsegaye, 2010 and Baldi *et al.* 2013) as the demand for food to feed the ever-increasing human population rises. In East Africa, Oslon (2006) reported that the spatial pattern of land-use change over the past 50 years had been characterized by increasingly intensively managed landscapes except in protected areas or in extremely marginal environments. They highlighted that the most important land-use conversions include, among others, the expansion of cropping into grazing areas, particularly in the semi-arid to sub-humid areas.

In Uganda, Lokere and Lokok catchments which is the main watershed in the semiarid Karamoja region is experiencing significant land use and land cover (LULC) change with reported shifting from extensive livestock production to crop agriculture and degazettement of protected areas (Majaliwa *et al*., 2012). The change in LULC includes degradation of woodlands into bushlands and grasslands and conversion into cultivated land, driven by particularly the promotion of cropping and sedentarization of pastoralists in efforts to address conflict among the Karamojong community in Uganda and the Pokot of Kenya (Stark, 2011; Vidal, 2011; Egeru, 2014). This change presents unintended negative impacts on the landscape and its adapted uses such as grazing and water conservation and thus threatening livelihoods (Penning de Vries *et al*., 2003). This trend is expected to continue given a wide range of efforts to popularize alternative livelihood strategies to pastoralism such as poultry farming, aloe vera production, crop and vegetable production (ACTED, 2010).

Some studies on LULC have been undertaken in Karamoja region and the “Cattle corridor” that comprise Uganda’s drylands area (Zziwa *et al*., 2010; Byenkya *et al*. 2014; Egeru *et al*., 2014; Nakalembe *et al.* 2017). Nakalembe *et al.* (2017) reported a 299 percent increment in cropland in Karamoja between 2000 and 2011. Egeru *et al*. (2014) and Byenkya *et al*. (2014) using Landsat imagery also observed an increase in small-scale farming, and transitions in all land use classified in the studies. Further, Zziwa *et al.* (2010) assessed land-use changes in Nakasongola District and reported woody encroachment as the major change in the area. The present study qualitatively established existing land use and land cover types, identified factors that have influenced it, and determined land use and land cover change, and trend from 1984 to 2013.

3.2 Materials and methods

3.2.1 Study area

Lokere and Lokok are the main catchments in the Karamoja sub-region and connect downstream to part of Teso sub-region (Figure 3.1), in Uganda's dryland strip, known as the "Cattle Corridor". Karamoja sub-region is part of the Karamoja cluster, a semi-arid area of land that straddles the borders between south-western Ethiopia, north-western Kenya, south-eastern South Sudan, and north-eastern Uganda. Lokere and Lokok catchments vegetation generally consists of savannah grasslands, woodlands, thickets, and shrublands which largely comprise *Acacia–Combretum–Terminalia* species associations, with principally C4 grass species (Egeru, 2014).

The Karamoja sub-regions topography consists of a plain sloping south-westward, intermixed with isolated highlands that include Mt. Moroto, Mt. Iriri, Mt. Kadam, and Mt. Labwor, in the higher elevated west. These highlands consist of rocks of the crystalline basement complex. Rivers and streams in the catchments originate from the highlands and are mainly ephemeral upstream and perennial in the downstream southwest. The catchments' streams are important sources of water in the semi-arid area, especially during the dry season (Mbogga, 2014). The catchments' hydrology oscillates with the stochastic climate events. Consequently, most of the rivers in the region are dominated by baseflow components for much of the year with a correlative response pattern to groundwater. Often than not, standing water with slow seepage characteristics is retained in the valley areas by underlying low permeability clay-rich soils of the region (Gavigan *et al*., 2009).

The sub-region experiences hot and dry weather characteristics of most semi-arid regions in Eastern Africa. Rainfall in Karamoja sub-region is unimodal, occurring from March to November and, ranging from < 500 mm in eastern Karamoja, 500-800 mm in central Karamoja to 700-1000 mm in west Karamoja and the isolated highlands. The Karamoja region has uneven rainfall and high run-off. Mean annual rainfall downstream of the Catchment, in Teso subregion, is about 1100-1200 mm, distributed between two seasons of March to July and September to November (Kisauzi *et al*., 2012). The temperatures are generally high throughout the year with an annual average of 28°C-33°C for minimum and maximum temperature respectively; leading to high evapotranspiration levels averaging 2072 mm per annum (Gavigan *et al*., 2009; Egeru, 2014 and Mbogga, 2014). Rainfall variability in the region leads to heterogeneity of landscape resources that influence pastoralism as both a coping and adaptation strategy (Grade, 2008; Egeru *et al*., 2014; Egeru *et al*., 2015).

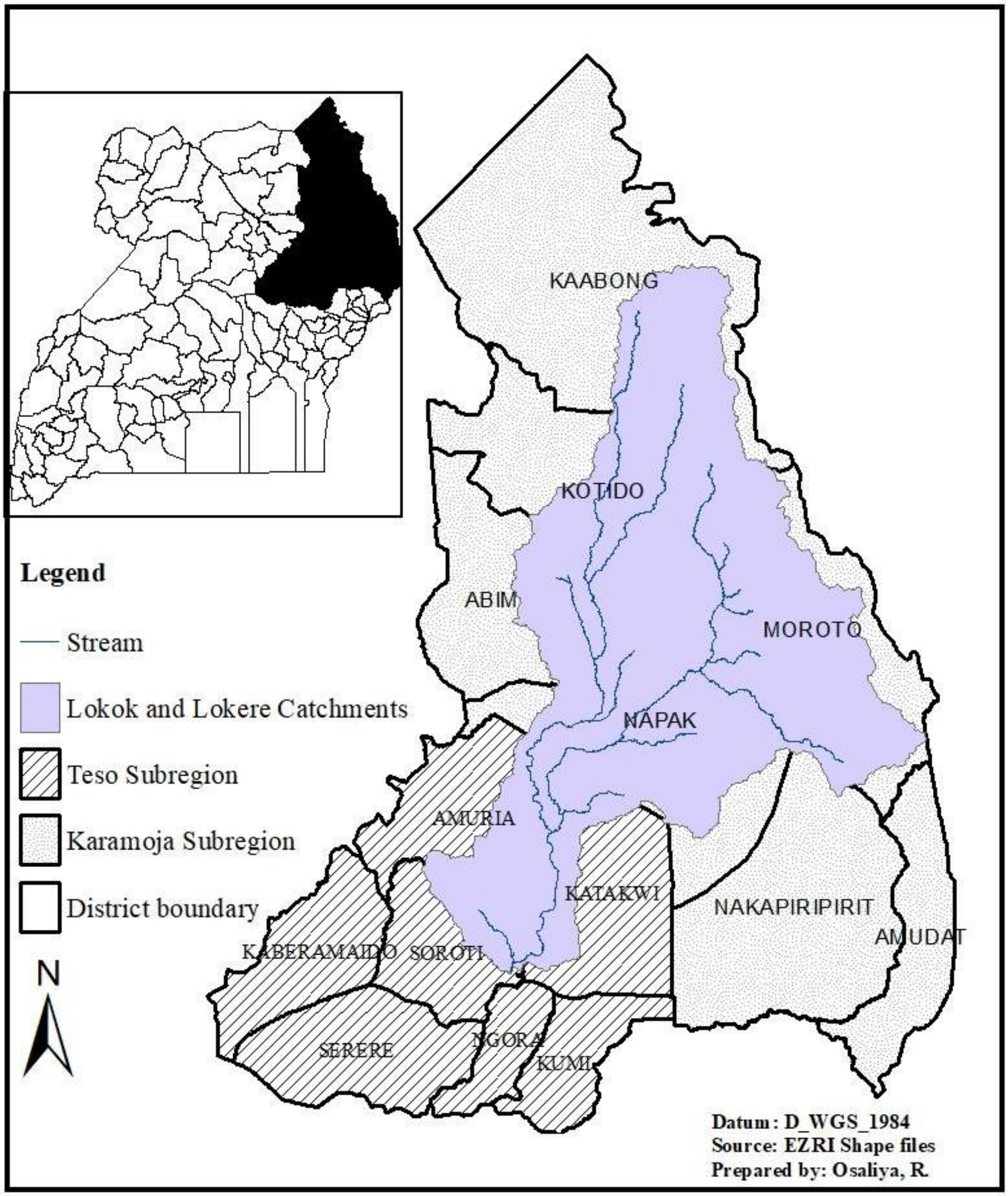


Figure 3.1: Location of study area Karamoja and Teso Subregions of Uganda

3.2.2 Determining land use/cover change

To assess land use and land cover change in the Catchment, spatial and temporal trends of land use/cover change in the period 1984-2013 were determined based both unsupervised and supervised classification (to optimize the strength of both approaches) of satellite images using Idrisi Selva and ArcGIS 10.3 tools and ground-truthing. Qualitative accounts were used to obtain a historical account of land-use change to aid ground-truthing and to identify drivers influencing land-use changes. The classified land cover aswas cross-compared in ArcGIS 10.3 for change detection. 1984-2013 was chosen to capture periods of increase of encroachment and degazettement of parts of conservation areas between 1972 and the early 1990s as well as periods after the 2001-2002 disarmament (OPM, 2007 and Rugadya and Kamusiime, 2013).

3.2.2.1 Perceptions of the community on land cover/use change and its drivers

Perceived LULC and its causes were obtained from the community and local government officers in charge of key departments through participatory mapping, focus group discussions (FGD), a combination of historical time lines and seasonal calendar tool, and key informant interviews. Each of the methods were applied with separate sets of participants, as described below.

Participatory mapping was used to understand the land use/cover categories, and to establish historical land use/cover through participant recall of the land use/cover over the years. Eleven (11) participatory mapping exercises were undertaken in eleven of the 45 sub-counties wholly or partly covered by the Catchment, following a modified approach described by Vajjhala (2005) and NOOA (2009).

Figure 3.2: Participatory mapping of land use/cover (a - in Kalapata, and b - in Panyangara, on 4th & 5th October 2013 in Kaabong and Kotido Districts respectively)

Each mapping session involved at least five participants who were at least 40 years old, assumed to be able to recall past LULC. The participants were mobilized with the help of the local government administration and were selected based on the perceived ability to comprehend and follow the exercise to the end. For the sub-counties in Karamoja sub-region where illiteracy is high, a local-based timeline of historical events was developed with the participants to present the different years and periods under study.

Using the historical events corresponding to 1984, 1994, and 2003, participants were asked to map cultivation land, grassland (grazing land), bushland, and woodland; and to show where shifts had occurred (Figure 3.2) over the years (1984 to 1994 and 1994 to 2003). During this process, participants were asked to identify LULC drivers and explain how the drivers influenced the LULC changes. A drive was then taken with some of the participants across representative areas of mapped LULC types for ground truthing and collection of GPS points. The coordinates for locations of the mapped LULC types were taken using a hand-held GPS device. For each of the coordinates taken, the LULC type for 1984, 1994 and 2003 was recorded. For areas that could not be accessed, the LULC types were digitized on the image by visually relating information on the participatory map and a topographic map as reference. The coordinates were used to digitize training sites during supervised image classification, and for accurate assessment of the preferred unsupervised land cover/use maps.

Interviews were undertaken with purposely selected 18 key informants – a sufficient number to inform the study as about ten are adequate to represent a community perspective (Guest *et al.*, 2006 and Muellmann *et al.*, 2021). They included one elder in each of the eleven sub-counties identified using snowballing technique; district local government officials in charge of agriculture, natural resource management, environment, land, and community development who had worked in the district for at least five years. The sampled districts were Moroto**,** Napak, Kaabong, Kotido, and Amuria.

Eleven (11) Focus group discussions were also conducted in the sub-counties where participatory mapping was undertaken, with 10 to 12 local people of at least 40 years of age. They were mobilized and selected as described for participatory mapping. Key informant interviews and focus group discussions were used to generate data on land uses that have occurred in the periods dating 0-10 (2010-2013), 10-20 (1994-2003), and 20-50 (the 1970s-1890s) years back and the internal and external causes of the perceived land use/cover changes.

To further describe how land use/cover patterns have evolved since the 1980s, historical timelines and seasonal calendars techniques were used, in the eleven (11) sub-counties where participatory mapping was undertaken. They were applied with five (5) who were also mobilized and selected as described for participatory mapping. Combined historical timelines and seasonal calendars were used to establish a qualitative description of trends of LULC in the 1980s, 1990s, 2000s, and 2010s (current) and patterns of LULC change for each calendar month, based on a perceived average trend for a calendar month in each decade. The procedure followed was a modified method for seasonal and historical timelines described by CARE International (2009).

3.2.2.2 Determining land use/cover change and trends

In addition to community assessment of land use/cover change, satellite imageries were used for land-use/cover change detection. Four series of Landsat images covering 1984, 1994, 2003 and 2013 were used. The images for the study area (Table 3.1), with less than 20 percent cloud cover, were downloaded through Earth Explorer (http://earthexplorer.usgs.gov/) and Global Visualization (GLOVIS) (http://glovis.usgs.gov/) websites. Blue, Red and Green (B,R,G) band combinations were used as they distinguish soil from vegetation and discriminate vegetation slopes (Barsi *et al.*,2014).

Table 3.1: Description of Landsat images used in the study

Year	Sensor	Path/Row	Acquisition date	Bands used
1984	TM	170/058	1984-12-31	1,3,2 (B,R,G)
	TM	170/059	1984-09-10	
	TM	171/057	1984-06-13	
	TM	171/058	1984-06-13	
	TM	171/059	1984-06-13	
1994	TM	170/058	1994-09-22	1,3,2 (B,R,G)
	TM	170/059	1994-09-22	
	TM	171/057	1994-12-18	
	TM	171/058	1994-12-18	
	TM	171/059	1995-04-09	
2003	ETM	170/058	2003-01-10	2,4,3 (B,R,G)
	ETM	170/059	2003-01-10	
	ETM	171/057	2003-01-17	
	ETM	171/058	2003-01-17	
	ETM	171/059	2003-01-17	
2013	OLI_TIRS	170/058	2013-05-21	2,4,3 (B,R,G)
	OLI_TIRS	170/059	2013-05-21	
	OLI_TIRS	171/057	2013-12-22	
	OLI_TIRS	171/058	2013-05-28	
	OLI_TIRS	171/059	2013-12-22	

(Source: Earth Explorer - http://earthexplorer.usgs.gov/ and GLOVIS - http://glovis.usgs.gov/)

3.2.2.3 Image classification

The acquired images were prepared and processed to meet the specific needs of the study using Idrisi Selva and ArcGIS 10.3 software. This included: image stacking; sub-setting using operations of Idrisi Selva and unsupervised classification using the ISOCLUST operation in Idrisi Selva was performed on the three of the single band mosaics for up to eight or more spectral classes. Supervised classification was also undertaken by defining regions of interest around areas of reference training sites identified during fieldwork. The classes were cultivated, grassland, bushland and woodland as well as classes for cloud cover and cloud shadow. The land cover/use categories were identified based on the 1996 land use map for Uganda (NBS, 2002).

The two classifications were then loaded and imported into ArcGIS 10.3 and compared. The unsupervised classification, because of having several spectral classes, was able to provide a better quality classification. Thus eight separable classes (small scale farming, grassland, bushland, woodland, wetland, built up, cloud, and cloud shadow) were identified.

The other spectral classes were aggregated into these eight whereby the associated spectral class was identified based on its digital reflectance number (DN) relative to the known class, and neighboring classes (Richards and Jia, 2006). Cloud cover and cloud shadow at every location on the map were aggregated to classes that they were observed to obscure, by editing in ArcGIS 10.3.

Preliminary land-use/cover maps were validated using ground reference data (X, Y coordinate points collected using a Global Positioning System (GPS) device, from areas that were accessible. This was done for 2013 land use/ cover. Corresponding detailed field notes and still photos were also taken. A total of 93 points was picked using a GPS device. Validation of land cover/use classes for 1984, 1994, and 2003 maps were based on ancillary data (pre-classified images, google earth, and topographic maps) and communities' participatory mapping. In addition, 238 random points were generated using ArcGIS.3. A combination of visual interpretations of which were obtained from the Department of Land Surveys and the Uganda Bureau of Statistics (UBOS), was applied to identify the land use/ cover classes represented by the random points. Thus, a total of 331 points were used for accuracy assessment.

The triangulation approach of using interviews and focus group discussions further helped validation of historical land cover/use. For example, areas north of Kotido town were stated as perpetually cultivated areas, while the forest above Kalapata sub-county, in Kaabong District, was stated to have since the 1970's been a woodland (described as forest by the residents). Furthermore, claims by the study participants were cross checked on topographic maps, for known locations.

In order to improve the classification accuracy and specificity of the land use/cover classification of the images, a post-classification refinement was undertaken (Harris and Ventura, 1995). This involved visual analysis and comparison with topographic maps, data from participatory mapping, google earth, and local knowledge of the catchment.

3.2.2.4 Detection of land use/cover change

Change in land use/cover was established by cross comparing pairs of land use/cover maps for each of the periods of 1984-1994, 1994-2004; 2003-2013 and 1984-2013 using ArcGIS 10.3 Spatial analyst tool > Zonal, tabulate area, to generate land-use change matrices for the pairs.

3.3 Results

3.3.1 Qualitative account of perceived land cover/use change and its drivers

The communities identify four traditional land uses in the catchment, which could be seen in the community activity patterns (Table 3.2). These are grazing, cultivation, hunting, and settlement. The other land use stated by the inhabitants of the catchment is tree planting as a recent land use practice. And, the major land uses varied among communities, and with time. Nonetheless, the four land uses have existed over several years including in the 1970s. Therefore, they have existed throughout the period (1980s -2013) considered for this study.

Table 3.2: Community activity patterns over a calendar year, averaged for each period

Month in Ngakari-mojong	Lokwang	Lodunge	Lomaruk	Locoto/ Titima	Titima /Eliel	Lolingacino/ lomodogec	Lorengerot	Lopoo/ Lotiak	Lolobai/ Losuban	Lotyak/ Lopo	Lorara	Lomuk
Month in English	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
!980s	T	T	T, Cl,	Tr	S	S	S, H	H. T	D, H	D, Hu	D, S.	D, T
1990s	T, Cl	T, Cl	Tr, Cl	S, Cw	S, Cw, H	H	T	Ts, H	Ts	Hu, Ts.	Ts, H.	D. T
2000s	T, Cl	T, Cl	Cl, Tr	C, S	Cw, S	Cw, H	Cf	H, Ts	H.	Hu, Tr.	H, Ts	D. T

Activities: T - transhumance grazing; S - sedentary grazing, Cl - clearing of bushes/gardens for cultivation, Cw - crops flowering, H - harvesting, hunting, Hu - hunting, Ts – Mixed transhumance and sedentary.

Over the study period, grazing was considered the major land use in the grasslands. Crop cultivation received less attention in preference to grazing due to a pastoral livelihood especially in the upstream of the catchment. The people turned to transhumance pastoralism. They were settled and grazed near homes, with community kraals. However, at the turn of the dry season, when pastures reduced in the community grazing areas, and watering points dwindled, men particularly drove cattle southwards in search of pastures and water. However, the upstream community of Kalapata sub-county in Kaabong district underlined that they have traditionally practiced cropping in sedentary agro-pastoral livelihood. Still, they indicated that cultivation was increasing.

All the eighteen (18) persons interviewed as well as all the eleven focus group discussions underlined that the land use types remain but with a shift towards cultivation. The communities are now engaged in crop cultivation more than in the past. They stated that settlements have increased, hunting has reduced and a sedentary lifestyle now overrides the pastoral one. One elder articulated: “cultivation is increasing because people are congested and people cannot go to vacant areas; commercial crops introduced and people are cultivating in larger quantities”.

Seven causes (drivers) of land-use change were identified by the study participants. These were: increase in rainfall, the soil being fertility, new agricultural technology, promotion of crop cultivation by government and Non-profit organizations, increase in agribusiness, rise in population, and return of peace in the sub-region.

Interviewees upheld that soil in the catchment was fertile and good for cultivation. ew technology which included the use of oxen which were not used fifty years ago, and the growth of fast-maturing crops encouraged cropping. The promotion of agriculture through among others advisory services by the Government (through the National Agricultural Advisory and Development Services, NAADS) and non-profit organizations resulted in increasing interest in cropping among the local populations. Several NGOs promoted cultivation through training. Promotion and new technologies resulted in crop diversification including the introduction of commercial crops (mostly sorghum in the past, now beans, cassava, groundnuts, Irish, sweet potatoes, millet, seasam, and sunflower) and promotion of agribusiness.

Sedentarization of animals and reduction in the number of animals following disarmament was also stated to have contributed to communities moving to green belts where they can cultivate crops. In addition, increasing education promotes sedentarization from pastoral mode of herding, and thus increasing the growing of crops. Key informants further stated that increase in population obviously translated into increased cultivation to feed more numbers of people. They also argued that peace, following the disarmament that started in 2001 had enabled settlement and consequently the growing of crops.

3.3.2 Land use/cover change from 1984 to 2013

The land use and land cover maps for the Lokere and Lokok catchments between 1984 and 2013, and the areas under each land cover and land use are presented in Figure 3.3 and Table 3.3 respectively. The major land uses/cover consisted of grassland (grazing land), which was the most dominant, covering from 43.64 percent in 1984 to 60.05 percent in 2013. Grassland increased in every period, with its largest increase – 27.31 percent– occurring between 1984 and 1994 (Table 3.4), at an annual rate of 2.5 percent (Table 3.5). It then continued to increase at a low rate, 0.5 percent and 0.4 percent in the 1994 to 2003 and 2003 to 2013 periods respectively. The overall annual rate of increase of grassland from 1984 to 2013 was 2.1 percent.

Grassland was distantly followed by bushland, throughout the years despite continually reducing from 24.39 percent in 1984 to 17.59 percent in 2013. By 2013, bushland had reduced by 27.7 percent compared to 1984, presenting an annual rate of loss of 0.9 percent. The largest loss of bushland however occurred in the 2003 to 2013 period, when 17.8 percent was lost, representing an annual rate of loss of 1.8 percent.

Woodland, which came third in area coverage in the earlier years, at 19.86 and 10.20 percent in 1984 and 1994 respectively was overtaken by small-scale farming – the fourth dominant in the earlier year. Woodland then became the fourth dominant in 2013 and 2013 with respective percentages of 4.65 percent and 4.49 percent. The land use cover type experienced the greatest percentage reduction between 1984 and 1994 and between 1994 and 2003, amounting to respective declines of 48.65 percent and 54.38 percent and corresponding percentage annual rates of loss of 4.86 and 21. 5. The overall annual rate of loss of woodland between 1984 and 2013 was 2.6 percent, as 77.3 percent of woodland was lost.

Small scale farming steadily rose from 9.67 percent area coverage in 1984 to 15.69 percent in 2013. The annual rate of increase during this period was 2.1 percent, however, the highest rate of increase was experienced between 1994 and 2003 at 4.2 percent when 514.2 km^2 (37.53 percent) became farmland.

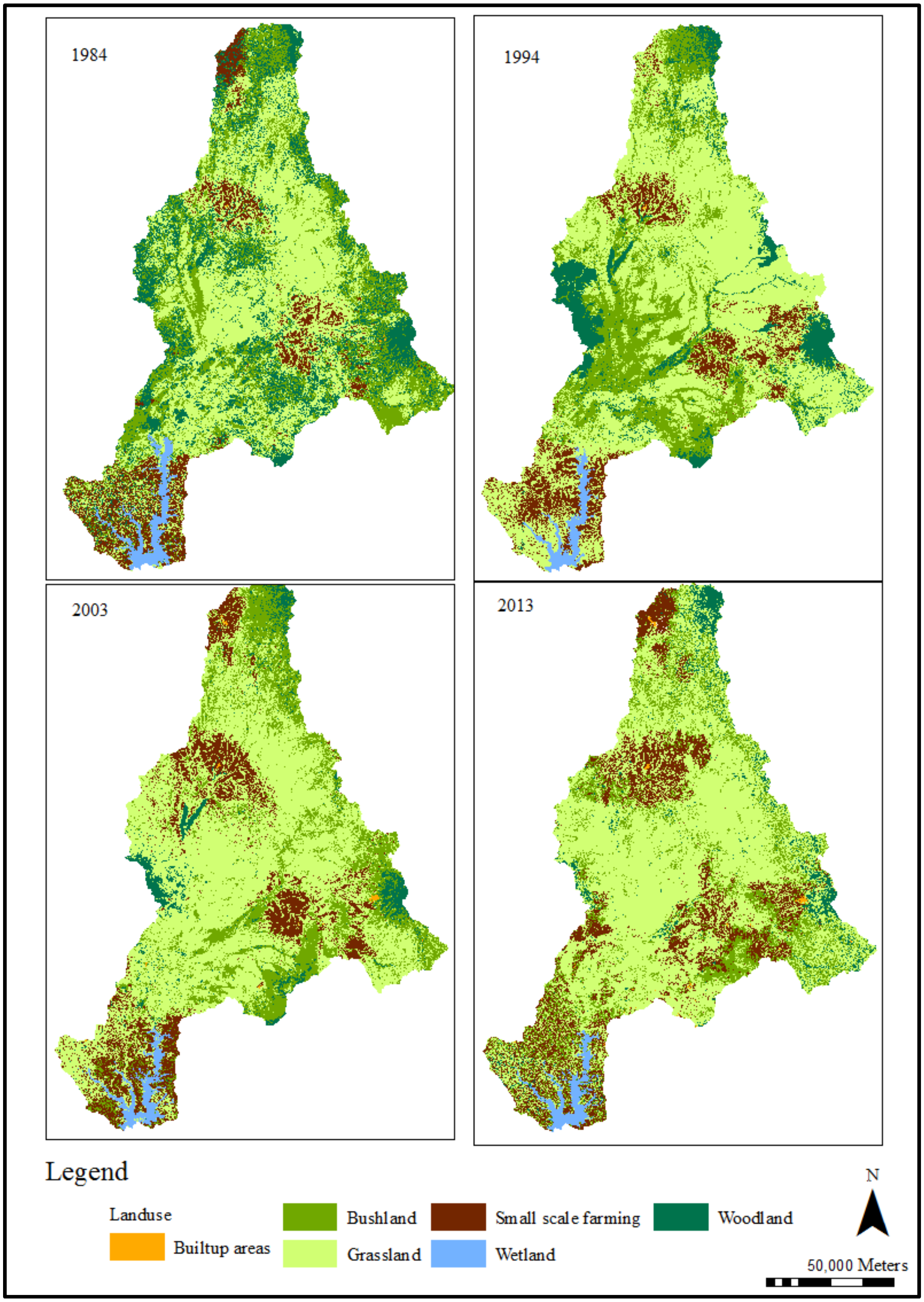


Figure 3.3: Land cover/use maps for the study areas of 1984, 1994, 2003 and 2013

Built-up areas covered the least area in the earlier years – 0.04 percent and 0.05 percent in 1984 and 1994 respectively – but overtook wetland areas in the later years to become the second least dominant, covering 0.12 percent and 0.20 percent in 2003 and 2013 respectively. The Wetland area remained relatively stable following a substantial decline from 2.39 percent in 1984 to 1.90 percent in 1994. Over the 1984 to 2013 period, Wetlands reduced at an annual rate of 0.6 percent while built-up areas increased by 14.7 percent.

It was observed that wetlands covered downstream of the catchment, in Amuria and Katakwi districts. Bushlands and woodlands were prominent along valleys and streams, although woodlands also nominated higher grounds, particularly of Mount Moroto area and upstream in Kalapata Subcounty Kaabong District. Grasslands were spread throughout the catchment but were more dominant in the center of the catchment, as one moved from Moroto, through Kotido towards Kaabong districts.

Table 3.3: Areas (km^2) under the different land cover/use in the study years

	1984	1994	2003	2013
Built-up areas	5.1 (0.04)	7.0 (0.05)	16.6 (0.12)	27.4 (0.20)
Bushland	3343.3 (24.39)	3053.7 (22.28)	2937.4 (21.43)	2414.1 (0.20)
Grassland	5981.3 (43.64)	7614.6 (55.56)	7962.1 (58.10)	8241.5 (0.20)
Small scale farming	1325.4 (9.67)	1370.1 (10.00)	1884.2 (13.75)	2153.0 (15.69)
Wetland	328.2 (2.39)	260.5 (1.90)	266.1 (1.94)	272.1 (1.98)
Woodland	2722.6 (19.86)	1398.1 (10.20)	637.9 (4.65)	616.4 (4.49)
Total	13705.8 (100)	13704.1 (100)	13704.2 (100)	13724.5 (100)

Figures in parentheses are percentages of the area under respective land cover/use

Table 3.4: Change in the area under different land cover/use in Lokok and Lokere catchments during the 1984-2013 period

	From 1984 to 1994	From 1994 to 2003	From 2003 to 2013	From 1984 to 2013
Built-up areas	2.0 (38.96)	9.6 (135.84)	10.8 (65.07)	22.3 (440.99)
Bushland	-289.6 (-8.66)	-116.4 (-3.81)	-523.2 (-17.81)	-929.2 (-27.79)
Grassland	1633.3 (27.31)	347.5 (4.56)	279.4 (3.51)	2260.2 (37.79)
Small scale farming	44.7 (3.37)	514.2 (37.53)	268.8 (14.27)	827.6 (62.45)
Wetland	-67.7 (-20.62)	5.6 (2.15)	6.0 (2.27)	-56.1 (-17.08)
Woodland	-1324.4 (-48.65)	-760.2 (-54.38)	-21.5 (-3.38)	-2106.2 (-77.36)
Total	-1.7 (-0.01)	0.2 (0.00)	20.3 (0.15)	18.7 (0.14)

Figures in parentheses are percentages of area under respective land cover/use

Table 3.5: Rate of change of land use/cover in Lokok and Lokere catchments during the 1984-2013 period

	1984-1994	1994-2003	2003-2013	1984-2013
Built-up areas	3.5	15.1	6.5	14.7
Bushland	-0.8	-0.4	-1.8	-0.9
Grassland	2.5	0.5	0.4	1.3

Small scale farming	0.3	4.2	1.4	2.1
Wetland	-1.9	0.2	0.2	-0.6
Woodland	-4.4	-6.0	-0.3	-2.6

3.3.3 Land cover/use transitions

The dynamics of land use/cover change in the 1984-2013 period may be better understood from the tabulation of transitions from one land use/cover type to another. Tables 3.5 – 3.8 show land uses /cover that gained from, or lost to, others in the subsequent years. In the 1984 to 1994 period, much of the 48.65 percent decline in woodland was transformed into small-scale farming land as 44.7 percent of 1984 woodland became small-scale farming land in 1994, 27.3 percent became bushland, while 23.9 percent remained as woodland (Table 3.6). However, woodland also gained 13.1 percent of bushland in 1994, and 5.3 percent of grassland area in 1984. Built-up area conversion into woodland, bushlands, and grassland of 12.5, 1.8, and 22 percent respectively could be due to the vegetation that is left to grow within the built-up areas.

Table 3.6: Transitions of land use/cover from 1984 to 1994

		Land use/cover types in 1994 (percentage)						
	Land use types	Built-up areas	Bushland	Grassland	Small scale farming	Wetland	Woodland	Total
Land use/ cover types in 1984 (percentage)	Builtup areas	**57.5**	1.8	22.4	5.8	0.0	12.5	100
	Bushland	0.0	**27.1**	53.8	5.8	0.2	13.1	100
	Grassland	0.0	22.8	**64.9**	6.8	0.2	5.3	100
	Small scale farming	0.1	2.7	45.7	**49.1**	1.6	0.7	100
	Wetland	0.0	0.9	25.4	7.6	**65.8**	0.3	100
	Woodland	0.0	27.3	44.7	3.9	0.2	**23.9**	100

Grassland was the land use type that retained the highest percentage after wetlands (which retained 65.8 percent), 64.9 percent, with much of that which was converted, 22.4 percent, becoming bushland. Some 6.8 percent of 1984 grassland became small-scale farming land in 1994. The latter retained 49.1 percent of its total area in 1984 as small-scale farming land in 1994 but lost 46 percent to grassland. Gains by small-scale farming were third lowest after wetlands and built-up areas, and ranged from 7.6 percent of wetland area to 5.8 percent of bushland. Up to 25.4 percent of wetland was converted into grassland. Further 53.8 percent of bushland became grassland, although 22.8 percent of grassland and 27.3 of woodland became bushland.

The land use/cover transitions in the 1994 to 2003 period were such that woodland and bushland retained the least proportions of their area covered in 1994, at 33.3 percent and 34.9 percent respectively (Table 3.7). Much of the loss in these land use/cover types was to grassland, which in 2003, gained 59.2 percent and 34.4 percent of areas covered by bushland and woodland in 1994. Despite incurring a huge loss, woodland gained quite a little, mostly, the 3.6 percent of the 1994 bushland. Small scale farming lost more to grassland, 25.1 percent, but also gained from it, as 11.7 percent of 1994 grassland was converted into small-scale farming land in 2003. Wetland which retained 72.6 percent of its coverage, lost mostly to grassland, 15.2 percent, and small-scale farming, 8.0 percent. This suggests shrinking and encroachment of wetlands.

Table 3.7: Transitions of land use/cover from 1994 to 2003

		Land use/cover types in 2003 (percentage)						
	Land types	Built-up	Bushland	Grassland	Small scale farming	Wetland	Woodland	Total
Land use/ cover types in 1994 (percentage)	Built-up areas	**81.6**	5.5	4.5	8.1	0.0	0.2	100
	Bushland	0.0	**34.9**	59.2	2.2	0.0	3.6	100
	Grassland	0.1	17.8	**68.8**	11.7	0.8	0.8	100
	Small scale farming	0.2	8.3	25.1	**64.8**	1.2	0.4	100
	Wetland	0.0	2.4	15.2	8.0	**72.6**	1.8	100
	Woodland	0.1	30.7	34.4	1.4	0.0	**33.3**	100

In the 2003 to 2013 transition period, wetland area nearly remained unchanged as 97.6 percent of 2003 wetland coverage remained, with some gains to it coming, mostly from small scale farming, 0.2 percent, and grassland and woodland, at 0.1 percent apiece (Table 3.8). Like in the earlier periods, bushland and woodland again (2003 to 2013) retained the least area under the land uses, at 25.5 percent and 37.7 percent respectively. Again, much of the loss was to grassland, which in 2013 gained 56.7 percent and 45.3 percent of 2003 bushland and woodland respectively. Small scale farming land, the third most volatile in the period, also lost, 38.9 percent, to grassland, from which it also gained 12.4 percent.

Table 3.8: Transitions from land use/cover from 2003 to 2013

		Land use/cover types in 2013 (percentage)						
	Land types	Built-up	Bushland	Grassland	Small scale farming	Wetland	Woodland	Total
Land use/ cover types 2003	Built-up areas	**78.1**	1.8	8.9	10.6	0.0	0.6	100
	Bushland	0.1	**25.5**	56.7	8.9	0.0	8.7	100
	Grassland	0.1	16.6	**69.6**	12.4	0.1	1.3	100

(percentage)	Small scale farming	0.2	13.7	38.9	**46.4**	0.2	0.6	100
	Wetland	0.0	0.2	1.6	0.3	**97.6**	0.3	100
	Woodland	0.1	12.8	45.3	4.0	0.1	**37.7**	100

Table 3.9 provides the long-term land use/cover change transitions, from 1984 to 2013. The built-up area, which is expected, mostly remained at large, 86.2 percent was not converted to other uses. It gained small percentages of all the others except wetland, adding to itself 0.5, 0.2, and 0.1 of small scale farming, woodland, and grassland and bushland respectively. The most dominant land use/cover type, grassland also retained a high percentage of its area, 70.4 percent, despite losing the rest to mostly bushland – 15.0 percent – and small scale farming – 12.6 percent. However, grassland also gained 34.6 percent of small-scale farming land and 58.3 percent of bushland. In addition, woodland, which retained 10.5 percent of its 1984 area, lost 56.5 percent to grassland in 2013, but only gained 1.7 percent of grassland. It's observed that woodland, followed by bushland continually transformed into grassland, and small-scale farming land, with reverse conversions only occurring minimally. Wetland area (64.6 percent) remained relatively stable, and the percentage lost was to grassland (20.4), bushland (7.3), small-scale farming (5.5) and woodland (2.1). It's from these that it gained some areas, probably as regenerated wetland areas.

Table 3.9: Transitions of change in land use/cover from 1984 to 2013

		Land use/cover types in 2013 (percentage)						
	Land types	Built-up	Bushland	Grassland	Small scale farming	Wetland	Woodland	Total
Land use/ cover types 1984 (percentage)	Built-up areas	**86.2**	1.6	6.0	5.4	0.0	0.9	100
	Bushland	0.1	**22.3**	58.3	12.8	0.4	6.0	100
	Grassland	0.1	15.0	**70.4**	12.6	0.2	1.7	100
	Small scale farming	0.5	13.8	34.6	**47.4**	2.2	1.4	100
	Wetland	0.0	7.3	20.4	5.5	**64.6**	2.1	100
	Woodland	0.2	20.7	56.5	11.9	0.2	**10.5**	100

3.4 Discussion

There were six major land uses/cover in Lokere and Lokok catchments over the 1984 to 2013 period: built-up areas, bushland, grassland, small-scale farming, wetland and woodland areas. These are consistent with uses and land cover identified by similar studies carried out in the subregion (Egeru, 2014, NBS, 2002) and rangelands in eastern Africa (Tsegaye, *et al.*, 2010). Grassland which covered the largest land area, from 43.64 percent in 1984 to 60.05 percent in

2013 was the most dominant. The dominance of grassland in the Catchment is expected, as water shortage limits plant (woody and bush) growth in grassland rangelands (Balks and Zabowski, 2016).

The overall annual rate of increase of grassland from 1984 to 2013 was 2.1 percent, while the overall annual rate of loss of woodland between 1984 and 2013 was 2.6 percent, as 77.3 percent of woodland was lost. Reduction in woodland in rangelands has been widespread in recent years. Baldi *et al*. (2013) found a dominant gradient of declining woody cover accompanied by lower and less stable productivity, in the tropics and subtropics of regions of Asia, Africa, Australia, and America. Tsegaye *et al*. (2010) reported a rapid reduction in woodland cover from 8.35 percent to 0.28 percent cover in the Northern Afar rangelands of Ethiopia between 1972 and 2007. Unlike in the present study, grassland also declined from 7.75 percent to 0.91 percent (Tsegaye *et al*., 2010). Tsegaye *et al*. (2010) also stated that the proportion of bushland trebled, while the area of cultivated land increased eightfold (Tsegaye *et al*., 2010). In the present study, bushland continually declined.

Built-up areas increased at a rate 14.7 percent over the 1984 period but most of this increase occurred in the 1994 to 2003 period when it was at 15.1 per annum, probably because of the disarmament exercise between 2001 and 2002 (OPM, 2007) forced people to move to settlement concentration areas. Nonetheless, the rates of growth of built-up areas established by this study are within the range of growth at the national level. From 1980 to 2015, Uganda's national urban population grew at an annual rate of between 2.56 percent in 1980 to 17.8 percent in 2006 (Nyakana *et al*., 2007).

Small scale farming was steadily rising from 9.67 percent area coverage in 1984 to 15.69 percent in 2013. The annual rate of increase during this period was 2.1 percent, however, the highest rate of increase was experienced between 1994 and 2003 at 4.2 percent when 514.2km^2 (37.53 percent) became farmland. An increase in cropping in rangelands is now a widespread phenomenon. Rufino *et al*. (2013) informed that some householders in agro-pastoral systems of east Africa, particularly in locations with annual rainfall higher than 800 mm, were increasing their crop and diet diversity.

Woodland, which retained 10.5 percent of its 1984 area, lost 56.5 percent to grassland in 2013, but only gained 1.7 percent of grassland. In the 1984 to 1994 period, much of the 48.65 percent decline in woodland was transformed into small-scale farming land as 44.7 percent of 1984 woodland became small-scale farming land in 1994, 27.3 percent became bushland, while 23.9 percent remained as woodland. Alongside cropping, the felling of trees to burn charcoal is facilitating woodland loss (Egeru, 2014). The practice of charcoal burning has the potential to degrade the catchment and threaten eastern Africa's rangelands. For example, Tsegaye *et al*. (2010), reported that charcoal and firewood sale was said to have been responsible for a reduction in woodland in Ethiopian rangeland. The sale of firewood served as a major source of income when coping with the effects of drought.

Bushland and woodland often retained the least area under the land use, losing principally to grassland. Small scale farming gains from woodlands and bushlands were often lost to. Clearance of woodlands and bushlands for cultivation appears to facilitate transitions to grassland, however, these areas are later re-cultivated for small-scale farming. It's thus observed that woodland, followed by bushland continually transformed into grassland, and small-scale farming land, with reverse conversions, only occurring minimally. Nakalembe *et al*. (2017) noted that in Karamoja (upstream of the catchment), over 55 percent of once cultivated land is left fallow due to lack of resources for agricultural inputs. It's therefore likely that woodland, bushlands, or even grasslands when left for long periods may begin to regenerate and re-transition.

The decline of wetlands from 1984 to 1994 is consistent with reports that wetlands in Uganda continued to decline from the colonial times, while the stability in wetland area in 2003 may have been due the government campaigns to conserve wetlands, with the Government working closely with the local leaders and communities, in 2001, embarking on the process of physical restoration of critical wetlands in the country (Aryamanya-Mugisha, 2011). Awoja wetland in Tesos subregion where the Lokere and Lokok catchments discharge into was one of the beneficiaries of the physical restoration.

The progressive engagement of pastoralists in cropping is globally acknowledged as agriculture continues to expand into arid and semiarid environments (Rufino *et al*. 2013). This trend is indeed a result of several but similar factors. Key informants and community perspectives underlined that sedentarisation policy following disarmament and protected kraals introduction is driving cropping. Sedentarisation has been seen as an approach being adopted by policy makers to transform the mobile herders of Karamoja to "settle down and farm in a modern way." (Vidal, 2011). Elsewhere, Tsegaye *et al*. (2010) also reported that key informants stated increased sedentarization of Afar (Ethiopia) pastoralists and a high influx of migrants resulted in an expansion of cultivation in the alluvial plains.

McCabe *et al.* (2010) showed that, among the Maasai, the integration of agriculture into traditional pastoralism was by some a move to reduce risk, while for others it was a reflection of changing cultural and social norms, was also influenced by power differentials among Maasai age sets and by government policies. This is consistent with key informants and community statements that NGO and government promotion, education, and promotion of crop diversification by government and NGOs were fueling increasing small-scale farm holding.

The view that sedentarization of pastoralists would increase their productivity is not only held in Uganda. Blench (2001) reported that some interest groups, which included the official view in Nigeria, argued that "pastoralists are inherently inefficient and self-destructive, and should be settled…" Such a policy, especially when it is spontaneous, must be approached with caution as sedentarisation does not necessarily result in increased productivity and food security. The role of pastoralism as a coping mechanism where the potential for crop cultivation is limited due to low and highly variable rainfall conditions or extreme temperatures is well documented (Sperandini and Sperandini, 2009, Oxfam, 2008), and should be considered when promoting livelihood diversification. However, upholding the view that pastoralism is a coping strategy is a challenge, given that many pastoralist communities are amongst the poorest in Africa: such as in Turkana and Marsabit, and Mandera in Kenya, the Karamojong in Uganda and Ngorongoro in Tanzania (Oxfam, 2008). Oxfam (2008) explains that direct economic value (such as meat and milk) generated by pastoralists is not retained in their communities, and the indirect value (such as wildlife conservation and tourism) is un-rewarded and even unacknowledged by decision-makers. While there is a need for pastoralists to adapt to the global and changing trends such as technologies, the skills pastoralists have learned over centuries of adapting to their harsh environments could be of huge value in the face of climate change. A means to enhance the direct and indirect benefits of pastoralism, often through enhancing household and community resilience, and increasing livelihood capacity and human capital ought to build on these skills.

3.5 Conclusion and recommendation

There is a substantial change in land use and cover in the Lokere and Lokok catchments, driven by sedentarisation and the quest for alternative livelihoods rather than mobile herding, as government and non-state actors promote crop cultivation in the rangelands. Key changes include woodlands and bushlands conversion into small-scale farmlands, with degradation of woodland and bushlands increasing grassland areas. Small-scale farming could also be facilitating degradation of woodlands and bushlands. Land use and land cover changes are likely to continue as population and settlement increase, a trend that has been illustrated by the increase in the built-up areas. Loss of woodland area, bushland, and degradation of land vehave the potential to make the inherent water shortage in the Lokere and Lokok catchments and Karamoja in general, with likely adverse impacts on livelihoods. There is, therefore, need for the Central and local governments, as well as non-state actors in the catchments' areas to regulate land use and land cover LULC change through the formulation of land use policies, participatory land-use planning, and involvement of the communities in sustainable land management practices.

CHAPTER FOUR

PREDICTED LAND USE AND LAND COVER OUTLOOK FOR SEMI-ARID LOKERE AND LOKOK CATCHMENTS IN KARAMOJA REGION, UGANDA

Abstract

The semi-arid Lokere and Lokok catchments in Northeastern Uganda are experiencing land use and land cover (LULC) change driven by policies and actions aimed at pastoralist sedentarisation. While these efforts present a trajectory of a landscape dominated by farming, livestock herding or grazing persists. The objective of this study was to project medium, and long-term LULC for Lokere and Lokok catchments in Karamoja, Uganda. We applied an automatic multi-perceptron neural network, built on Markov chain modeling method, along with multi-criteria evaluation strategies; all embedded in the IDRISI Land Change Modeler (LCM) to project the catchments' LULC to the years 2030 and 2050. The model was trained using 1994 and 2003 LULC and validated with 2013 LULC. Results of three modeled policy scenarios; business as usual (BAU), pro-livestock and pro-farming; to the years 2030 and 2050 showed that small-scale farming (SSF) would increase in all scenarios, even if policy shifts to promote livestock rearing. Pro-farming policies would, in both 2030 and 2050, result in the reduction of grassland as SSF increases; doubling the 2003 land area by 2050. The results of this study facilitate assessment of potential impacts of the future LULC and policy evaluation in the catchments.

Pastoralism, sedentarisation, multi-criteria evaluation, Land Change Modeler, Land policy evaluation

4.1 Introduction

Arid and semi-arid areas of Eastern Africa are particularly experiencing land use and land cover (LULC) change-driven, among others things, by climatic variability and change, and community and government response to either mitigate and adapt (Olson, 2006; Tsegaye *et al*., 2010; Rufino *et al*., 2013). Society and government responses are influenced by the prevailing biophysical, social, and economic factors (Bürgi *et al*., 2004). The direction chosen will hugely influence future LULC, and with attendant ramifications.

In Uganda's dryland strip codenamed the "cattle-corridor", particularly in the semi-arid Karamoja in the northeast, land use and land cover change associated with shifting from livestock (grazing) production to cropping and degazettement of protected areas, is increasing (Majaliwa *et al*., 2012). Over the last 60 years, livestock herding in Karamoja had been characterized by seasonal movement, due to natural causes, particularly shortage of water and pasture (Waiswa *et al.,* 2019); but also seasonal movement to safety due to insecurity particularly inter-communal conflicts that were characterised by violent raids (Burnett and Evans, 2014). These factors have often contributed to the loss of livestock due to disease, shortage of water and feed, and theft/raids.

The region has also been labeled the poorest without comparing the financial value of their livestock with the income of counterpart households in other rural areas of Uganda (Aklilu, 2016). In addition to the official report of high poverty (UBOS, 2019), the seasonal mobility of livestock in search of pasture and water has been considered primitive and unproductive (Waiswa *et al*., 2019). As a result of the aforementioned, development agencies have focused on policies aimed at pastoralist sedentarisation and the introduction of alternative livelihoods (ACTED, 2010; Stark, 2011). The disarmament campaign of the government from 2006 - 2011 that included the introduction of a protected kraal system led to concentration of livestock in confined space (Burnett and Evans, 2014). Furthermore, following the return of relative peace, there is increased exploration and development of mines, especially by private companies on land that was previously used for livestock by the local population (Burnett and Evans, 2014; Aklilu, 2019). This has pushed small scale farmers and others to mining activities, and also private companies have fenced large areas for mining, thus reducing grazing land and favouring sedentarisation.

Sedentarisation may be defined as the settling of pastoralists; who would traditionally freely move with their herds in search of water and pasture, to practice mixed crop-livestock farming and derive livelihoods from other non-pastoral activities (Wurzinger *et al*., 2009). Sedentarisation-driven LULC conversion in Karamoja has seen a decline in woody vegetation, and an increase in land under cultivation. Nakalembe *et al*. (2017) reported a 299 percent increase in cropland area in Karamoja, between 2000 and 2011. Osaliya *et al.* (2019) reported an annual rate of increase of land under small-scale farming in Lokere and Lokok Catchments, during 1984-2013 at a rate of 2.1 percent; while the annual rate of loss of woodland in the same period was 2.6 percent. With peace and sedentarisation, there is growth of new centers, which have made it become more of a marketplace, especially for meat. This movement of people has contributed considerably to the development of the urban centers in the catchments and the region (Aklilu, 2019).

Although poverty levels, insecurity, and a poor understanding of pastoral livelihoods have contributed to a policy environment where sedentary cropping has been favored, households with livestock survive shocks, particularly drought better than their farming counterparts (Aklilu, 2016). Livestock is part of the culture in the region and is also an intervention that supports the resilience of pastoral livelihoods (Rota and Sperandini, 2009; Muhereza, 2017). Nonetheless, the policy view that sedentary crop farming is more productive than mobile livestock herding and part of a solution to insecurity and cattle rustling is likely to continue as the government seeks to maintain security in the region and eradicate poverty.

Therefore, both sedentarisation-based policies and pastoral, agro-pastoral or related livestock-based strategies as a means to cope with the variability and instability of rangeland environments contribute to change in LULC in Lokere and Lokok catchments. However, what is not known is what the outlook of land use change in the medium and long term would be. The changes in land use will impact water resources in an area that is already experiencing significant water stress due to recurrent droughts. Climate models are further showing a significant rise in temperature and minimal increase in precipitation (Egeru *et al*., 2019). The rates of evapotranspiration induced by the change in climate in this area are high resulting in intensified water scarcity within the region's key water catchments, Lokok and Lokere (Gavigan *et al*., 2009) which could jeopardize efforts to improve food security, reduce poverty and reduce the vulnerability of communities to water stress.

It is therefore important to understand the likely overall future direction of LULC to aid in the assessment of impacts as well as planning for sustainable livelihood strategies and catchment management. The objective of this study was to project the medium to long-term outlook of LULC for Lokere and Lokok catchments in Karamoja, in order to facilitate the assessment of likely impacts on water resources.

4.2 Materials and methods

4.2.1 Study area

This study was conducted in the Lokere and Lokok catchments of Northeastern Uganda. They comprise the main watershed in the Karamoja sub-region, connecting downstream to part of Teso sub-region in Uganda's dryland strip, codenamed the "Cattle Corridor". Karamoja sub-region is part of the Karamoja cluster, an area of land that straddles the borders between Southwestern Ethiopia, Northwestern Kenya, Southeastern South Sudan, and Northeastern Uganda (Gaur and Squires, 2018).

Lokere and Lokok catchments vegetation generally consist of savannah grasslands, woodlands, thickets and shrublands, which largely contain *Acacia–Combretum–Terminalia* species associations, with principally C4 grass species (Egeru, 2014). The Karamoja sub-region's topography consists of a plain sloping south-westward, intermixed with isolated highlands (Mt. Moroto, Mt. Iriri, Mt. Kadam, Mt. Labwor) in the higher elevated west. These consist of rocks of the crystalline basement complex. Rivers and streams in the catchment originate from the highlands and are ephemeral upstream and perennial in the downstream southwest. The catchment streams are important sources of water in this semi-arid area, especially during the dry season (Mbogga, 2014). Catchment hydrology oscillates with the stochastic climate events in the sub-region. Consequently, streamflow in most of the rivers in the region is dominated by the baseflow component for much of the year, with a correlative response pattern to groundwater. More often than not, standing water with slow seepage characteristics is retained in the valley areas by underlying low permeability clay-rich soils of the region (Gavigan *et al*., 2009).

The sub-region experiences hot and dry weather, characteristic of most semi-arid regions in Eastern Africa. Rainfall in Karamoja sub-region is unimodal, occurring from March to November, and ranging from < 500 mm in eastern Karamoja, 500-800 mm in central Karamoja to 700-1000 mm in west Karamoja and the isolated highlands (Mbogga, 2014). The Karamoja region, which includes the upstream of the catchments, has uneven rainfall and high run-off. Downstream of the catchments falls in the Teso subregion, which has a mean annual rainfall of about 1100-1200 mm, distributed between two seasons of March to July and September to November (Kisauzi *et al*., 2012). Temperatures are generally high throughout the year, with an annual average of 28-33°C for minimum and maximum temperature, respectively; leading to high evapotranspiration levels averaging 2072 mm per *annum* (Gavigan *et al*., 2009).

Land use and land cover in the catchments has traditionally been characterized largely by grazing in a landscape dominated by grasslands, cultivation, hunting, and settlement (Osaliya *et al*., 2019); and has included conservation, since the 1964 when three game reserves (Matheniko, Bokora, and Pian-Upe) were gazetted in Karamoja, parts of which are found upstream of the catchments (Rugadya and Kamusiime, 2013). However, LULC change over the last three to four decades in the catchments has resulted in the conversion of woodlands and bushlands into small-scale croplands, increase in grassland due to degradation of woodland and bushlands, and degazettement of protected areas (Majaliwa *et al*., 2012). This saw small-scale farming and grassland area increase from 10 and 44 in 1984 to 16 and 60 percent in 2013 (Osaliya *et al*., 2019).

4.2.2 Variables and data sets

Land use and land cover for 1994, 2003 and 2013 prepared by Osaliya *et al.* (2019) for the catchments were used as the data for this study. The 1994 and 2003 layers were used for model calibration, while the 2013 layer was used for model validation. Commonly applied drivers of LULC change were listed from literature (Serneels and Lambin, 2001; Veldkamp and Lambin, 2001; Agarwal *et al*., 2000; Linkie *et al*., 2004; Wilson and Weng, 2011; Ahmed and Ahmed 2012; Nyeko, 2012; Sleeter *et al*., 2012). However, for this study, the drivers used were obtained from Osaliya *et al*. (2019).

According to Osaliya *et al*. (2019), the community (among other actors) perceived that the return of peace in the sub-region was among the drivers of land cover and land-use change, particularly, the increase in cultivated land and reduction in woody and bushy lands. For a region that had volatile insecurity due to cattle rustling, including episodes of raids by the neighbouring Pokot from Kenya, security is a key factor in the use of land. This study assumed that the prevailing security would remain uninterrupted. The promotion of crop cultivation and use of new agricultural technology was considered a policy intervention and an exogenous change that was causing a shift to increased cropping in a region otherwise traditionally dominated by pastoralism (grazing). This provided a basis for the assumption that sedentarisation policies could result in increased land area under small-scale farming. Evidence likelihood of LULC change was included as an explanatory variable, to account for practices and decisions that influence change; and that would possibly not be explained by the model, as described by Eastman (2016a&b). Evidence of the likelihood of change was created by determining the relative frequency with which different LULC types occurred within the areas that transitioned from 1994 to 2003.

Nine explanatory variables/drivers and sources of data were utilized in this study. Five of the drivers were applied to model both transitions to small-scale farming and grassland. These are: (a) distance from streams calculated from streams vector layer obtained from a digital elevation model (DEM) based catchment delineation in ArcSWAT; (b) distance from roads, calculated in ArcGIS from a layer of road network obtained from the Uganda National Bureau of Statistics (UBOS); (c) slope calculated from a 30 meters Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) which was downloaded from http://www2.jpl.nasa.gov/srtm/ portal and projected to the UTM WGS 1984 zone 36N; (d) population density layer calculated to sub-county level in ArcGIS, by using the administrative boundaries layer and population from the 2002 Census, obtained from UBOS; and (e) distance from small towns and urban centers within and close to catchment boundary calculated from a layer obtained from UBOS. In addition, distance from small-scale farms was calculated after extracting the land cover in question from the 1994 LULC layer; and evidence of the likelihood for change to small-scale farming was used only in modeling transmission to small-scale farming. On the other hand, total livestock values (TLU) and evidence likelihood for change to grassland was used only in modeling transmission to grassland. The likelihood for change layers was prepared in IDRISI's TerrSet Geospatial Monitoring and

Modeling System as described under "Preparation and selection of explanatory variables" from 1994 and 2003 LULC layers. Distance layers were calculated using the "Euclidean distance" tool in ArcGIS 10.3 Spatial Analyst.

All the input datasets, that is, drivers also called factors, constraints and incentive, and LULC layers were prepared at a 30-meter spatial resolution, to the same number of rows (5153) and rows (7194), background values and projected to the UTM WGS 1984 zone 36N, for consistency that is required for executing overlay in GIS environments. These derivations were executed in ArcGIS 10.3, converted into GeoTiff format, and imported into IDRISI's TerrSet Geospatial Monitoring and Modeling System for transformation and modeling in accordance with desired scenarios.

4.2.3 Modeling land use and land cover change

Several modeling techniques have been developed to evaluate and project LULC that could result from different growth and policy scenarios (Agarwal *et al;* 2000; Wainger *et al*., 2007). They include (a) empirical-statistical models, (b) stochastic models, (c) optimization models, (d) dynamic process-based simulation models, and (e) the connectionist models (Gonzales, 2009). The suitability of a modeling approach selected depends on the intended use (Wilson and Weng, 2011).

As a selected modeling approach should capture the most critical aspects of LULC particularly heterogeneity, interactions, and dynamics (Plantinga *et al*., 2006), the projection was attained by applying a combination of methods embedded in the IDRISI Land Change Modeler (LCM) software, as described by several reports (Pontius *et al*. 2004; Eastman, 2009; Bernetti and Marinelli, 2010). The methods are: (a) identifying historical LULC change (transitions) by cross-comparison of two images; (b) multivariate analysis of transition potential using artificial neural networks, particularly the multi perceptron neural network (MLP), to develop an empirical model of the relationship between the historical LULC transitions and a set of explanatory variables; (c) future LULC demand calculation by the Markov chains; and (d) multi-objective land allocation. While the LCM has three empirical model development tools, the MLP was chosen because is capable of modelling complex nonlinear relationships between variables, able to detect and model interaction effects among variables, and is robust for modelling the potential transitions (Eastman, 2009 and Nor *et al*., 2017). The LCM was chosen because of its ability to combine these methods and the handiness of its interface through the organization of key modeling tasks into tabs for change analysis, transition potentials, change prediction, and planning. The study applied these tools to postulate that future (2030 and 2050) LULC would result from a combination of local biophysical and socio-economic drivers that can be extrapolated by analysis of long term (1994 – 2003) past occurrences, the exogenous changes caused by the implementation of long-term land policies and by land-use constraints and incentives. The tools were applied as described below.

4.2.4 Identification of major transitions

Major LULC transitions that occurred in the 1994-2003 period were identified by cross-comparison (Pontius *et al*. 2004 and Bernetti and Marinelli, 2010) of 1994 and 2003 LULC raster images in the LCM change analysis tab. The LCM was set up to ignore transitions less than 20 Km^2 (Eastman, 2016b). Thus, transitions involving the built-up areas were ignored (Figure 4.1).

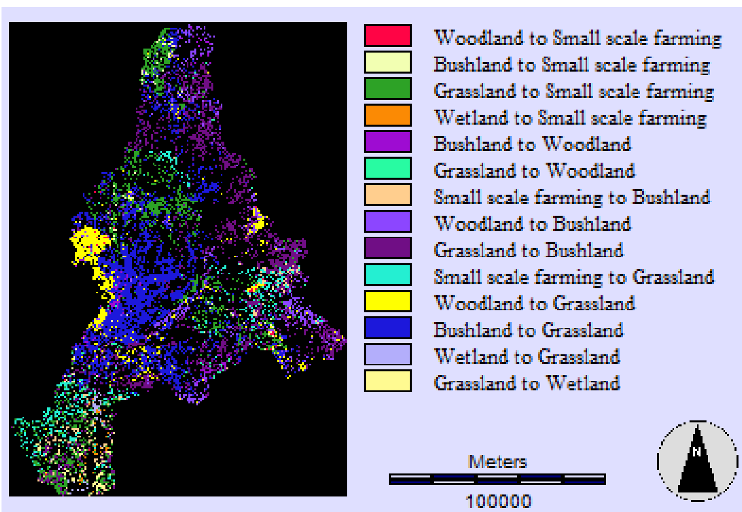


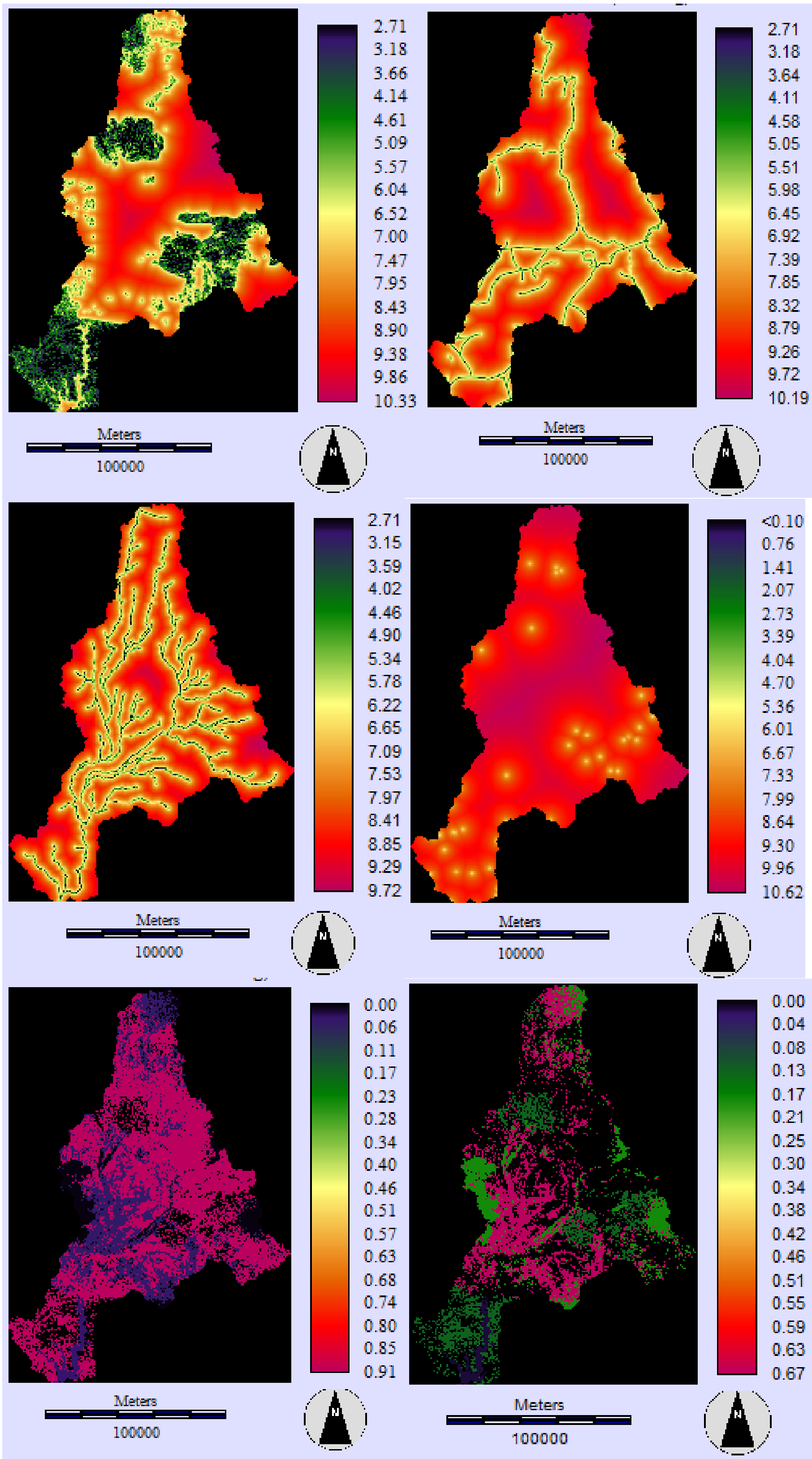
Figure 4.1. Land use and land cover transitions (greater than 20- Km^{-1}) from 1994 to 2003 Lokere and Lokok catchments in Karamoja region, Uganda.

The LCM transition tab allows for the organization of transitions into transition sub-models that can consist of a single land cover transition or a group of transitions that have the same explanatory variables and can be modeled in one go, using the LCM's MLP (Eastman 2016a). To model increased small-scale farming, it was assumed that only transitions from all of the other LULC types to crop farms would be important. Thus, these were grouped into a single transition sub-model, "All_to_Farm". Likewise, to model increased grazing, only transitions to grassland were assumed to be important, and were grouped into one transition sub-model, "All_to_Grass".

4.2.5 Preparation and selection of explanatory variables

The candidate explanatory variables, drivers (Figure 4.2) were not subjected to Cramer's V coefficient test, as LULC transitions were modeled using the Multilayer Perceptron neural network, which has a much stronger evaluation procedure incorporated into its development process (Eastman, 2016a). Although the MLP does not require variable layers to be transformed as it does not require variables to be linearly related, a transformation could enhance its performance and accuracy, particularly where there is strong non-linearity (Eastman, 2016a). Thus, the Variable Transformation Utility of the LCM, which is a natural log transformation, was applied to the distance layers as recommended for distance decay variables (Eastman, 2016a). The root-square transformation was applied on the population density, slope, and Total Livestock Units (TLUs) density layers.

Evidence likelihood of change layers was prepared by (i) obtaining layers of transition of all LULC classes in 1994 to small scale farming, and to grassland in 2003, using the Change Analysis module of LCM; (ii) using the RECLASS module in Terrset to obtain Boolean images of transition; and (iii) using the Boolean images with the 1994 layer as the input image variable name, to derive the evidence livelihood of change of LULC to small scale farming and grassland, respectively. The most sensitive variables were selected after running the MLP and are presented under "modelling of transition potentials" below.


2.71
3.18
3.66
4.14
4.61
5.09
5.57
6.04
6.52
7.00
7.47
7.95
8.43
8.90
9.38
9.86
10.33
Meters
100000
N
2.71
3.18
3.64
4.11
4.58
5.05
5.51
5.98
6.45
6.92
7.39
7.85
8.32
8.79
9.26
9.72
10.19
Meters
100000
N
2.71
3.15
3.59
4.02
4.46
4.90
5.34
5.78
6.22
6.65
7.09
7.53
7.97
8.41
8.85
9.29
9.72
Meters
100000
N
<0.10
0.76
1.41
2.07
2.73
3.39
4.04
4.70
5.36
6.01
6.67
7.33
7.99
8.64
9.30
9.96
10.62
Meters
100000
N
0.00
0.06
0.11
0.17
0.23
0.28
0.34
0.40
0.46
0.51
0.57
0.63
0.68
0.74
0.80
0.85
0.91
Meters
100000
N
0.00
0.04
0.08
0.13
0.17
0.21
0.25
0.30
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0.51
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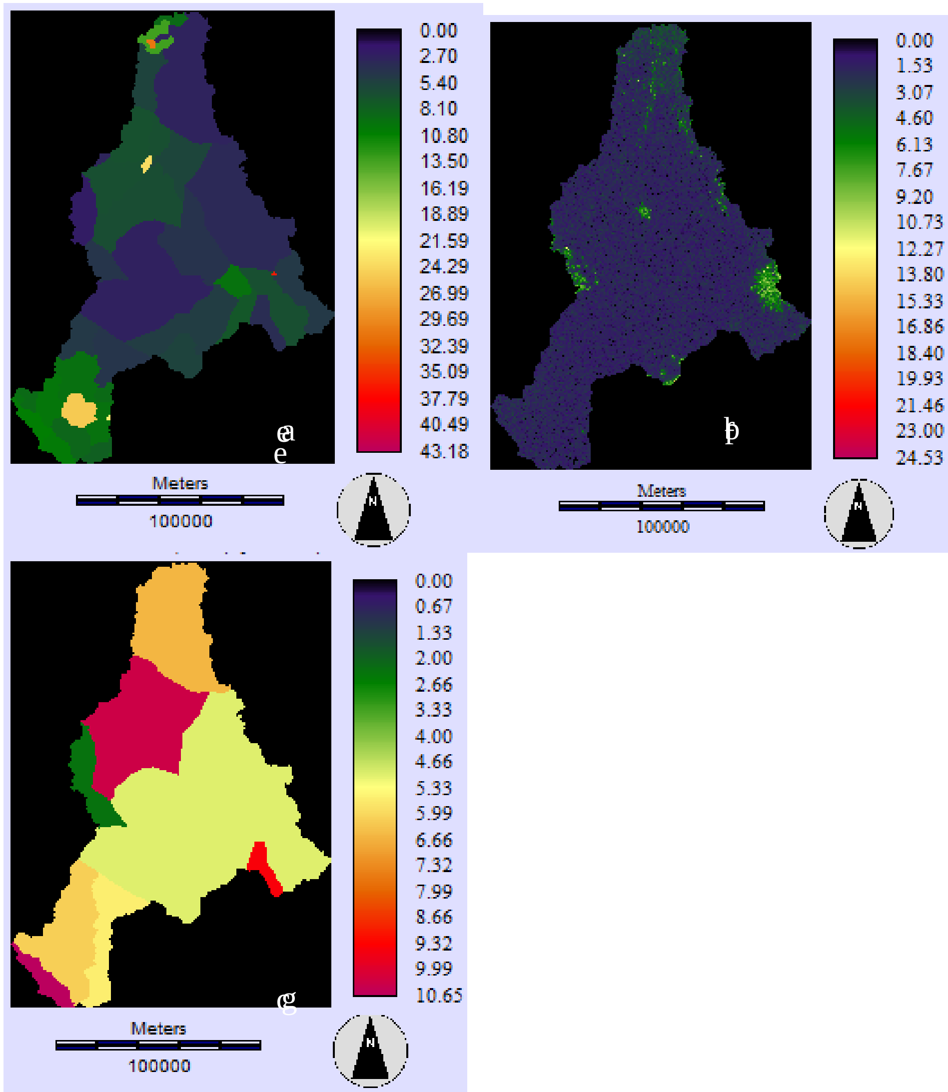

Figure 4.2. The candidate explanatory variables used in land use and land cover modeling (a) distance from small scale farming in 1994, (b) distance from roads, (c) distance from streams, (d) distance from towns, (e) evidence likelihood of transition to small scale farming, (f) evidence likelihood of transition to grassland (g) population density, (h) slope, and (i) total livestock value in 2002.

4.2.6 Modeling of transition potentials

Using the drivers and historical land cover and land use images, transition raster images were developed, using the MLP neural network. The MLP was chosen due to its ability to model non-linear processes and run multiple transitions, up to 9, per sub-model (Eastman, 2012a).

The LCM's Multi-Layer Perceptions (MLPs) have a back-propagation learning algorithm (Li and Yeh, 2002; Eastman, 2009; Bernetti and Marinelli, 2010). The MLP neural network consisted of three layers; namely input (*I*), hidden (*H*), and output (*O*) (Figure 4.3) and was implemented through training and simulation. The minimum sample of cells that transitioned from other LULC classes during the 1994-2003 period was 22,625 and 43,615 for "all_to_farming" and "all_to_grass" sub-models, respectively, while 209,116 persisted. The MLP uses one-half of the sample for training and the other for testing of model skill and accuracy (Eastman, 2016a).

Training involves the definition of inputs into the ANNs for the simulation, which is cell-based. Thus, each cell has a set of *n* attributes or variables as the inputs into the ANNs. It was hypothesized that the probability of transition from one LULC to another was determined by site attributes or variables discussed above.

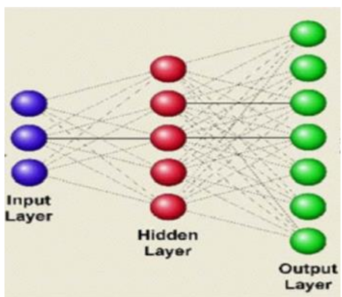

Figure 4.3: Example of architecture of artificial neural network (Adopted from Eastman, 2012b)

The MLP output includes an analysis of model sensitivity to independent variables, as well as their interactive prediction skill. This enabled the selection of explanatory variables that were applied in the prediction.

Tables 4.1 and 4.2 show how the "all_to_farming" and "all_to_grass" sub-models, respectively, performed when one variable was held constant, and when run with the less influential variables held as constant, starting with holding the least influential alone and continuously removing the remaining least influential. The "all_to_farming" sub-model performed worst when evidence of livelihood change to farming was excluded from the model run, indicating that it was the most influential variable. It was followed by distance from small-scale farming and population density. Distance from roads was the least influential variable. It was, therefore, removed and re-trained the model with six variables for parsimony.

Table 4.1. Variation in "all_to_farming" sub-model skill with different combinations of variables, or one, held constant

Model with one variable held constant				Model skill with less influential variables held constant			
Variable held constant	Accuracy (%)	Skill measure	Influence order	Variables held constant	Variables included	Accuracy (%)	Skill measure
None	73.36	0.6956	N/A	None	All variables	73.36	0.6956
[1]	73.16	0.6932	7	Step 1: [1]	[2,3,4,5,6,7]	73.16	0.6932
[2]	72.89	0.6902	6	Step 2: [1,2]	[3,4,5,6,7]	72.79	0.689
[3]	72.42	0.6848	5	Step 3: [1,2,3]	[4,5,6,7]	72.6	0.6868
[4]	70.15	0.6588	4	Step 4: [1,2,3,4]	[5,6,7]	71.01	0.6687
[5]	65.76	0.6087	3	Step 5: [1,2,3,4,7]	[5,6]	55.65	0.4931
[7]	63.03	0.5775	2	Step 6: [1,2,3,4,7,5]	[6]	37.16	0.2818
[6]	19.15	0.076	1				

Numbers in parentheses represent variables: 1 is distance from roads, 2 is distance from towns, 3 is distance from streams, 4 is slope, 5 is population density (2002), 6 is evidence of likelihood of change to small scale farming, and 7 is distance from small scale farming in 1994.

Table 4.2. Variation in "all_to_Grass" sub-model skill with different combinations of variables, or one, held constant

Model with one variable held constant				Model skill with less influential variables held constant			
Variable held constant	Accuracy (%)	Skill measure	Influence order	Variables held constant	Variables included	Accuracy (%)	Skill measure
None	64.98	0.5998	N/A	None	All variables	64.98	0.5998
[1]	64.16	0.5904	7	Step 1: [1]	[2,3,4,5,6,7]	64.16	0.5904
[7]	64.1	0.5897	6	Step 2: [1,7]	[2,3,4,5,6]	64.6	0.5955
[5]	62.94	0.5764	5	Step 3: [1,7,5]	[2,3,4,6]	62.11	0.567
[2]	62.61	0.5727	4	Step 4: [1,7,5,2]	[3,4,6]	58.46	0.5252
[6]	60.26	0.5459	3	Step 5: [1,7,5,2,6]	[3,4]	56.23	0.4997
[3]	59.11	0.5327	2	Step 6: [1,7,5,2,6,3]	[4]	50.12	0.4299
[4]	18.46	0.0681	1				

Numbers in parentheses represent variables: 1 is population density (2002), 2 is distance from roads, 3 is slope, 4 is evidence of likelihood of change to grassland, 5 is total livestock values, 6 is distance from towns, 7 is distance from streams.

The "all_to_grass" sub-model, holding population density (2002), distance from towns, and total livestock values each at a time, as well as all of them together, had the least effect on model performance in that order (Table 4.2). These model variables were removed from the model that was trained for the prediction for model parsimony. The variables that had the most influence were evidence of the likelihood of a change to grassland, slope, and distance from town, in that order.

Although presently, there is not a specific acceptable threshold for the Skill measure, user experiences show that "any value greater than 0.5 is generally acceptable and values greater than 0.7 are quite good." (Jamieson, Clark Labs, communication through the Terrset Support Center in response to Request #1345 on performance threshold, 09:41 EDT, Mar 26 2018). Thus, the performance of the MLP during the test was satisfactory (Table 4.3) because it attained an accuracy of 73.4 and 65.0 percent; and skill measures of 0.70 and 0.60; for the "all_to_farming" and "all_to_grass" sub-models respectively. The MLP runs prediction with the identified variables attained an accuracy of 74.6 and 65.3 percent, and a skill measure of 0.71 and 0.60 for the "all_to_farming" and "all_to_grass" sub-models, respectively.

Table 4.3: Multi-Layer Perceptron performance for Lokere and Lokok catchments for Karamoja region in Uganda

Parameter	All_to_Grass		All_to_Grass	
	Test	prediction	Test	prediction
Input layer neurons	7	6	7	5
Hidden layer neurons	7	7	7	6
Output layer neurons	8	8	8	8
Requested samples per class	10000	10000	10000	10000
Final learning rate	0.0001	0.0000	0	0
Momentum factor	0.5	0.5	0.5	0.5
Sigmoid constant	1	1	1	1
Acceptable RMS	0.01	0.01	0.01	0.01
Iterations	10000	10000	10000	10000
Training RMS	0.2126	0.2173	0.2376	0.2383
Testing RMS	0.2145	0.2172	0.2387	0.2392
Accuracy rate (percent)	73.36	74.81	64.98	65.34
Skill measure	0.6956	0.7121	0.5998	0.6038

4.2.7 Prediction of land cover and land use change

In the LCM, future demand for (quantity of) land cover and land-use change in each transition was modeled using a Markov Chain analysis. Markov chains method determines the amount of change using the earlier/past and later/present LULC images along with the specified future date based on a projection of the transition potentials into the future and creates a transition probabilities matrix (Eastman, 2009, 2016a; Bernetti and Marinelli, 2010). The probability of moving from one state, *i* to another state, *j* is called a transition probability, Pij, and it is given for every ordered set of states. These probabilities can be represented in the form of a *transition matrix*, P, as in the Markov equation:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{2\,2} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}$$

In order to define the geographical localisation of transitions obtained from the Markov chain procedure, the multi-objective land allocation algorithm (Eastman *et al*., 1995) and cellular automata, built in the IDRISI's Land Change Modeler was used. As the process involves using suitability maps for spatial allocation of predicted time transitions, the aggregation of transition potentials of all selected sets of transitions, to obtain the predicted LULC was achieved through calculation of the "logical OR".

4.2.8 Model validation

The Relative Operating Characteristic (ROC) (Eastman, 2009; 2016b; Pontius and Schneider, 2001; Eastman, 2009) module of the IDRISI GIS, was used to validate the quality of LULC prediction. The ROC technique measures how well a modelled continuous map of suitability of the likelihood of a land cover and land use class occurring predicts locations given the actual map of the distribution of the class (Pontius and Schneider, 2001 and Eastman. 2016b).

Therefore, Boolean images of change from all classes in 2003 to small scale farming, and to grassland, in 2013, were respectively used in the ROC module as reference images (actual LULC layer) along with their corresponding soft prediction images as input images, to validate the trained sub-models for predictions of changes to farming and grassland. No constraints or incentives were applied in predictions for validation purposes. Using default settings and 100 as the number of thresholds, the ROC analysis showed that the models' prediction of transitions to small-scale farming and to grassland was strong, with ROC values of 0.83 and 0.94, respectively; illustrating the robustness of the prediction. (Pontius and Schneider, 2001). The validated model was then used to generate LULC for 2030 and 2050, after incorporating scenarios.

4.2.9 Incorporation of scenario development into prediction

The LCM planning module was used to incorporate three policy scenarios by defining constraints and incentives for change allocation and prediction (Eastman, 2016a and b). Handled or prepared in the same manner, constraints and incentives layers were used to bar (constraints, with to values of 0 on the layer), discourage (incentive, with values less than 1 but greater than 0) or encourage (incentives, with values greater than 1) change in the specified locations, in favor of, or against, small scale farming or grassland (grazing).

In defining scenarios that were modeled, major historical, present and plausible future LULC were considered, along with endogenous and exogenous influences in the catchment in particular, and the region in which it is located. Lokere and Lokok catchments, particularly upstream, falls in rangeland, characterised by climate variability, where livestock herding, mainly pastoralism, has over the years been the economic or livelihood mainstay of the people. Although cropping had also been practiced, it was limited to traditional crops, mainly sorghum, grown on a very small scale; making grassland and grazing the dominant land cover and land use over the years. (Largely endogenous aspects.)

Recent developments in the sub-region particularly following disarmament exercise between 2001 and 2002 (OPM, 2007), have seen aggressive promotion of agriculture by Government and non-state actors. For example, Karamoja subregion, in 2016, had 54 non-governmental organisations (NGOs) which were implementing 142 active projects (Karamoja Resilience Support Unit, 2016). Government Policy analysis has blamed among others, overreliance on livestock resources as one of the causes of poverty and chronic food insecurity in the sub-region, and has embarked on developing and implementing programs that, while seeking to improve on quality of livestock, promote growing and marketing of a diversity of crops (OPM, 2007; 2009), with the Karamoja Integrated Disarmament and Development Programme (KIDDP), being the main development program for the region. (Largely exogenous aspects.)

4.2.9.1 Business as usual scenario

The BAU scenario assumed that trends of land use/cover change between 1994 and 2003 will continue as influenced by the identified and evaluated drivers of LULC change. This development would not occur in forest reserves, wildlife reserves, and wetlands – thus assume effective conservation of these areas. A constraint layer with these areas with 0 values was used in the prediction, which included “all_grass” and “all_farming” sub-models. Net transitions to woodland and bushland were assumed insignificant.

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4.2.9.2 The pro-farming policy scenario

This scenario assumed that government policy and actions of state and non-state actors would promote the growing of crops leading to prioritisation of cultivation by LULC change agents. An incentive layer with values of 1.2 was created to increase the rate of change of LULC to farming. As a result of increased attention to farming, grazing areas could either reduce, not increase or increase at a lower rate than the present. Therefore, a disincentive of 20 percent, which would reduce the normal values on the incentive layer from 1.0 to 0.8 was created for the "all_to_grass" sub-model.

4.2.9.3 The pro-livestock policy scenario

The pro-livestock policy scenario assumed increased livestock production leading to increased grazing land and subsequently grassland cover. To model this scenario, a normal rate of change (values of 1) was assumed in wildlife and forest reserves, bar wetlands, and an incentive of 1.2 values on the incentive layer was placed for the rest of the catchment – for the "all_to_grass" sub-model. As a result of increased attention to livestock husbandry, farming could either reduce, not increase or increase at a lower rate than the present. A disincentive of 20 percent, which would reduce the normal values on the incentive layer to 0.8 was created for the "all_to_farming" sub-model.

4.3 Results

The projected LULC for the three future (2030 and 2050) scenarios are presented in Figure 4.4, while the area that would be covered by the LULC types are presented in Table 4.4. Compared to the baseline, the projections show that land under small-scale farming would increase, and the increase would be highest in the pro-farming policy scenario, by 14.2 and 16.5 percentage points in 2030 (Figure 4.5) and 2050 (Figure 4.6). This suggests that small scale farming would under the pro-farming policy scenario in 2050 cover more than double (30.3 percent) the 2003 land area (13.8 percent, Table 4.5).

Grassland would increase under the BAU and pro-grazing scenarios, by 11.8 and 11.7 percentage points in 2030 (Figure 4.5), and 10.9 and 9.6 percentage points in 2050 (Figure 4.6). However, in the pro-farming policy scenario, grassland would reduce by 10.8, from 58.1 to 47.3 percent in 2030 and 11.8 to 46.3 percent in 2050, as respective areas under small scale farming will increase from 13.8 to 28 and 30 percent, respectively. Bushland will reduce in all scenarios and future years (Figure 4.5 and 4.6). The decline in bushland could be substantially higher in the BAU and pro-grass scenarios, by 16.5 and16.1 percentage points in 2030; and 16.4 and 14.7 percentage points in 2050, respectively, compared to only 2.8 in 2030 and 3.8 in 2050 in the pro-farming scenario. There will also be a slight decline in area under woodland in all scenarios and years, ranging from 0.5 in the pro-farming scenario in 2030 to 3.8 percentage points in the pro-grazing and BAU scenarios in 2050.

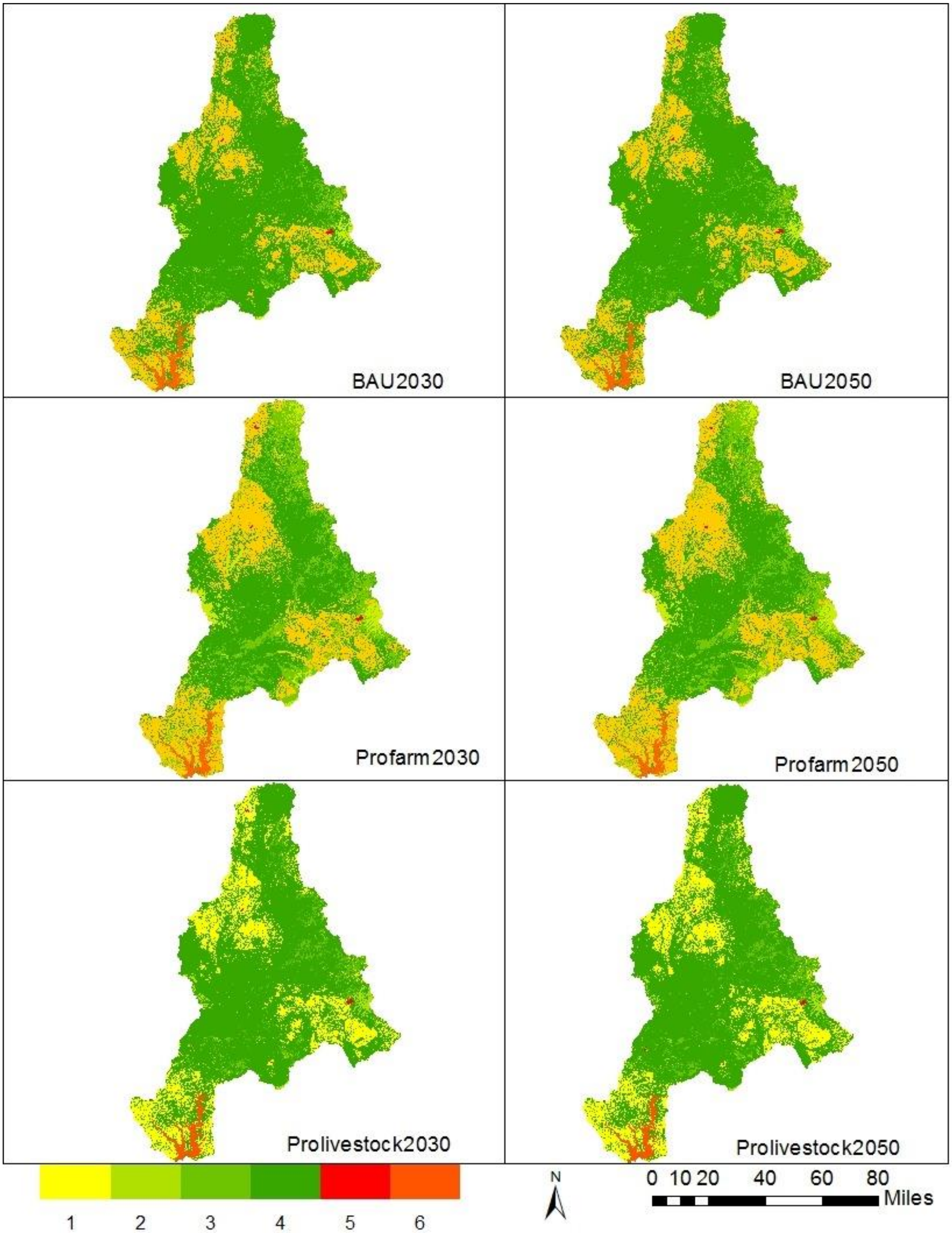

Figure 4.4. Projected LULC to the years 2030 and 2050 (1 = small scale farming, 2 = woodland, 4 = grassland, 5 = built-up, 6 = wetland; BAU = Business as usual scenario, profarm = pro-farming scenario, prolivestock = pro-livestock scenario).

Table 4.4: Projected LULC for pro-grazing, pro-farming and business as usual scenarios (area in Km2) and in the Lokere and Lolok catchments in Karamoja in Uganda

Land use and land cover type	2003	2030			2050		
	Baseline	BAU	Pro-grazing	Pro-farming	BAU	Pro-grazing	Pro-farming
Small scale farming	1,891.2	2,996.3	2,940.2	3,832.7	3,125.9	3,070.6	4,158.4
Woodland	644.1	199.3	193.2	575.5	166.2	166.1	532.4
Bushland	2,932.7	666.8	732.7	2,549.0	691.0	918.3	2,406.6
Grassland	7,962.1	9,572.9	9,572.4	6,480.6	9,455.7	9,283.7	6,340.3
Built-up areas	16.4	14.5	16.1	16.1	16.1	16.2	16.2
Wetland	260.4	254.4	249.7	250.4	249.3	249.3	250.2
Total	13,706.9	13,704.2	13,704.2	13,704.2	13,704.2	13,704.2	13,704.2

Table 4.5: Projected LULC for pro-grazing, pro-farming and business as usual scenarios (percentage) and in the Lokere and Lolok catchments in Karamoja in Uganda

LULC type	2003[a]	2030			2050		
	Baseline	BAU	Pro-grazing	Pro-farming	BAU	Pro-grazing	Pro-farming
Small scale farming	13.8	21.9	21.5	28.0	22.8	22.4	30.3
Woodland	4.7	1.5	1.4	4.2	1.2	1.2	3.9
Bushland	21.4	4.9	5.3	18.6	5.0	6.7	17.6
Grassland	58.1	69.9	69.8	47.3	69.0	67.7	46.3
Built-up areas	0.12	0.1	0.1	0.1	0.1	0.1	0.1
Wetland	1.9	1.9	1.8	1.8	1.8	1.8	1.8
Total	100	100	100	100	100	100	100

[a]Based on Osaliya *et al.* (2019)

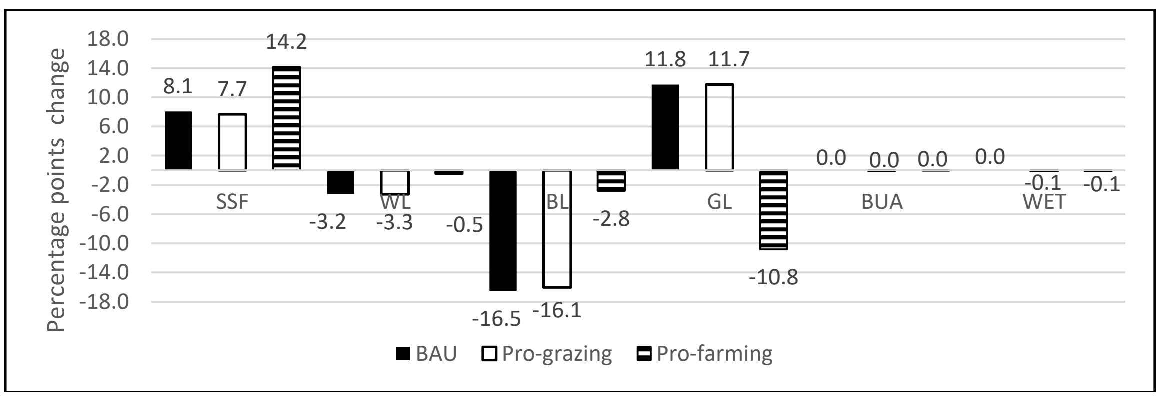

Figure 4.5: Change in Land use and land cover from the baseline under the Business as usual (BAU) and pro-farming and prolivestock policy scenarios in 2030 and in the Lokere and Lolok catchments in Karamoja in Uganda.

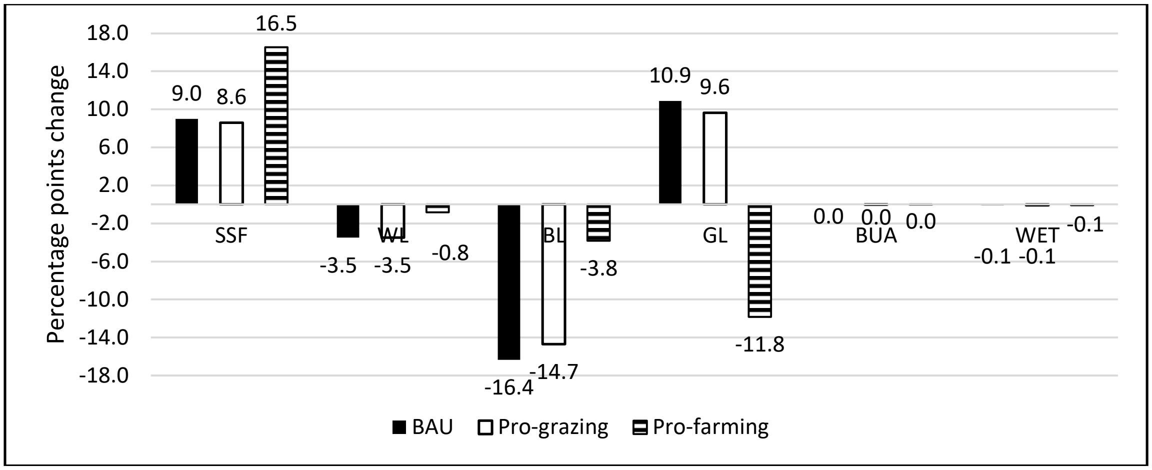

Figure 4.6: Change in Land use and land cover from the baseline under the Business as usual (BAU) and profarming and prolivestock policy scenarios in 2050 and in the Lokere and Lolok catchments in Karamoja in Uganda.

4.4 Discussion

The results show that small scale farming would increase in the medium and long term under all policy scenarios, ranging from 7.7 and 8.6 percentage points in the pro-livestock policy scenario to 14.2 and 16.5 percentage points in the pro-farming policy scenario, in 2030 and 2050 respectively. Increase in small scale farming in the business as usual scenario (BAU) was expected because the model is predicting past trends to continue. While increase in small scale farming in the pro-grazing scenario would not be surprising, similarity in the amount of increase with that in the BAU scenario suggests that the present influence on farms would persist to the year 2050, even if policy shifts to promote livestock rearing. This would be consistent with reports that the people of the semi-arid Karamoja have practiced agropastoralism since the 1880s, with crop farming and transhumance livestock keeping being mutually reinforcing (Cullis, 2018). However, the large decline in grassland, from 58.1 to 47.3 percent in 2030 and 46.3 percent in 2050, as small-scale farming doubles in the pro-farming scenario would result in a huge reduction in land for grazing as greater effort is placed on cropping.

Reliance on cropping could increase the vulnerability of the population to climate variability in the catchments and the greater semi-arid Karamoja region (Aklilu, 2016) where herding has been both a culture and a coping mechanism (Muhereza, 2017), unless pro-farming policies are backed with strategies to mitigate short-fall in crop production. And, as cultural practices are difficult to change, and transhumance livestock herding has been reported as more suited to semi-arid environments (Rota and Sperandini, 2009), strategies that improve both crop and livestock production could be more beneficial to the population. Such strategies could cover on-farm and catchment water management practices, crop science, and feed and pasture management (Ben-Gal *et al*., 2006 and Adugna and Aster, 2007; Tilahun *et al*., 2017).

Although the decline in bushland and woodland as grassland and small scale farming increase would be consistent with past historical trends established in the catchments (Osaliya *et al*., 2019), the lower change in their percentage in the pro-farming scenario where increase in small scale farming was highest contradicts this trend. This trajectory would spur restoration of degraded lands and protection of woodlots, especially in protected areas (Matheniko, Bokora and Pian-Upe).

Grassland would also remain the most dominant LULC in 2030 and 2050, even under the pro-farming policy scenario, where its land area would have declined to 47 and 46 percent, respectively; compared to 58 percent in 2003 (Table 3). This could support livestock herding to allow the communities to continue to benefit from this more climate resilience livelihood (Aklilu, 2016); however likely fragmentation due to increasing croplands could disconnect the formerly intact grasslands, and hinder the mobility of livestock (Galvin, 2009) and sharing of grazing grounds. Nonetheless, livestock herding strategies that allow for coping with the variable semi-arid environment could still be possible.

4.5 Conclusion

This study shows that land under small scale farming would increase in the medium (2030) and long term (2050) if present LULC trends continue (business as usual policy scenario), policies promote cropping or livestock herding; and that influence of present efforts to promote crop cultivation would persist to the year 2050 even if policy shifts to particularly promote livestock rearing. The increase in small scale farming land area could by 2050 be double its 2003 land area if pro-farming policies dominate livelihood and development programs, as a large reduction in grassland and substantial increase in small scale farming would occur, in 2030 and 2050. However, grassland would still be more dominant but could be less supportive to livestock herding due to fragmentation by cropland and restriction to sharing of grazing grounds. Reliance on cropping in a semi-arid area where mobile herding is more adaptive to climate variability could increase the vulnerability of the population unless effective strategies that mitigate shortfall in crop production are implemented. Strategies that improve both crop and livestock production could be more beneficial to the population. Such strategies could cover on-farm and catchments, water management practices, crop science, and feed and pasture management. Research on these aspects should be part of the policy and development agenda for the semi-arid catchments. The projected LULC, and insights on likely change over the next one to three decades provide useful data for assessing potential impacts on water resources and information for planning and policy evaluation in Lokere and Lokok Catchments.

CHAPTER FIVE

CLIMATE VARIABILITY TRENDS IN THE SEMI-ARID LOKERE AND LOKOK CATCHMENTS, NORTHEASTERN UGANDA

Abstract

Frequent and severe droughts associated with climate change are making water scarcity more acute in arid and semi-arid areas of Eastern Africa, thus affecting food and forage availability. The objective of this study was to assess spatio-temporal trends and variability in temperature and rainfall over the semi-arid region of Kapir catchment in Karamoja and Teso, Uganda. Mean temperature and rainfall time series (1980-2009) were examined. Analysis of Variance (ANOVA) and Dunn's post-hoc test was used to compare means in four data points (Stations), Ordinary Least Squares (OLS) regression and Cumulative Sum (CUSUM) chart were used for detecting trends and sequential shifts in time series, while the standard temperature index (STI) and standard rainfall anomaly (SRA) were used to detect hot and dry years, respectively. There was an increase in both temperature and rainfall at the catchments scale, though only the temperature increase was significant ($p < 0.05$). While minimum temperature (Tmin) rose faster than maximum temperature (Tmax), especially during the rainy season, in the dry season, Tmax significantly increased and was more variable than Tmin. The increase in rainfall was lowest in Amuria station, which received the highest rainfall. On the other hand, total annual rainfall significantly increased in Kotido and Moroto Stations. October rains significantly increased in all areas, except Amuria, and resulted in a significant increase in Catchment SON rainfall. January rainfall increased significantly only in Kaabong Station. Variability of both temperature and rainfall was higher in the first decade of analysis, than in the third decade. Positive shifts in temperature trends occurred after 2000. Climate adaptation options in the catchment should consider between and in season climate variability.

Key words: Rainfall, spatio-temporal, temperature, catchment

5.1 Introduction

Global warming presents major challenges to the maintenance of healthy ecosystems, a steady supply of water resources, food security, and poverty reduction (Singh, 2012). This is particularly crucial in Sub-Saharan Africa where poverty rates are high and the population largely depends on direct extraction of natural resources and rain-fed agriculture. Warming of 1.5 to 3ºC is expected by 2050, and further upwards thereafter (IPCC, 2007). It is anticipated that mean annual and seasonal temperatures, and rainfall over east Africa will rise, by 3.2, and 3.1, respectively (DJF, SON) and 3.4 °C (JJA), and rainfall by 7 %, between the 2000s and 2080s (Goulden *et al*., 2009). In Uganda, an unprecedented rise in average temperatures by up to 1.5 ºC by 2030 and up to 4.3 ºC by the 2080s is expected (Mubiru, 2010), with changes in rainfall patterns and amounts, though less certain than changes in temperature (GoU, 2007). Climate extreme events, particularly floods and droughts, are also expected to increase in both frequency and intensity (GoU, 2007).

Recent studies (e.g Stark, 2011; Egeru *et al*., 2014; Mugerwa *et al*., 2014; Nimusiima *et al*., 2014) show that communities in the semi-arid areas of Uganda attest to an increase in temperatures, increased frequency of droughts and unpredictable rainfall patterns. The frequency in the extreme events has become prevalent in semi-arid areas, for example, Karamoja sub-region experienced four consecutive years of drought by 2010 (ACTED, 2010; Egeru *et al*., 2014). These areas are also witnessing a surge in the number of flood events; for instance, the period between 2004 and 2009 had more extreme wet events in Karamoja than 1984 and 2003 (Egeru *et al*., 2014).

The increasing variability poses serious implications on natural resources and livelihoods, particularly in pastoral areas of Uganda; and has been attributed to climate change. In this regard, updating of trends in temperature and rainfall is crucial in developing adaptation strategies (Hadgu *et al*., 2013) for building the resilience of the ecosystem and community to climate variability and change. However, recent studies (e.g. Dan Church Aid, 2010; Mubiru, 2010) documented only change in rainfall. A more detailed assessment was conducted by Egeru *et al*. (2014) who applied the coefficient of variation and variability indices, on Climate Forecast System Reanalysis (CFSR) data for 1979-2009, as indicators of rainfall and temperature variability and variability intensity in the catchment. The objective of this study was to assess Spatio-temporal trends and variability in temperature and rainfall (1980-2009) over the semi-arid region of Kapir catchment.

5.2 Materials and methods

5.2.1 Study area

This study was conducted in the semi-arid region of Kapir catchment (which covers Lokok and Lokere catchments), connecting downstream to part of the Teso sub-region in Northeastern Uganda. Karamoja sub-region is part of the Karamoja cluster, an area of land that straddles the borders between Southwestern Ethiopia, Northwestern Kenya, Southeastern South Sudan and Northeastern Uganda. The sub-region experiences hot and dry weather characteristics of most semi-arid regions in Eastern Africa. Rainfall in Karamoja sub-region is uneven and unimodal, occurring from March to November, and ranging from < 500 mm per year in eastern Karamoja, 500-800 mm in central Karamoja to 700-1000 mm in west Karamoja and the isolated highlands (Mbogga *et al*., 2014). Mean annual rainfall downstream of the Catchment, in Teso subregion, is about 1100-1200 mm, distributed between two seasons of March to July and September to November (Kisauzi *et al.*, 2012). Temperatures are generally high throughout the year, with an annual average of 28 and 33 °C for minimum and maximum, respectively; leading to high evapotranspiration levels averaging 2072 mm per annum (Mbogga *et al*., 2014). Rainfall variability in the region leads to heterogeneity of landscape resources including the availability of pasture and water that influences the pastoral way of life as both a coping and adaptation strategy (Egeru *et al*., 2014).

5.2.2 Rainfall and temperature data

The Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) daily climate data were obtained from the Agricultural Model Intercomparison and Improvement Project (AgMIP). Four stations, representing the different rainfall gradients were considered. These were Amuria, Moroto, Kaabong and Kotido stations. The data was downloaded from the AgMERRA website for the four stations for the 1980-2009 period, corresponding to a 30-year climatological period. Amuria and Moroto data points (stations) were located downstream of the Catchment. Furthermore, a larger portion of the upstream Catchment section is under the influence of the Kaabong and Kotido stations adjoining it as shown in the rainfall distribution for the 1980-2009 period (Figure 5.1).

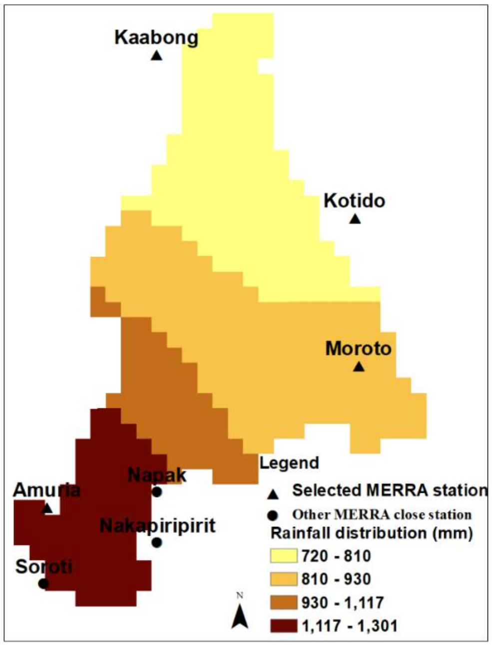

Figure 5.1: Rainfall distribution over the catchment in the 1980-2009 period in Karamoja, north-eastern Uganda.

AgMERRA is a high-resolution (0.25° lat/lon) climate forcing dataset which was designed to meet the needs of AgMIP and related agricultural impacts assessments (Ruane *et al.*, 2015). It is based on the MERRA, produced by NASA's Global Modeling and assimilation Office (GMAO), to provide an hourly output of surface meteorological fields on a 1/2˚ latitude by 2/3˚ longitude grid for the satellite era (post-1979), with a particular focus on the water cycle (Rienecker *et al*., 2011). AgMERRA also utilised a supplemental and improved set of land surface hydrological fields (''MERRA-Land'') generated by rerunning a revised version of the land component of the MERRA system to provide corrections to limitations in the MERRA surface meteorological forcing (Reichle, 2012). AgMERRA data have been applied in examining the agricultural impacts of climate variability and climate change in AgMIP studies, including for gap filling and replacing spurious records (Rao *et al*., 2015).

5.2.3 Analyzing periodic distribution of rainfall and temperature

Rainfall and temperature distribution of rainfall across the catchment was established by calculating annual and seasonal means for each station, over the 1980-2009 period, and comparing the means using Analysis of Variance (ANOVA) and Dunn's post-hoc test at a 5 percent level of significance. The seasons were March-April-Mary (MAM); June-July-August (JJA) and December-January-February (DJF). The analysis was performed using the Paleontological Statistics Software Package for Education and Data Analysis (Past 4.03).

5.2.4 Analyzing trends of the Catchments' rainfall and temperature

The parametric ordinary least square regression method was used to assess the trend of monthly, seasonal and annual temperature means and rainfall totals over time. The significance of the linear model was tested at a probability of 0.05 (Helsel and Hirsch, 2002 and von Storch and Zwiers, 2003).

Cumulative Sum (CUSUM) chart were used for detecting regime shifts, small and sustained changes or slow fluctuations in the mean values of annual and seasonal time series of temperature and rainfall; chosen because of its simplicity and better graphical representation of results (MacDonald *et al*. 2010, Shapiro *et al*. 2010 and Singh *et al*., 2015), CUSUM is a cumulative sum of the deviations of a time series about a target value or mean of time series, and is given as (Montgomery, 2012):

$$C_i = \sum_{j=0}^{i} \left(\underline{x}_i - \mu_0\right)$$

Where C_i is the cumulative sum up to and including the i^{th} sample; $\underline{x}_i$ is the mean of the i^{th} sample (i^{th} value of a single time series), and μ_0, the process means or mean of the time series. The value of C_i will shift upwards (positive) if $\underline{x}_i > \mu_0$ and downwards (negative shift) if $\underline{x}_i < \mu_0$

For a tabular CUSUM for monitoring the mean of a time series:

$$C_i^+ = max[0, x_i - (\mu_0 + K) + C_{i-1}^+]$$

$$C_i^- = max[0, x_i - (\mu_0 - K) + C_{i-1}^-$$

Where C_i^+ and C_i^- are referred to as one sided upper and lower CUSUMs respectively; starting values are $C_i^+ = C_i^- = 0$. K is the allowable value (of deviation from target mean) and is half of the excess of the i^{th} sample mean (or i^{th} value of time series) from the target mean; given as:

$$K = \frac{\delta}{2}\sigma = \frac{|\mu_0 - \mu_i|}{2}$$

The process (trend) was considered to significantly shift if C_i^+ or C_i^- outstrips the decision interval ($Upper\ or\ Lower\ Cusum$) H, which should not exceed 5σ. In this study, 2σ was applied. A non-random pattern of variability was estimated from the chart if it was beyond ± 2σ (Singh *et al*. 2015)

5.2.5 Variability analysis of rainfall and temperature time-series

Two rainfall and temperature variability indicators were also estimated. These include the Standard Rainfall Anomaly (SRA) and Standard Temperature Index (STI). **SRA** was used to further examine the trend and describe variability in rainfall (Bewket and Conway, 2007; Ayalew *et al*., 2012; Hadgu *et al*., 2013) for each station and catchment average as follows:

$$SRA = (R_t - R_m)/\sigma$$

Where: R_t is annual rainfall in year *t*; R_m is the long-term mean annual rainfall over the study period (1980-2009) and; σ is standard deviation. The drought severity classes are: extreme drought (SRA < -1.65), severe drought (-1.28 > SRA > -1.65), moderate drought (-0.84 > SRA > -1.28), and no drought (SRA > -0.84). The STI was derived for each annual mean by subtracting the mean and dividing by the standard deviation of the time series (1980-2009). The following heat severity classes were identified: "extremely hot" (STI≥2.0), "very hot" (1.5≤STI<2.0), "extremely cold" (STI≤-2.0), "very cold" (-1.5≥-STI>-2.0); and normal (-1.5≤STI<1.5) (Singh *et al*., 2015; Wendleder *et al*., 2018).

$$SRA = (R_t - R_m)/\sigma R_t R_m \sigma$$

5.3 Results

5.3.1 Spatio-temporal trend in Temperature

5.3.1.1 Mean temperature

The long-term (1980-2009) average annual and seasonal mean temperature (Tmean), maximum temperature (Tmax), and minimum temperature (Tmin) over the catchments are presented in

Tables 5.1, 5.2, and 5.3 respectively. The long-term average annual Tmean and Tmax over the catchments was 23.7±0.4 and 30.2±0.4 ^{o}C, respectively. The long-term average annual Tmin over the catchments was 17.0±0.5 ^{o}C.

Temperature was relatively lower in Kaabong station, followed by Moroto Station and higher in Amuria Station as the mean annual Tmean varied from 23.0±0.4 in Kaabong to 25.1±0.5 ^{o}C in Amuria. Mean annual Tmin and Tmax also ranged from 16.2±0.5 and 29.8±0.4 ^{o}C in Kaabong to 18.5±0.6 and 31.6±0.5 ^{o}C in Amuria, respectively. The mean annual temperatures were not significantly different in Kaabong and Moroto Stations ($p > 0.05$). However, Amuria and Kotido stations' mean annual temperatures were each significantly different from all others ($p < 0.05$).

In the 30-year period, seasonal temperatures were such that the June-August (JJA) season was the coolest in the catchment, with Tmean of 22.3±0.4 ^{o}C which was significantly different ($p < 0.05$) from seasonal Tmean in all the other stations (Table 5.1). DJF Tmean was the hottest season (24.8±0.7 ^{o}C), however, it was similar with MAM, the second hottest ($p > 0.05$). DJF and JJA seasons had the hottest and coolest Tmax which were each significantly different from all the stations, while MAM and SON had similar Tmax (Table 5.2). Tmin (Table 5.3) was hottest in MAM when it was significantly different from that in all the other seasons ($p < 0.05$). And, Tmin in the coolest season, JJA and DJF were significantly different ($p < 0.05$) however were both similar to SON Tmin.

The temperatures were highest in Amuria in all the seasons and lowest in Moroto Station in MAM and Kaabong Station in the SON. In the coolest season, JJA, Tmean ranged from 23.6±0.6 in Amuria Station to 21.6±0.4 in Kaabong station. In the hottest season, DJF, Tmean ranged from 24.1±0.7 ^{o}C in Kaabong to 26.4±0.8 ^{o}C in Amuria. All seasonal Tmean, Tmax and Tmin for Amuria station were significantly different from that of the rest of the stations ($p < 0.05$). DJF and MAM Tmean were similar in the rest of the stations ($p > 0.05$). However, JJA and SON Tmean for Kaabong station were significantly different from their respective Kotido station Tmean but similar to Moroto Station Tmean which was also similar to Kotido station Tmean.

Table 5.4 shows that February was the hottest month in the catchments with Tmean of 25.6±0.9 ^{o}C followed by March (25.4±0.8 ^{o}C), while July was the coolest month (22.2±0.6 ^{o}C), followed by August (22.4±0.6 ^{o}C) and June (22.4±0.4 ^{o}C). Further, because June and August are the coolest months, the June-August (JJA) season was the coolest with Tmax, Tmin and Tmean of 28.2 ^{o}C, 16.5 ^{o}C and 22.3 ^{o}C respectively. DJF was the hottest season with Tmax, and Tmean of 32.0 ^{o}C and 24.8 ^{o}C respectively, but it was MAM which had the hottest Tmin (17.7 ^{o}C).

Table 5.1. Average annual and seasonal mean temperature along the rainfall gradient of Lokok and Lokere catchments (the semi-arid region of Kapir Catchment), north-eastern Uganda (1980-2009)

	Amuria	Kaabong	Kotido	Moroto	Catchment
DJF	26.4±0.8^{a}	24.1±0.7^{b}	24.5±0.6^{b}	24.1±0.7^{b}	24.8±0.7^{a}
MAM	25.5±0.6^{a}	23.8±0.6^{b}	24.0±0.6^{b}	23.5±0.6^{b}	24.2±0.6^{a}
JJA	23.6±0.6^{a}	21.6±0.4^{b}	22.3±0.4^{c}	21.8±0.4^{b}	22.3±0.4^{b}
SON	24.8±0.6^{a}	22.6±0.4^{b}	23.4±0.4^{c}	22.9±0.5^{b}	23.4±0.5^{c}
Annual	25.1±0.5^{a}	23.0±0.4^{b}	23.5±0.4^{c}	23.1±0.4^{b}	23.7±0.4

Figures with the same letter against them within the same row for stations and same column for catchments, are similar; at 5% significant level according to ANOVA and Dunn's post hoc test.

Table 5.2: Average annual and seasonal maximum temperature along the rainfall gradient of Lokok and Lokere catchments (the semi-arid region of Kapir Catchment), north-eastern Uganda (1980-2009)

	Stations				Catchments
	Amuria	Kaabong	Kotido	Moroto	
DJF	34.3±0.8^{a}	32.1±0.6^{b}	32±0.6^{b}	31.8±0.7^{b}	32±0.6^{a}
MAM	31.8±0.8^{a}	30.5±0.7^{b}	30.6±0.6^{b}	30.3±0.6^{b}	30.6±0.6^{b}
JJA	28.9±0.8^{a}	27.3±0.5^{b}	28.2±0.5^{c}	27.9±0.5^{c}	28.2±0.5^{c}
SON	31.4±0.7^{a}	29.5±0.6^{b}	30.1±0.6^{c}	29.7±0.5^{bc}	30.1±0.6^{b}
Annual	31.6±0.5^{a}	29.8±0.4^{b}	30.2±0.3^{c}	29.9±0.4^{b}	30.2±0.4

Figures with the same letter against them within the same row for stations and same column for catchments, are similar; at 5% significant level according to ANOVA and Dunn's post hoc test.

Table 5.3: Average annual and seasonal minimum temperature along the rainfall gradient of Lokok and Lokere catchments (the semi-arid region of Kapir Catchment), north-eastern Uganda (1980-2009)

	Stations				Catchments
	Amuria	Kaabong	Kotido	Moroto	
DJF	18.4±0.8^{a}	16.1±0.8^{b}	16.9±0.8^{c}	16.4±0.8^{b}	16.9±0.8^{b}
MAM	19.1±0.6^{a}	17.1±0.6^{bc}	17.5±0.6^{b}	16.8±0.6^{c}	17.7±0.6^{a}
JJA	18.3±0.5^{a}	15.9±0.5^{b}	16.3±0.5^{c}	15.7±0.5^{b}	16.5±0.5^{c}
SON	18.2±0.6^{a}	15.8±0.6^{b}	16.7±0.6^{c}	16±0.6^{b}	16.7±0.6^{bc}

Annual	18.5 ± 0.6^a	16.2 ± 0.5^b	16.9 ± 0.5^c	16.2 ± 0.5^b	17.0±0.5

Figures with the same letter against them within the same row for stations and same column for catchments, are similar; at 5% significant level according to ANOVA and Dunn's post hoc test.

Table 5.4: Average monthly temperature in Lokok and Lokere catchments (the semi-arid region of Kapir Catchment), north-eastern Uganda (1980-2009)

Time-series	Tmax	Tmin	Tmean
Jan	32.1±0.6	16.7±0.9	24.7±0.7
Feb	33.1±0.9	17.6±0.9	25.6±0.9
Mar	32.3±0.9	18.1±0.8	25.4±0.8
Apr	30.4±0.9	17.7±0.7	24.2±0.8
May	28.9±0.6	17.1±0.6	23.1±0.6
Jun	28.3±0.7	16.6±0.5	22.4±0.4
Jul	27.9±0.7	16.6±0.5	22.2±0.6
Aug	28.4±0.7	16.4±0.6	22.4±0.6
Sep	30±0.8	16.4±0.7	23.1±0.6
Oct	30±0.6	16.7±0.6	23.4±0.5
Nov	30.2±0.7	16.9±0.8	23.8±0.6
Dec	31.1±0.8	16.7±1.0	24.1±0.8

5.3.1.2 Trend analysis of temperature time series

Temperature (Tmean, Tmax and Tmin) in the catchments revealed a rising but spatially distinguished pattern. Annual Tmean significantly ($p < 0.05$) rose during the 1980-2009 period, at 0.05 °C per year (R^2=0.58) for Amuria station and 0.03 °C per year (R^2=0.54) for catchments average and the rest of the stations (Figure 5.2). The rise in seasonal Tmean was significant ($p < 0.05$) for DJF, MAM, and JJA at both Catchment level and for all the stations (Table 5.5). The rise in Tmean during SON was significant in all locations except for Kaabong and Kotido. At the monthly scale, only June, July, and October did not experience a significant ($p > 0.05$) rise in Tmean at catchments level and Kaabong, Kotido, and Moroto station (Table 5.5). The rise in November temperatures was also not significant in Kaabong and Kotido as was September in Kaabong. It is also notable that the relatively warmer Amuria registered higher slope values and a significant ($p < 0.05$) increase in Tmean during all the months, seasons and at annual scale.

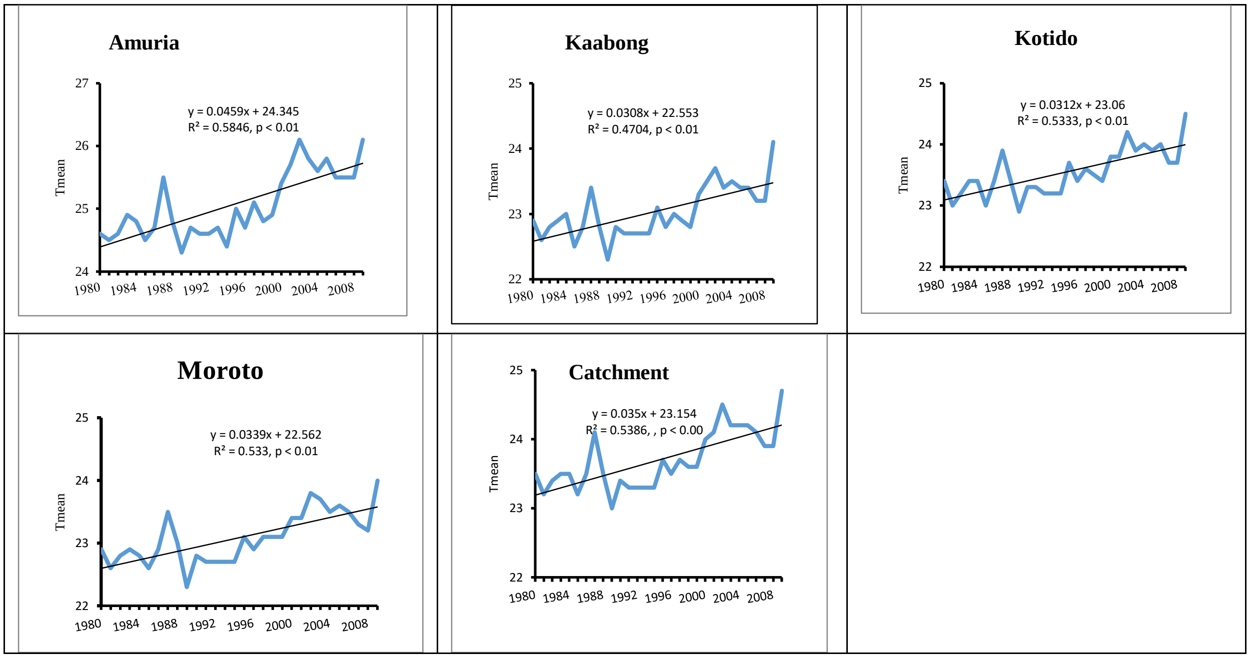

Figure 5.2: Observed trend line of annual mean air temperature for the stations and Lokok and Lokere catchments, north-eastern Uganda, with significant (p<0.05) trends for the period 1980–2009

Annual Tmax over the period under study significantly ($p < 0.05$) rose by 0.3 °C (slope of 0.03, R^2=0.56) in Amuria and 0.2 °C (slope of 0.02, $R^2 < 0.33$) over the catchments and the rest of the stations (Figure 5.3). Increase in seasonal Tmax was mixed, being significant for DJF and MAM in the Catchment and all stations, with high slope values for Amuria of 0.06 and 0.05 respectively, compared to the rest (Catchment and Kotido: 0.03 &0.04; Kaabong and Moroto: 0.04 all) (Table 5.6). Rise in JJA and SON Tmax was significant only in Amuria and Kaabong. Monthly Tmax showed even more mixed trends, with significant ($p < 0.05$) increases in December, May, and January Tmax across all stations. However, there was no significant ($p < 0.05$) increase in October Tmax across all stations. Further, except for Amuria, there has been a significant increase in Tmax over the catchments and the rest of the stations. For the rest of the months, there has been no significant increase of Tmax at Catchment level, Kotido and Moroto but Amuria (June-Sept) and Kaabong (August-September).

Tmin rose at higher rates than Tmean and Tmax, and the rise was significant ($p < 0.05$) in all cases, with the exception of the month of June, and only in Amuria and Kaabong stations (Figure 5.4 and Table 5.7). At the catchment level, annual Tmin rose by 0.4 °C (slope of 0.04, R^2=0.53) compared to 0.3 ^{o}C and 0.2 ^{o}C for Tmean and Tmax respectively. This contrast is observed across the stations, and at all the temporal scales.

Table 5.5: Magnitudes and p-value of trends in annual mean air temperature for the catchment and stations

	Catchment average		Amuria		Kaabong		Kotido		Moroto	
Time series	Slope	p-value	Slope	p-value	Slope	p-value	Slope	p-value	Slope	p-value
Jan	0.04 (0.3)	0.00	0.05 (0.2)	0.01	0.04 (0.3)	0.00	0.03 (0.2)	0.01	0.04 (0.2)	0.01
Feb	0.06 (0.3)	0.00	0.07(0.4)	0.00	0.06 (0.3)	0.00	0.05 (0.3)	0.00	0.06 (0.3)	0.00
Mar	0.04 (0.3)	0.00	0.05 (0.3)	0.00	0.04 (0.2)	0.01	0.04 (0.2)	0.01	0.04 (0.3)	0.00
Apr	0.05 (0.3)	0.00	0.05 (0.2)	0.01	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.4)	0.00
May	0.04 (0.3)	0.00	0.04 (0.3)	0.00	0.04 (0.3)	0.00	0.04 (0.3)	0.00	0.03 (0.3)	0.00
Jun	**0.01 (0.1)**	**0.07**	0.03 (0.3)	0.00	**0.01 (0.2)**	**0.48**	**0.01 (0.1)**	**0.10**	**0.01 (0.1)**	**0.12**
Jul	**0.02 (0.1)**	**0.05**	0.03 (0.2)	0.02	**0.02 (0.1)**	**0.05**	**0.02 (0.1)**	**0.13**	**0.02 (0.1)**	**0.11**
Aug	0.03 (0.2)	0.01	0.05 (0.3)	0.00	0.02 (0.2)	0.03	0.03 (0.2)	0.01	0.03 (0.2)	0.01
Sep	0.03 (0.2)	0.01	0.05 (0.2)	0.01	**0.02 (0.1)**	**0.08**	0.02 (0.1)	0.03	0.03 (0.2)	0.01
Oct	**0.01 (0.1)**	**0.13**	0.03 (0.2)	0.02	**0.00 (0.0)**	**0.86**	**0.01 (<0.1)**	**0.36**	**0.02 (0.1)**	**0.10**
Nov	0.03 (0.1)	0.03	0.05 (0.3)	0.00	**0.02 (0.1)**	**0.09**	**0.02 (0.1)**	**0.17**	0.03 (0.2)	0.03
Dec	0.06 (0.4)	0.00	0.06 (0.4)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.4)	0.00
DJF	0.04 (0.3)	0.00	0.05 (0.34)	0.00	0.04 (0.4)	0.00	0.04 (0.3)	0.00	0.04 (0.3)	0.00
MAM	0.04 (0.4)	0.00	0.04 (0.36)	0.00	0.04 (0.4)	0.00	0.04 (0.4)	0.00	0.04 (0.4)	0.00
JJA	0.02 (0.3)	0.01	0.04 (0.31)	0.00	0.02 (0.3)	0.02	0.02 (0.2)	0.01	0.02 (0.2)	0.02
SON	0.03 (0.2)	0.01	0.04 (0.38)	0.00	**0.01 (0.5)**	**0.15**	**0.02 (0.1)**	**0.06**	0.02 (0.2)	0.01

Only series whose slope and p – values bold had no significant trends (at 0.05 significance) level

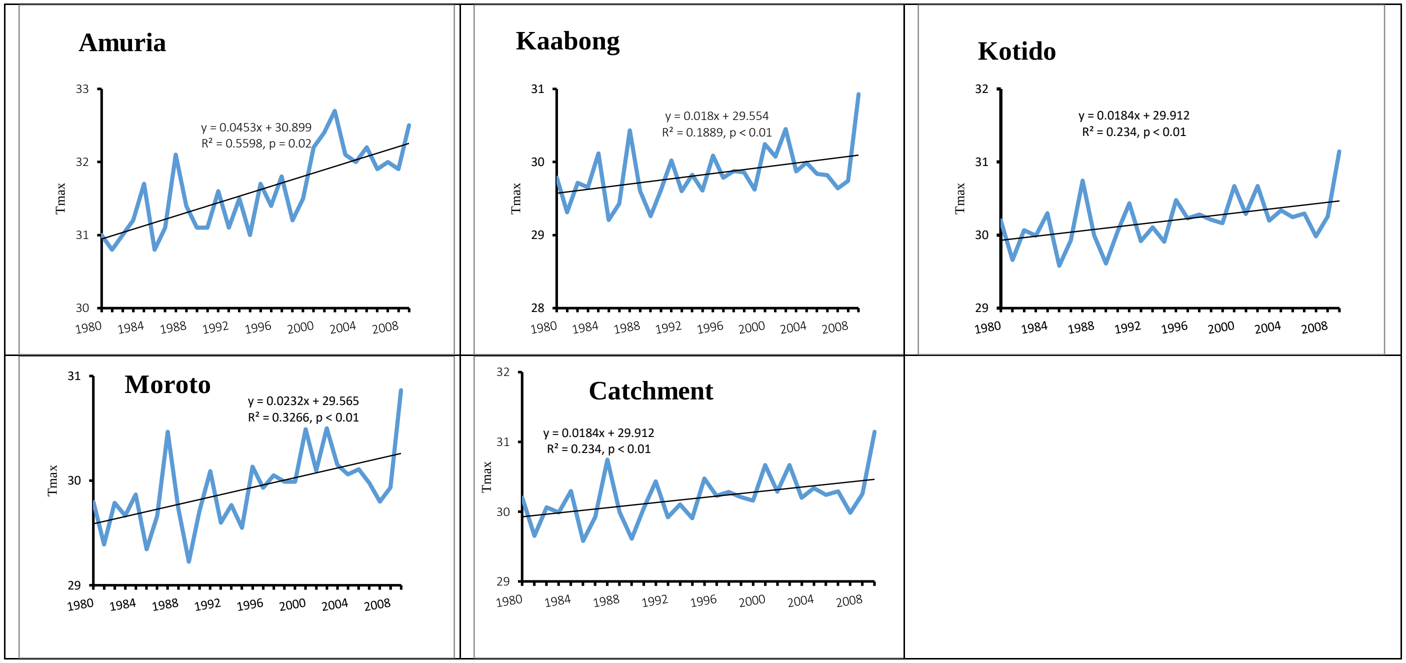

Figure 5.3: Observed trend line of annual Tmax for the catchment and at the stations, with significant trends for the period 1980–2009

Table 5.6: Magnitudes and p-value of trends in annual Tmax for the catchment and stations.

	Catchment		Amuria		Kaabong		Kotido		Moroto	
Time series	Slope	p-value	Slope	p-value	Slope	p-value	Slope	p-value	Slope	p-value
Jan	0.03 (0.2)	0.03	0.04 (0.2)	0.02	0.04 (0.3)	0.00	0.03 (0.1)	0.03	0.03 (0.2)	0.01
Feb	0.05 (0.3)	0.00	0.07 (0.3)	0.00	0.06 (0.3)	0.00	0.05 (0.3)	0.00	0.06 (0.3)	0.00
Mar	**0.04 (0.1)**	**0.05**	0.04 (0.1)	0.04	0.04 (0.3)	0.00	0.04 (0.1)	0.05	0.04 (0.1)	0.04
Apr	0.05 (0.2)	0.01	**0.05 (0.1)**	**0.05**	0.05 (0.3)	0.00	0.05 (0.2)	0.01	0.05 (0.2)	0.01
May	0.04 (0.2)	0.01	0.04 (0.2)	0.01	0.04 (0.3)	0.00	0.04 (0.2)	0.01	0.03 (0.2)	0.01
Jun	**0.00 (0.0)**	**0.81**	0.04 (0.2)	0.01	**0.01 (0.1)**	**0.07**	**0 (0.0)**	**0.81**	**0 (0.0)**	**0.99**
Jul	**0.01(0.0)**	**0.59**	0.05 (0.2)	0.02	**0.02 (0.1)**	**0.05**	**0.01 (0.0)**	**0.59**	**0.01 (0.0)**	**0.54**
Aug	**0.01 (0.2)**	**0.45**	0.05 (0.2)	0.02	0.03 (0.2)	0.01	**0.01 (0.0)**	**0.45**	**0.01 (0.0)**	**0.41**
Sep	**0.00 (0.0)**	**0.93**	0.05 (0.2)	0.01	0.03 (0.2)	0.01	**0 (0.0)**	**0.93**	**0.01 (0.0)**	**0.63**
Oct	**-0.02 (0.1)**	**0.17**	**0.04 (0.1)**	**0.09**	**0.01 (0.1)**	**0.13**	**-0.02 (0.1)**	**0.17**	**-0.01 (0.0)**	**0.45**
Nov	**-0.01 (0.0)**	**0.63**	**0.02 (0.0)**	**0.33**	0.03 (0.2)	0.03	**-0.01 (0.0)**	**0.63**	**0 (0.0)**	**0.86**
Dec	0.03 (0.1)	0.04	0.04 (0.2)	0.01	0.06 (0.4)	0.00	0.03 (0.1)	0.04	0.04 (0.2)	0.03
DJF	0.03 (0.2)	0.02	0.06 (0.3)	0.00	0.04 (0.3)	0.00	0.03 (0.2)	0.02	0.04 (0.2)	0.01
MAM	0.04 (0.3)	0.00	0.05 (0.3)	0.00	0.04 (0.4)	0.00	0.04 (0.3)	0.00	0.04 (0.3)	0.00
JJA	**0.01 (0.0)**	**0.52**	0.05 (0.3)	0.00	0.02 (0.2)	0.01	**0.01 (0.0)**	**0.52**	**0.01 (0.0)**	**0.39**
SON	**-0.01 (0.0)**	**0.41**	0.05 (0.3)	0.00	0.03 (0.2)	0.01	**-0.01 (0.0)**	**0.41**	**0 (0.0)**	**0.96**

Only series whose slope and p – values in bold had no significant trends, at 0.05 level of significance

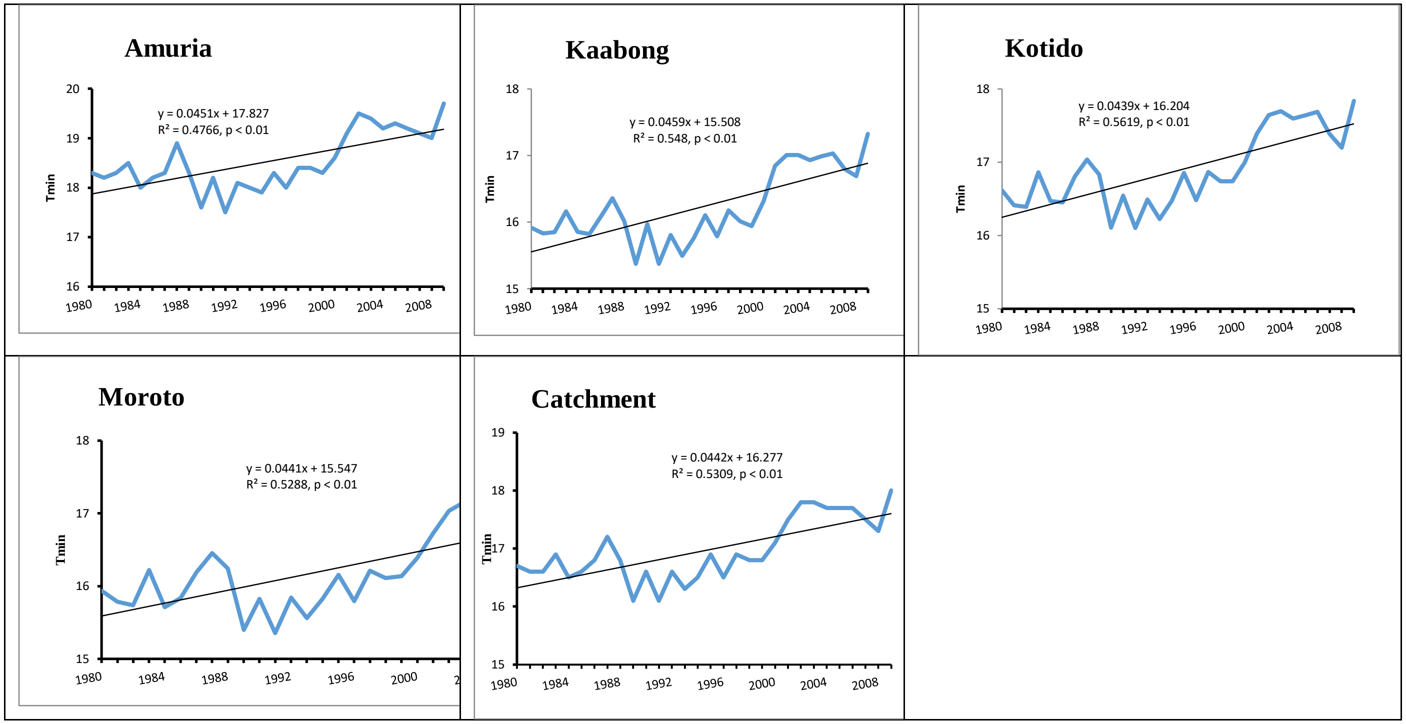

Figure 5.4: Observed trend line of annual Tmin for the catchment and at the stations, with significant trends for the period 1980–2009.

Table 5.7: Magnitudes and p-value of trends in annual minimum temperature for the catchment and stations

	Catchment		**Amuria**		**Kaabong**		**Kotido**		**Moroto**	
Time series	Slope	p-value	Slope	p-value	Slope	p-value	Slope	p-value	Slope	p-value
Jan	0.05 (0.2)	0.01	0.05 (0.2)	0.01	0.06 (0.3)	0.00	0.04 (0.2)	0.01	0.04 (0.2)	0.01
Feb	0.06 (0.3)	0.00	0.07 (0.3)	0.00	0.06 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00
Mar	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00
Apr	0.05 (0.4)	0.00	0.04 (0.3)	0.00	0.05 (0.4)	0.00	0.05 (0.4)	0.00	0.05 (0.4)	0.00
May	0.03 (0.2)	0.01	0.03 (0.2)	0.02	0.04 (0.3)	0.00	0.04 (0.3)	0.00	0.03 (0.3)	0.00
Jun	0.02 (0.2)	0.02	0.02 (0.1)	0.06	0.02 (0.1)	0.07	0.03 (0.2)	0.01	0.03 (0.2)	0.01
Jul	0.03 (0.2)	0.01	0.02 (0.1)	0.04	0.03 (0.3)	0.00	0.03 (0.2)	0.01	0.03 (0.2)	0.02
Aug	0.05 (0.4)	0.00	0.04 (0.3)	0.00	0.04 (0.3)	0.00	0.04 (0.4)	0.00	0.04 (0.3)	0.00
Sep	0.04 (0.3)	0.00	0.05 (0.4)	0.00	0.05 (0.4)	0.00	0.05 (0.5)	0.00	0.05 (0.4)	0.00
Oct	0.04 (0.4)	0.00	0.04 (0.4)	0.00	0.04 (0.4)	0.00	0.04 (0.3)	0.00	0.04 (0.4)	0.00
Nov	0.05 (0.3)	0.00	0.06 (0.4)	0.00	0.05 (0.3)	0.00	0.05 (0.2)	0.01	0.05 (0.3)	0.00
Dec	0.07 (0.4)	0.00	0.07 (0.4)	0.00	0.07 (0.4)	0.00	0.07 (0.4)	0.00	0.07 (0.4)	0.00
DJF	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00	0.05 (0.3)	0.00
MAM	0.04 (0.4)	0.00	0.04 (0.3)	0.00	0.05 (0.4)	0.00	0.05 (0.4)	0.00	0.04 (0.4)	0.00
JJA	0.03 (0.3)	0.00	0.03 (0.2)	0.01	0.03 (0.3)	0.00	0.03 (0.3)	0.00	0.03 (0.3)	0.00
SON	0.05 (0.5)	0.00	0.05 (0.5)	0.00	0.04 (0.5)	0.00	0.04 (0.4)	0.00	0.05 (0.5)	0.00

Only series whose slope and p – values are highlighted have no significant trends, at 0.05 level of significance

5.3.2 Spatio-temporal trend in rainfall

5.3.2.1 Mean rainfall

The catchments mean annual rainfall over the 1980-2009 period was 897.1±122.1 mm and ranged from 701.6±105.9 in Kotido to 1302.5±156.7 mm in Amuria (Table 5.8). The mean annual rainfall in Amuria Station was significantly different from that in all the other stations, as was rainfall in Moroto Station, the second highest ($p < 0.05$). However, mean annual rainfall in Kaboong and Kotido Stations were similar ($p > 0.05$).

On the seasonal front (Table 5.8), rainfall in the catchments was highest in the JJA season (322.5±69.6 mm), closely followed by MAM (284.8±54.0 mm). DJF was the driest, with 58.6±36.4 mm, nearly four-times drier than the SON (230.1±62.0 mm), the second driest. In all the seasons, rainfall was significantly higher in Amuria than in any of the other stations ($p < 0.05$). MAM and SON Rainfall were the second highest in Moroto, and significantly different from any other station, however similar for Kaabong and Kotido Stations. Moroto and Kaabong Stations had significantly different DJF rainfall but similar to that in Kotido. But it was in the JJA season where rainfall in Kaabong and Kotido was significantly different ($p < 0.05$) but were both similar to rainfall in Moroto ($p < 0.05$).

Table 5.8: Long-term (1980-2009) mean annual and seasonal rainfall (mm) in Lokok and Lokere catchments, north-eastern Uganda

	Seasons				Annual
	DJF	MAM	JJA	SON	
Catchment	58.6±36.4	284.8±54.0	322.5±69.6	230.1±62.0	897.1±122.1
Amuria	95.2±58.2[a]	401.3±71.9[a]	380.5±81.3[a]	424±85.7[a]	1302.5±156.7[a]
Kaabong	39.6±30.9[b]	210.9±59.0[b]	329.1±102.3[b]	148.2±58.0[b]	728.4±147.4[b]
Kotido	40.9±25.8[bc]	233.4±47.5[b]	284.2±62.1[c]	142±53.5[b]	701.6±105.9[b]
Moroto	58.7±38.1[c]	293.6±52.3[c]	296±57.1[bc]	206.1±62.6[c]	855.7±117.9[c]

Figures with the same letter against them within the same column are similar while those with different letters are different, at 5% significant level according to ANOVA and Dunn's post hoc test.

Analysis of rainfall at the monthly time scale shows that DJF was the driest season in the catchments because it had the driest months, namely January (13.7±10.5), February (21.9±17.3) and December (24.1±20.0) (Table 5.9). On the other hand, August (118.4±38.6), July (115.3±35.6), May (110.1±30.7) and April (114.8±35.4) were the wettest months. This pattern of the rainfall amounts for the wetter and drier months was consistent with that of all the stations except for Amuria where it was August, April, October, and September were the wettest (in reducing order of wetness). Substantial rainfall over the catchment has been occurring from March to November.

Table 5.9: Long-term mean annual, seasonal and monthly rainfall in Lokok and Lokere catchments, north-eastern Uganda

Month	Catchment	Amuria	Kaabong	Kotido	Moroto
Jan	13.7±10.5	27.8±10.5	6.5±6.2	7.1±6.6	13.2±11.8
Feb	21.9±17.3	30.9±17.3	16.1±19.1	17.2±6.6	23.3±18.6
Mar	60.0±28.3	92.7±28.3	38.4±23.3	47.1±24.0	61.5±30.7
Apr	110.1±30.7	157.1±30.7	86.1±35.6	84.8±30.7	112.3±33.7
May	114.8±35.4	151.5±35.4	86.4±42.4	101.5±31.6	119.8±34.3
Jun	88.8±22.8	99.2±22.8	91.1±33.7	81.6±20.8	83.3±20.3
Jul	115.3±35.6	115.1±35.6	127.4±62.0	109.3±34.3	109.4±28.7
Aug	118.4±38.6	166.2±38.6	110.6±51.8	93.3±31.6	103.3±29.9
Sep	84.0±34.3	152.5±34.3	57.7±30.7	57.3±28.2	68.7±30.9
Oct	81.2±34.9	153.6±34.9	51.0±35.4	43.8±24.9	76.1±33.3
Nov	65.0±36.1	117.9±36.1	39.6±35.0	40.9±35.1	61.3±34.7
Dec	24.1±20.0	37.9±20.0	17.6±17.8	17.7±16.3	23.4±21.1

5.3.2.2 Trend in rainfall

An overall increase in rainfall over the Catchment was observed during the 1980-2009 (Figure 5.5 and Table 5.10). Mean annual rainfall increased across all the stations. Only the MAM season showed decreasing rainfall at catchment level and all the stations with the exception of Kaabong where it increased over the period under study. January, April and August-December experienced an increase in rainfall, while May experienced a decrease in rainfall, in all stations. Whereas there was increase in catchments rainfall in February and July despite observed decrease in Kotido and Amuria, March, May and June showed decreased rains.

The trends in rainfall were largely not significant, with total annual rainfall being only significant ($P < 0.05$) in Kotido and Moroto ($R^2 = 0.17$); and all the observed decreases were not significant. SON was the only season where increase in total rainfall was significant at Catchment level and all the stations, with the exception of Amuria. Significant increase of SON rainfall can be attributed to the increase in October rainfall in those stations. A significant change in total rainfall for January was only observed only in Kaabong.

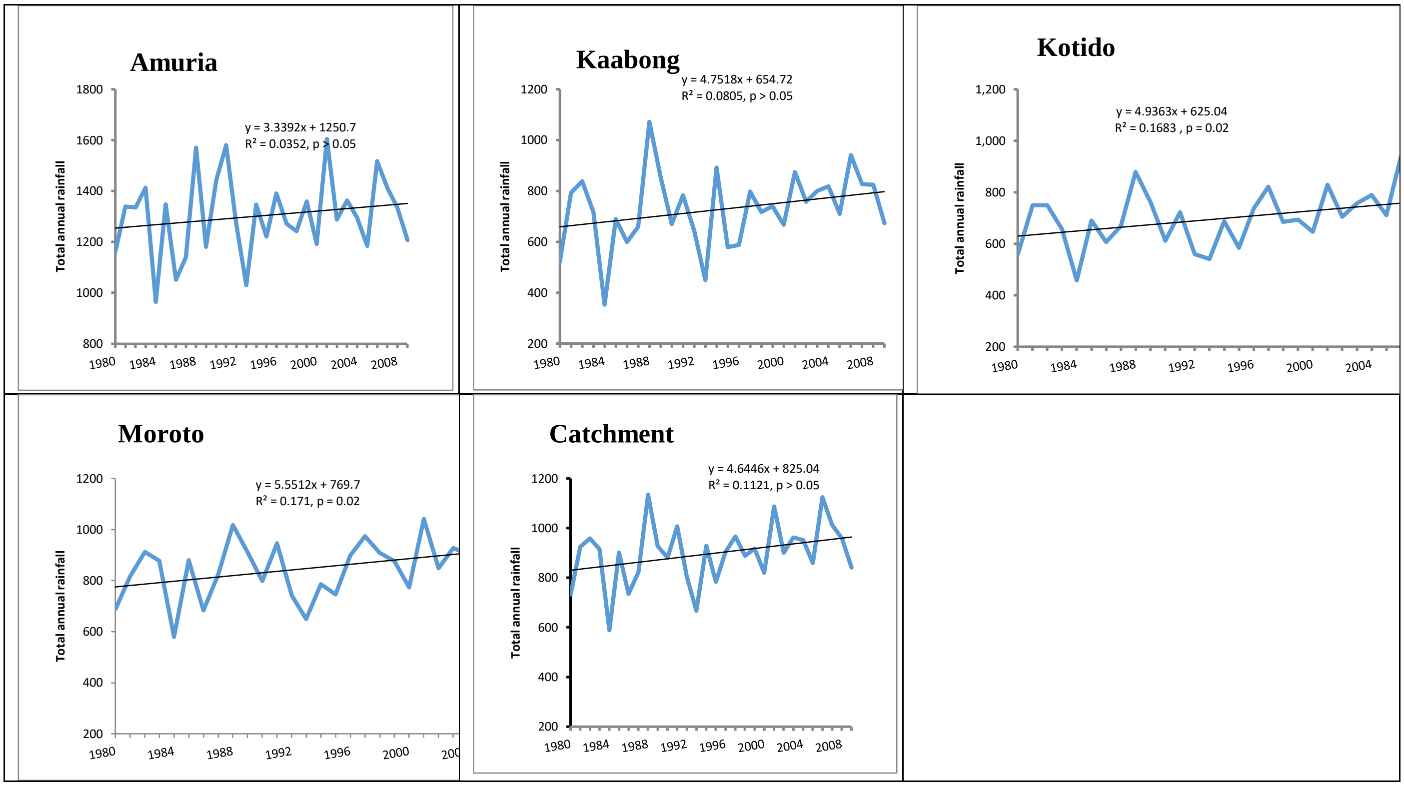

Figure 5.5: Observed trend line of annual rainfall for the stations and the semi-arid region of Kapir Catchment, north-eastern Uganda, during the period 1980–2009 (with bold equations, Moroto and Kotido, are significant trends, $p < 0.05$)

Table 5.10: Trend analysis of annual rainfall for the stations and Lokok and Lokere catchments, north-eastern Uganda, for the 1980-2009 period

	Catchment		Amuria		Kaabong		Kotido		Moroto	
Time series	Slope (R^2)	p-value	Slope (R^2)	p-value	Slope (R^2)	p-value	Slope (R^2)	p-value	Slope (R^2)	p-value
Jan	0.4 (0.1)	0.07	0.68 (0.1)	0.1	**0.31 (0.2)**	**0.02**	0.24 (0.1)	0.08	0.38 (0.1)	0.13
Feb	0.05 (0.0)	0.9	0.17 (0.0)	0.75	0.02 (0.0)	0.96	-0.08 (0.0)	0.77	0.08 (0.0)	0.84
Mar	-0.34 (0.0)	0.58	-0.83 (0.0)	0.35	0.14 (0.0)	0.78	-0.3 (0.0)	0.57	-0.36 (0.0)	0.58
Apr	0.31(0.0)	0.64	0.18 (0.0)	0.83	0.79 (0.0)	0.3	0.21 (0.0)	0.75	0.08 (0.0)	0.92
May	-0.54 (0.0)	0.48	-0.98 (0.0)	0.34	-0.83 (0.0)	0.36	-0.06 (0.0)	0.93	-0.27 (0.0)	0.71
Jun	-0.13 (0.0)	0.79	0.11 (0.0)	0.88	-0.63 (0.0)	0.38	-0.18 (0.0)	0.69	0.19 (0.0)	0.67
Jul	0.54 (0.0)	0.48	-0.07 (0.0)	0.94	0.57 (0.0)	0.67	0.93 (0.1)	0.2	0.73 (0.1)	0.23
Aug	0.52 (0.0)	0.53	0.02 (0.0)	0.98	0.29 (0.0)	0.8	0.97 (0.1)	0.15	0.81 (0.1)	0.2
Sep	1.08 (0.0)	0.14	1.72 (0.1)	0.15	0.95 (0.1)	0.15	0.69 (0.0)	0.25	0.97 (0.1)	0.14
Oct	**1.58 (0.2)**	**0.03**	1.57 (0.1)	0.16	**1.62 (0.2)**	**0.03**	**1.45 (0.3)**	**<0.01**	**1.69 (0.3)**	**0.01**
Nov	0.43 (0.0)	0.58	0.11 (0.0)	0.91	0.83 (0.0)	0.27	0.41 (0.0)	0.59	0.39 (0.0)	0.6
Dec	0.72 (0.1)	0.09	0.66 (0.0)	0.28	0.69 (0.1)	0.06	0.65 (0.0)	0.06	0.86 (0.1)	0.05
DJF	0.79 (0.1)	0.34	1.2 (0.0)	0.36	0.69 (0.0)	0.33	0.42 (0.0)	0.47	0.85 (0.0)	0.32
MAM	-0.56 (0.0)	0.63	-1.64 (0.0)	0.29	0.1 (0.0)	0.94	-0.15 (0.0)	0.88	-0.56 (0.0)	0.62
JJA	0.94 (0.0)	0.53	0.06 (0.0)	0.97	0.23 (0.0)	0.92	1.73 (0.1)	0.19	1.74 (0.1)	0.15
SON	**3.1 (0.2)**	**0.01**	3.39 (0.1)	0.06	**3.41 (0.3)**	**0**	**2.55 (0.2)**	**0.02**	**3.05 (0.2)**	**0.02**

Values in bold indicate an increasing and significant trends at 0.05 level of significance

5.3.3 Analysis of inter-annual variability and regime shift in temperature and rainfall during 1980-2009

5.3.3.1 Inter-annual variability and abrupt regime shift in temperature

Across the catchment, years after 1995 were generally hotter than the earlier years (Figures 5.6), 5.7 & 5.8). Tmax was generally below the mean (negative STI) of the time-series from 1980-1994, and above the mean (positive STI) in 1984 (negative for Moroto), 1987, and 1991. STDs were positive from 2000 to 2009 with negative STIs recorded in 2007 (remained positive for Amuria) and only for Kaabong in 2008 (Figure 5.6).

"Extremely hot" Tmax occurred in Amuria in 2002 and, in all the stations in 2009, with the exception of Amuria where it was "very hot". With the exception of Amuria, where Tmax was within normal range, it was "very hot" in 1987 in all the stations. "Very hot" temperatures were also recorded in Moroto in 2000 and 2002, in Amuria in 2001, and in Kotido in 2002.

“Extremely cold” Tmax was only recorded in Moroto in 1989and with the exception of Amuria, it was “very cold” in the rest of the districts. All the stations recorded “very cold” Tmax in 1985; and similarly in 1981, with the exception of Kaabong.

With the exception of 1987, minimum temperature was generally low in the 1980-1999 period (Tmin negative STI). During this period, minimum temperatures were negative from 1980-1999, and Tmin was “very cold” in 1989 and 1991, for all the stations (Figure 5.7). However, Tmin It then became warmer positive from 2000 to 2009 period (positive STI); and it was in 2009 “extremely hot” in Kaabong, “very hot”; when averaged over the catchments as well as in Amuria, Kotido and Moroto stations.   and “Extremely hot” in Kaabong and Amuria and “very hot” in the rest of the stations and catchment average, in 2009. Minimum temperature was also “Very hot” in all stations, Amuria, Kotido, Moroto and when averaged over the catchments in 2002 – with the exception of Kaabong – in 2002; Moroto in 2005, and Kotido and Moroto in 2006.

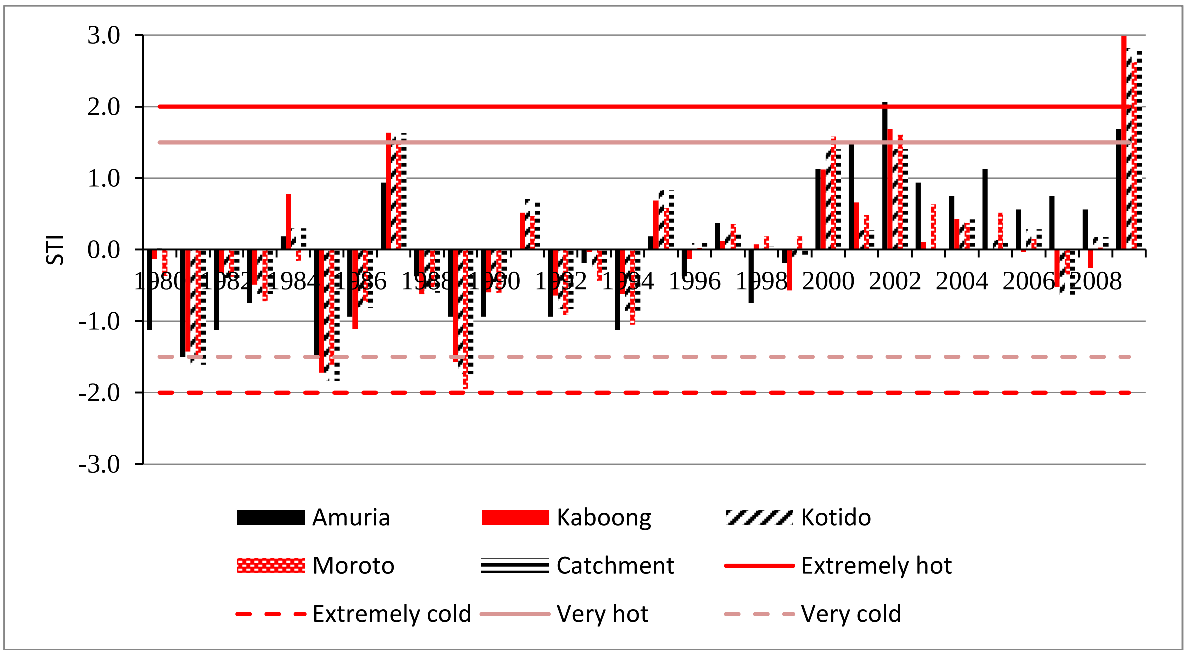

Figure 5.6: Standard temperature indices (STI) for maximum temperature in the stations and Lokok and Lokere catchments , northeastern Uganda, for the period 1980–2009

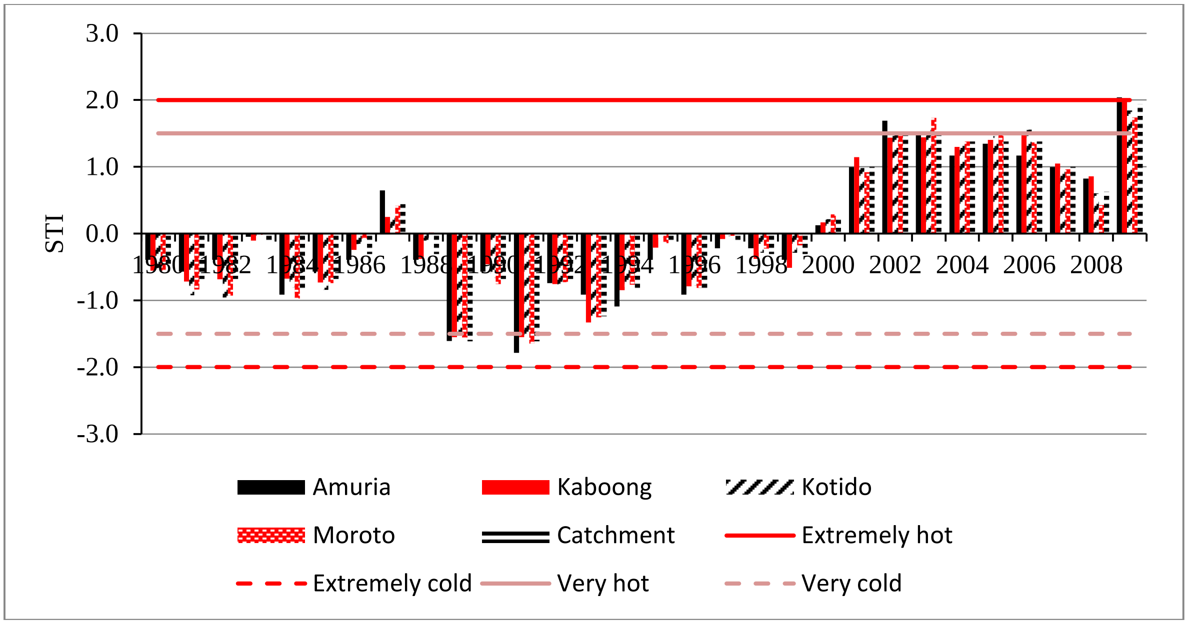

Figure 5.7: Standard temperature indices (STI) for minimum temperature in the stations and Lokok and Lokere catchments, northeastern Uganda, for the period 1980–2009

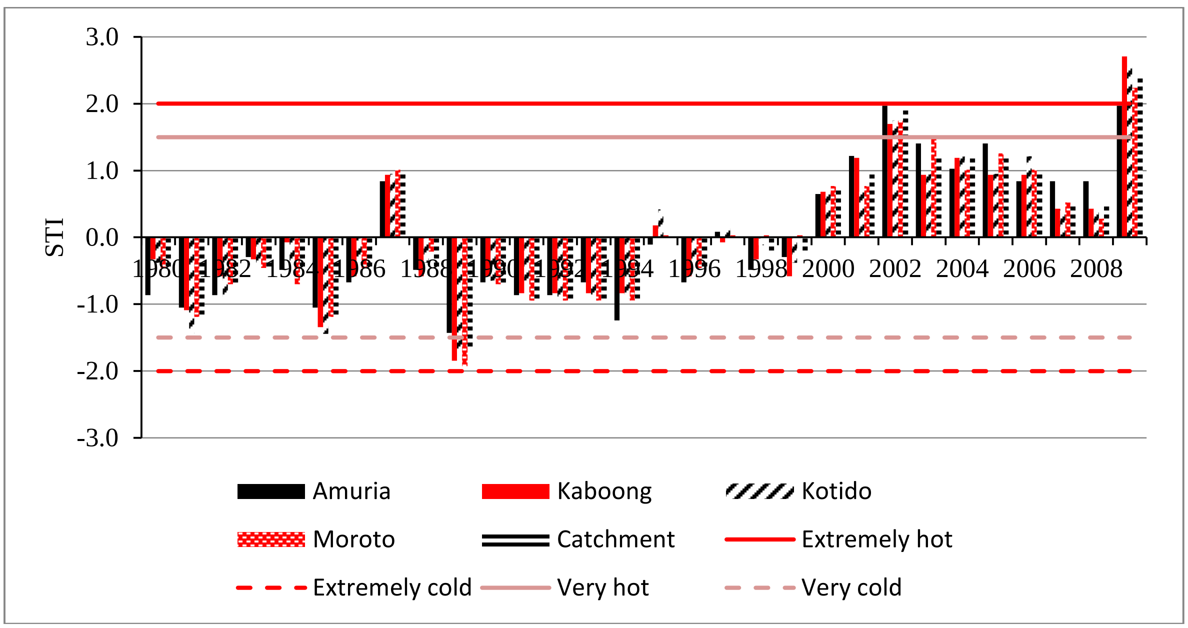

Figure 5.8: Standard temperature indices (STI) for mean temperature in the stations and Lokok and Lokere catchments, northeastern Uganda, for the period 1980–2009

The standard temperature indices for Tmean followed a similar pattern as Tmin, except for 1987. Tmean STI was negative from 1980-1999, and was "very cold" 1989 and 1991, for all stations, except for Amuria where it was within the normal range (Figure 5.8). The mean temperature STI was positive from 2000 to 2009, and "extremely hot" in all stations in 2009. Tmean was also "extremely hot" in Amuria and "very hot" in the rest of the stations and catchment. "Very hot" Tmean was registered in 2003 but only in Moroto.

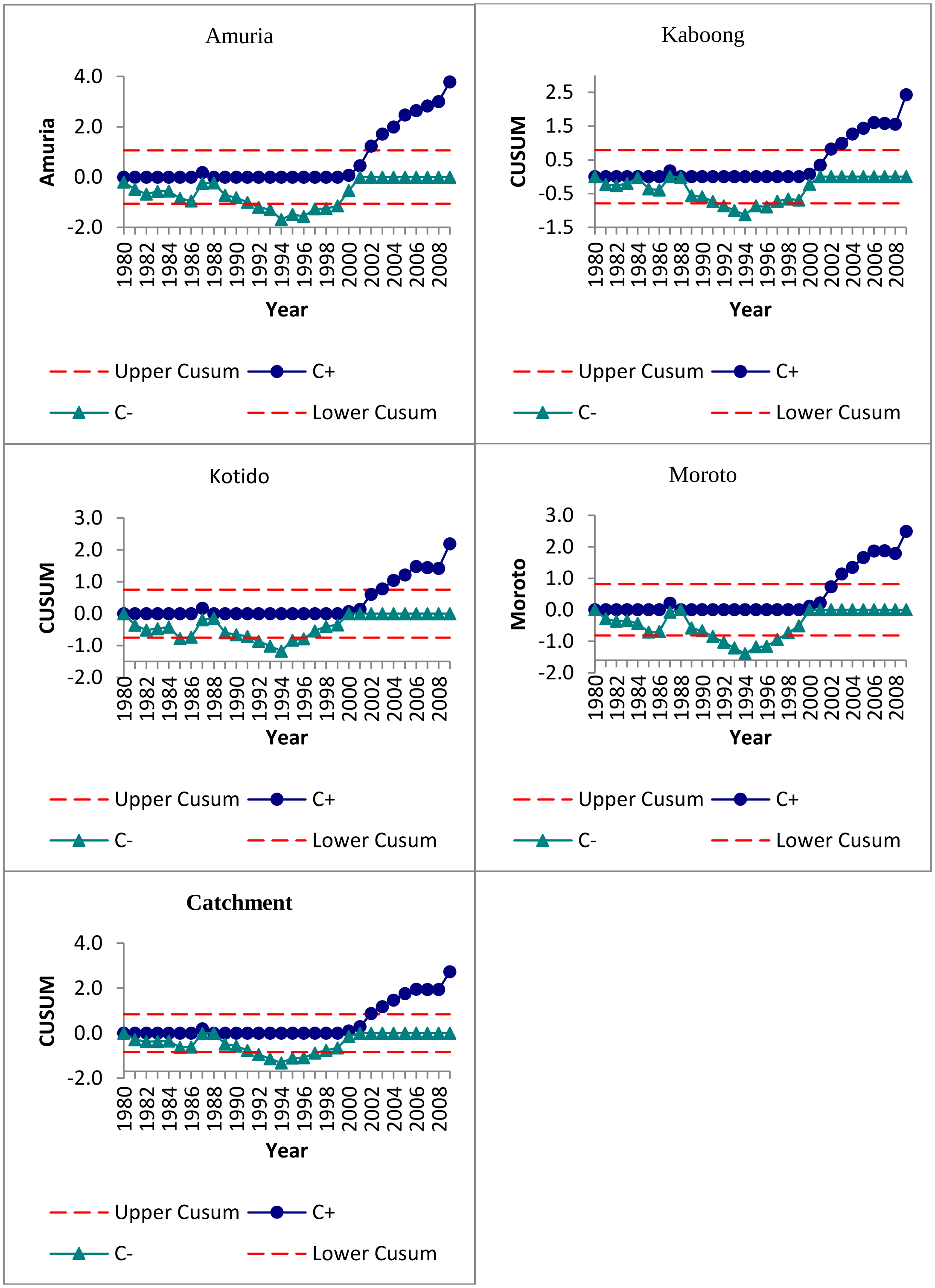

Figure 5.9: CUSUM chart for Tmean in the Lokok and Lokere catchments, north-eastern Uganda, for the period 1980–2009

When CUSUM control chart was applied, Tmean in all the stations, with the exception of 1987 when it was just above the mean, remained below average until 2000, when an upward trend began and got out of range from 2002 (Figure 5.9). Tmean was also below average and out of range from 1991 to 1999, showing a non-random pattern of variability. Deviation from the mean remained within range from 1980 to1990 and 2000 to 2001.

In Amuria, Tmax presented a similar pattern as Tmean, and remained below average until 2000, when it rose above the average and shifted from 2002. It also showed a below-average non-random pattern of variability from 1981 to 1984 and from 1988 to 1996.

The rest of the stations and the catchments' average Tmax showed a pattern different from Amuria. Random fluctuations occurred below average Tmax between 1980 and 1993, with the exception of 1987 and between 1999 and 2009 when it was above average (Figure 5.10). In Kaabong, Kotido and catchment levels, a non-random variability (regime shift) occurred in 2009. The pattern slightly differed in Moroto as below average Tmax shift was detected in 1986, and a positive shift in 2002 before returning within range in 2005. A sharp rise in CUSUM occurred in 2008 before a non-random variability (shift) occurred in 2009.

Tmin, in all the stations followed a pattern which is similar to Tmean (Figure 5.11). The Tmin CUSUM remained below average but within allowable deviation from mean until 1991 when a negative shift was detected. It then flattened, and steadily rose from 1994, crossing to above the mean in 2001 and registering a positive shift from 2003 when it projected upward.

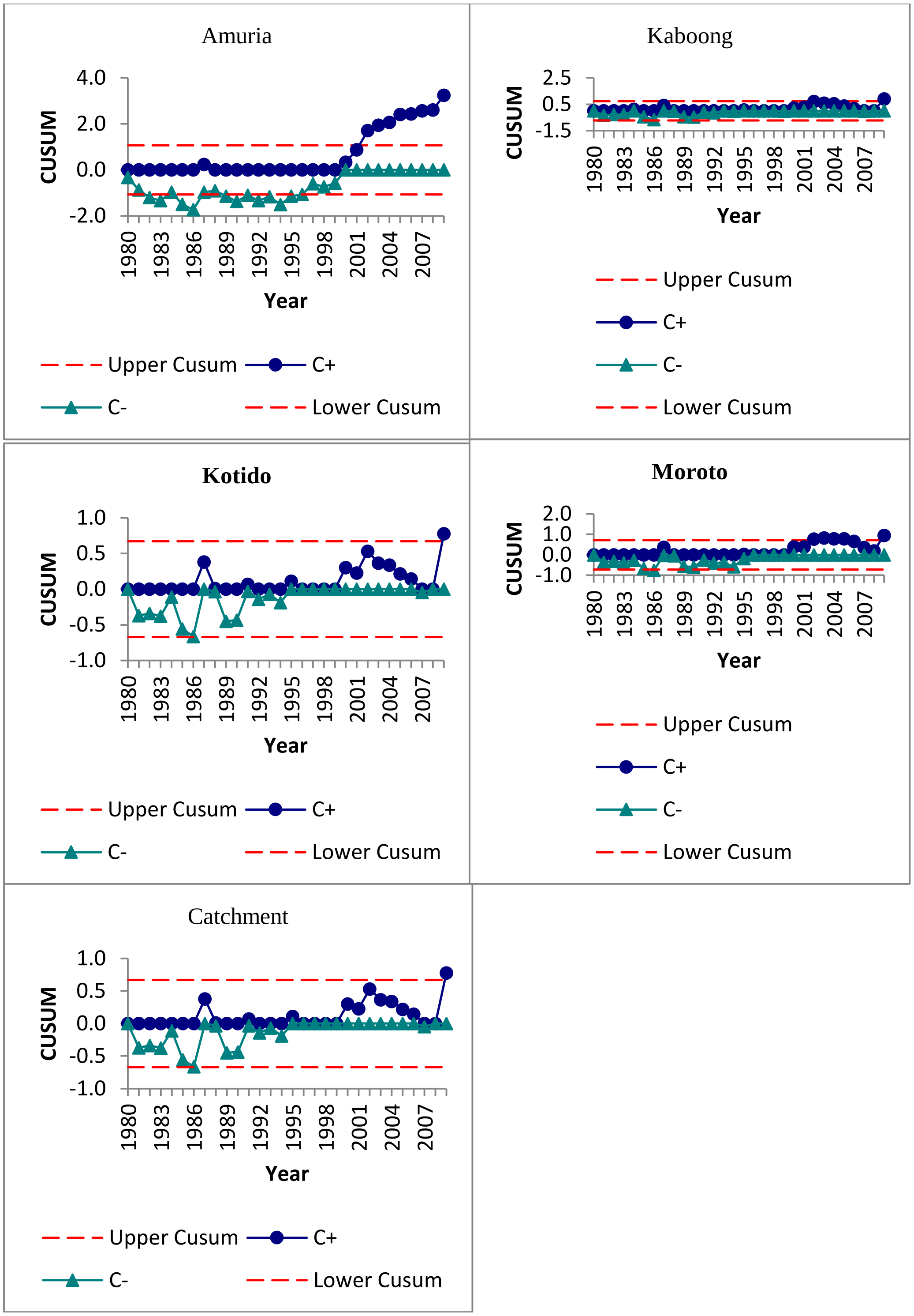

Figure 5.10: Stations and catchments CUSUM chart for Tmax for the period 1980–2009

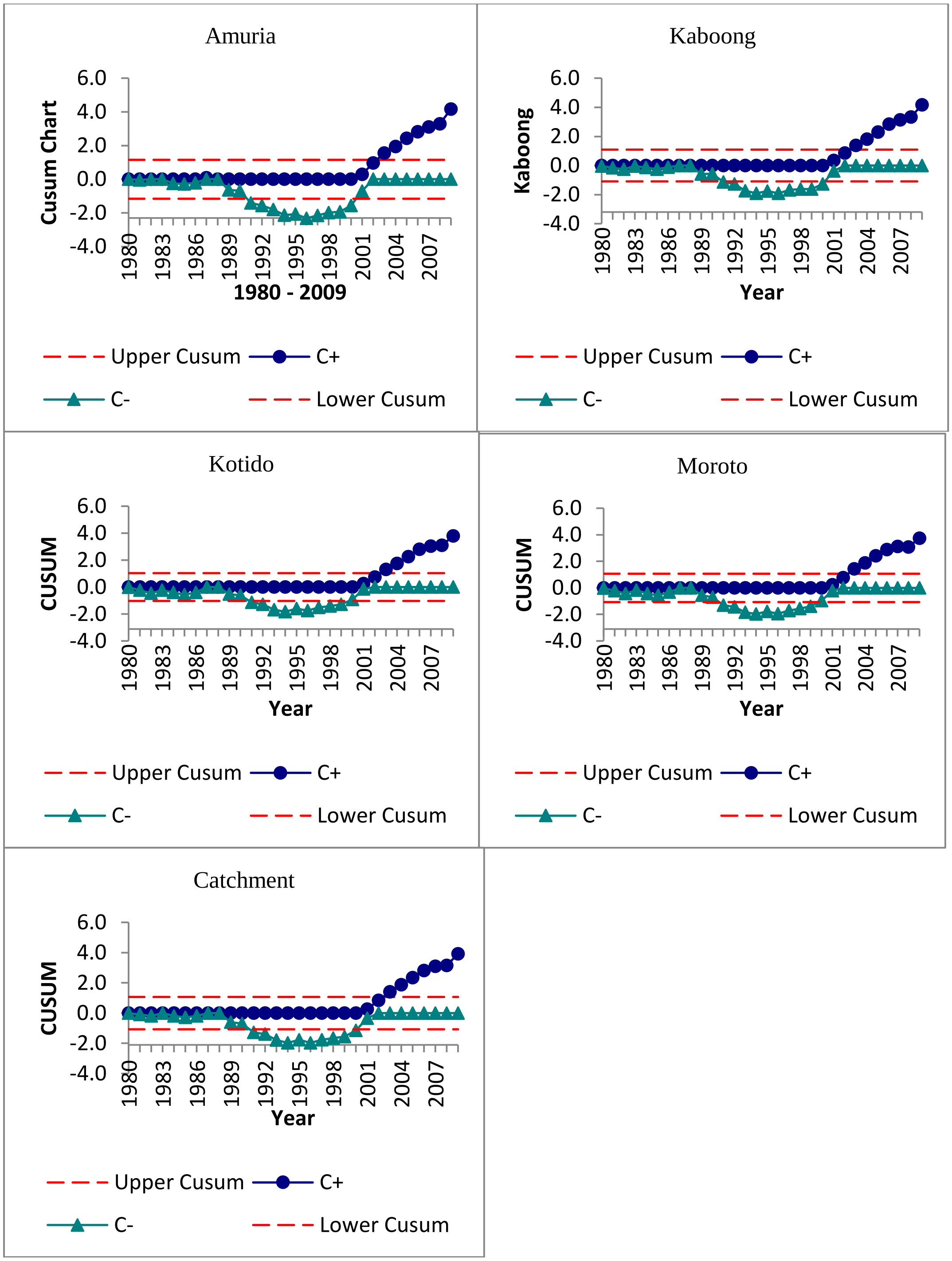

Figure 5.11: Stations and catchments CUSUM for Tmin for the period 1980–2009

5.3.3.2 Regime shift and inter-annual rainfall variability

Rainfall over the Catchment was characterized by inter-annual variability with a tendency of persistence. Therefore, a year of negative SRA was generally followed by another, as did years of positive SRA (Figure 5.12).

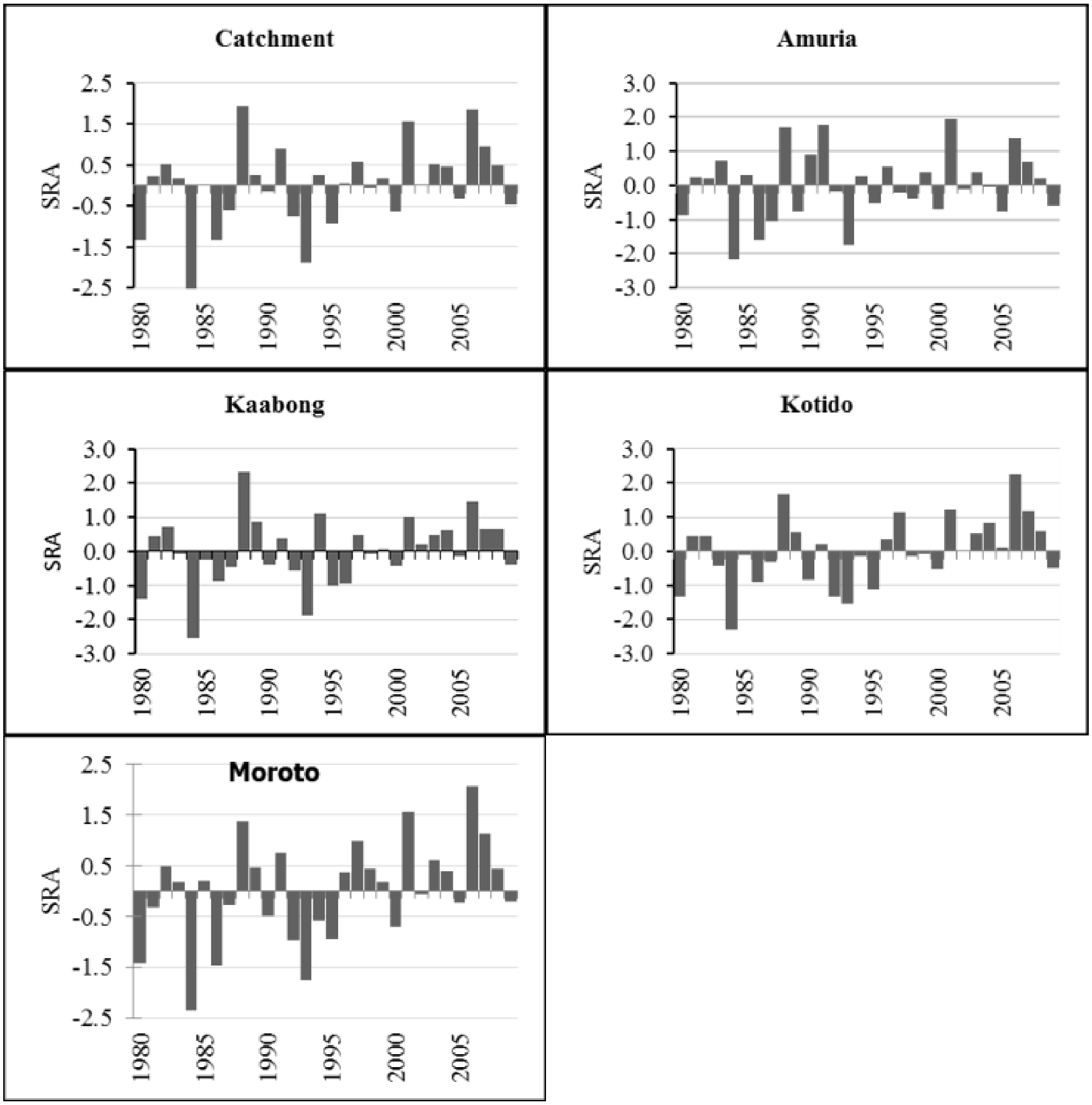

Figure 5.12: Catchments average and station level standard rainfall anomaly (SRA) for the 1980-2009 period

The period 1980-1989 was the driest of the three decades of analysis. Meanwhile the period 2000-2009 was the wettest as seen in the number of years with positive SRA (Catchment: 5,5,7; Amuria: 5,5,6; Kaabong: 6,6,7; Kotido: 6,6,6; Moroto: 5,5,6; for 1980-1989, 1990-1999, and 2000-2009 respectively). The wettest period barely had drought years (Catchment: 3,2,1; Amuria: 4,1,0; Kaabong: 3,3,0; Kotido: 3,3,0; Moroto: 3,3,0 for 1980-1989, 1990-1999, and 2000-2009 respectively).

Extreme drought events occurred in 1984 in all stations and in 1993 in all except in Kotido where there was severe drought the same year. Severe drought occurred in 1980 in all the stations, except in Amuria (where it was moderate). It also occurred in 1986 in Amuria and Moroto stations as well as at the catchment scale. In 1992, a severe drought event occurred only Kotido. However, a moderate drought occurred in 1986 in Kaabong and Kotido, in 1995 at catchments scale in Kaabong and Kotido; as it was in 1987 in Amuria and 1996 in Kaabong. There was no drought registered in the 2000-2009 decade.

Analysis of the annual rainfall time-series with CUSUM control chart showed fluctuations which, however, largely remained within the decision interval (Figure 5.13). Generally, below mean fluctuations occurred in the first one and half-decade, and above mean fluctuations in the final half. Also, regime shifts detected were followed by a return to normal (random variability).

In Amuria stations, below average fluctuations were observed between 1983 and 1990. A sharp drop below average rainfall occurred from 1985 to 1987, which characterized a non-random variability, with a regime shift occurring in 1986. A sudden return to random variability occurred in 1988. From 2002, annual total rainfall values remained above the mean total annual rainfall over the 1980-2009 period. A similar pattern was observed with Kaabong, however, an abrupt negative shift occurred in 1984, before another shift upwards in 1987 resulted in a sudden positive non-random shift in 1989 followed by a sudden decline. Above average random fluctuations were then maintained after 2000.

In Kotido and Moroto stations, below average fluctuations occurred before 1997, with the exception of 1988 and 1989 where upward slope was observed, followed by a negative non-random shift occurring in 1995. Positive fluctuations occurred after 1997, as annual rainfall increased in the stations. A similar pattern to that of the districts was observed in the catchments annual rainfall, with negative non-random shifts occurring in 1984 and 1986.

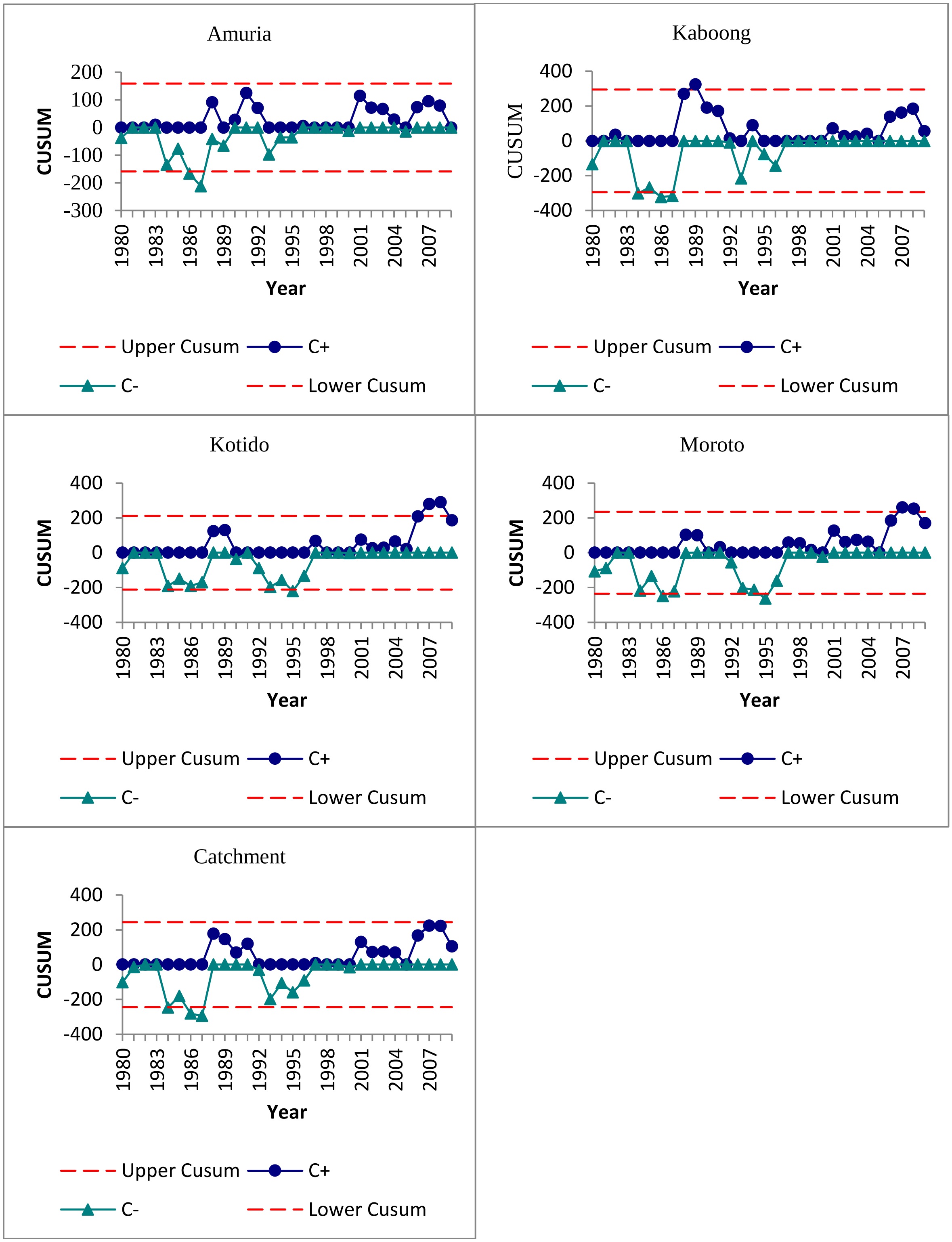

Figure 5.13: CUCUM chart for rainfall in the semi-arid region of Lokok and Lokere catchments, north-eastern Uganda, for the 1980-2009 period

5.4 Discussion

5.4.1 Spatio-temporal Trend and variability of temperature

The average Tmean over the catchment of 23.7 ^{o}C was higher than the 21.5 ^{o}C reported for Karamoja by Mbogga *et al*. (2014), however it was consistent with the 24 ^{o}C reported by USAID (2017). The findings are in agreement with both Egeru (2014a) who analysed the CFSR temperature time series for the 1979-2009 period and Mbogga (2014) that February and March are the hottest, and July and August are the coolest months in the sub-region. Whereas the lower limit of average Catchment Tmax and Tmin which ranged from 29.8 ^{o}C to 31.1 ^{o}C and 16.1^{o}C to 18.0 ^{o}C was outside the respective ranges of 28 ^{o}C to 32.5 ^{o}C or 33 ^{o}C and 15 ^{o}C to 18 ^{o}C reported for Karamoja (Mubiru, 2010 and Egeru, 2014), its upper limit was within this range. It should be noted that Amuria station which is inside this Catchment is not part of the Karamoja subregion considered by the cited studies (but Teso subregion), and was warmer than the rest of the stations. This may partially explain the discrepancy, as higher temperature values from Amuria contributed to a higher catchment average temperature.

Findings that air temperature in the catchment has been rising significantly is consistent with other studies. Egeru *et al*. (2014) showed that long-term (1979-2009) temperatures averaged over 16 CFSR districts in Karamoja sub region significantly rose by 0.9 °C, 1.6 °C, and 1.3 °C for Tmin, Tmax, and Tmean respectively. The corresponding rises showed in this study are 1.2 °C, 0.9 °C and 0.6 °C. Despite the discrepancies in the rates (and Tmin rising faster than Tmax) of rise in temperature between this study and Egeru *et al*. (2014), it is clear that the temperatures are rising over the Catchment, in the subregion, and Uganda in general. Funk *et al*. (2012) noted that over the 1975 to 2009 period, temperature increased over most of Uganda by 1.5 °C, at a rate of about 0.2 °C per decade.

Recent reports have also indicated that there has been an increase in annual and seasonal mean temperature in many areas of Ethiopia, Kenya, South Sudan, and Uganda over the last 50 years (Niang *et al.,* 2014). GoU (2007) reported an average temperature rise of 0.28 °C per decade in Uganda between 1960 and 2010, with temperatures for the months of January and February being the most affected, rising at an average rate of 0.37 °C per decade. However, this study finds that it is December and February that were the most affected by the warming, with mean temperature rise of 0.06 ^{o}C per year at catchment level.

Despite decreasing trends in October and November Tmax, their Tmin increased significantly. This resulted in significant increasing trends in their Catchment Tmean for November. Based on average catchments Tmean, June and October (0.01 ^{o}C per year each) and July (0.02 ^{o}C per year) were the months that experienced the lowest rate of rise in temperature, with non-significant trends. These months fall within the Karamoja uni-modal rain season which runs from April to November (Stark, 2011). While this suggests that temperatures could remain relatively low during rainy months, the increase in the catchments Tmin was significant in all seasons and months (except June in Amuria and Kaabong). The overall outcome was a significant increase in Tmean in all seasons (at 0.02-0.04 ^{o}C per year), except for SON not in Kaabong and Kotido. It's clear that Tmean did not increase significantly in SON due to negative trends in October and November Tmax. These months are however at the end of the rainy season where temperatures were relatively low and did not significantly increase.

The results revealed that Tmin was rising faster than Tmax, significantly in all temporal scales (save for June in Amuria and Kaabong). Hulme *et al.* (2001) also reported that Tmin warmed faster than Tmax in the last 50 to 100 years over most parts of Africa. Mubiru *et al*. (2009) and Mubiru (2010) reported rise in average daily temperature from records in Namulonge Station, central Uganda during 1950 to 2008. The rise in Tmin suggests that nights and cooler days are becoming warmer. This in turn means evapotranspiration which increases with temperature is increasing with impacts on water resources and crops, which is a concern.

STI and CUSUM analysis show temporal and spatial variability in temperatures. The temperatures were more variable in the first one and half decades of the study period, lower temperature being observed in the former than in the latter period. Temperatures generally began rising steadily in 1994 from below average level, until positive shifts in trends occurred after 2000, with non-random variability occurring after 2002. The relatively stable temperatures before 1994 explains why the early period of this study was cooler, despite patterns of severe or extreme dryness that were reported by Egeru *et al*. (2014) to have occurred in Karamoja subregion from 1984 to early March, 1985.

Amuria station showed more distinct temperature patterns, particularly from that of Kotido station, while Moroto and Kaabong intermittently showed varied or similar patterns with other districts. Tmax, Tmin and Tmean were “extremely hot” in all the districts in 2002 and in 2009. However, Tmax was only “extremely cold” in 1989 in Moroto and “very cold” in all the districts in 1985. Tmax was above average in all the stations in 1987, despite being below average in the early decade of the study period. Hulme *et al.* (2001) reported that in the period up to 2000, all the 6 warmest years in Africa occurred from 1987.

Below average and high fluctuations in Tmax occurred in early periods in Amuria. The station experienced non-random variability from 1981 to 1984 and 1988 to 1996, before registering an above average shift from 2002-2009. In Kaabong and Kotido stations, a positive shift in Tmax occurred in 2009, a different pattern recorded in Moroto station where a negative shift occurred in 1986 and positive shift in 2002 before the pattern returned to normal and shifted again in 2009. On the other hand, Tmin was very cold in all the stations in 1989 and 1991.

5.4.2 Spatio-temporal Trend and variability of rainfall

There was a general but non-significant increase in average catchment rainfall. Based on observed data from Kotido weather station, Mubiru (2010) reported a decreasing trend over the 1947 to 1985 period, and noted that the rains received annually had decreased by about 15-20 percent since the 1960s. Considering that the first decade (1980-1989) of the present study was the driest, Mubiru’s (2010) reports may not be considered contrary to the current results. The present study has shown below average fluctuations in rainfall in the 1980s, with negative shifts detected in catchment rainfall in 1984 and 1986. Egeru *et al.* (2014) had shown results in direct agreement with this study that over the 1979-2009 period, rainfall in Karamoja increased but not significantly. However, rainfall increase showed spatial and temporal differences as the increase in total annual rainfall was significant only in Kotido and Moroto. This is so despite a negative non-random shift in annual rainfall trend occurring in 1995 in the stations. In Kaabong, a negative shift occurred in 1984 followed by an upward shift in 1987 which resulted in a sudden positive non-random shift in 1989.

In Amuria station, a non-random shift upwards occurred in 1987. Further, it was only the increase in October rainfall in all stations, except Amuria, and January rainfall increase in Kaabong station that were significant. The significant increase in October rainfall also led to significant increase in SON rainfall in the stations. This result further confirms the spatial fluctuations in rainfall in the sub-region where the Catchment is located. Spatial fluctuations in rainfall even within areas of similar ecological characteristic are possible. In the Amhara Regional State of Ethiopia which receives erratic rainfalls, Ayalew *et al*. (2012) reported significant increasing trends of annual and seasonal rainfall in Bahir Dar, Gondar and Metema but significantly decreasing annual rainfall in Debark.

With regard to drought occurrence and inter-annual variability, the observed high frequency of drought during the 1980-1989 decade, and extreme drought years of 1984 and 1993, are consistent with findings of previous studies. According to Okonkwo *et al*. (2014), there was a strong ENSO event from 1983–1987 which led to intense drought in the Sahel region. Ayalew *et al*. (2012) reported drier conditions in 1982, 1984, 1987, 1997, 2002, and 2004 in Amhara Regional State, Ethiopia. In Karamoja subregion, Egeru *et al*.2014 reported that much of 1984 to early (March) 1985 had the most severe-to-extreme dryness intensity patterns of the 1979-2009 period. Masih *et al*. (2014) observed that the extreme droughts of 1972-1973, 1983-1984, and 1991-1992 were continental in nature, suggesting that rainfall was generally low across Africa during these periods. While they do not pinpoint 1984 as a drought year in Uganda, or Ethiopia where some studies have done so (such as Bewket and Conway, 2007; Ayalew, *et al*. 2012 and Egeru *et al*., 2014), they noted that in-country variability exists.

5.5 Conclusion

The study established that temperature over Lokere and Lokok Catchments are significantly increasing with time. Temperatures are also most variable during MAM as rainfall sets-in and are more stable in JJA, which is the rainfall peak. It was also established that Tmin is rising faster than Tmax, especially during the rainy season, with the former rising significantly at monthly, seasonal and annual temporal scales. However, during the dry season, Tmax is increasing and more variable than Tmin. This warming increases concerns over rising evapotranspiration.

Rainfall increase showed spatial and temporal differences, with relative increase lowest in the wetter Amuria. Total annual rainfall significantly increased only in Kotido and Moroto, and October rains significantly increased in all the stations, except Amuria, resulting in significant increase in SON rainfall in the stations, while January rainfall increased significantly in only Kaabong. Generally, increased annual average rainfall, although non-significant, was observed over the Catchment.

There is high inter-annual variability in rainfall over the basin, and was highest from 1980-1989 where three (four in Amuria) drought events occurred, and lowest from 2000-2009. Rainfall variability is also highest during the onset period of MAM, which may result in uncertainty and indecision by farmers with respect to timing of planting. Spatial variability of rainfall exists in the Catchment as evident in variable SRA across the stations. Thus it is crucial to consider characterizing vulnerability and adaptation options among the different sites in the catchments in order to implement measures that are well suited to each location. Location-specific studies especially in the arid and semi-arid areas are helpful in characterizing vulnerability and adaptation options.

CHAPTER SIX

PROJECTED TEMPERATURE AND RAINFALL IN THE SEMI-ARID LOKERE AND LOKOK CATCHMENTS, NORTHEASTERN UGANDA

Abstract

Trends in global warming over the past decades have been predicted to increase over the 21st Century, causing concerns for disaster preparedness in arid and semi-arid regions which are prone to drought, water scarcity and famine. This study utilized downscaled district or station level future temperature and rainfall scenarios obtained from twenty IPCC climate models embedded in the Agricultural Model Intercomparison and Improvement Project (AgMIP). The three periods included 2010–2039 – (early century); 2040–2069 – Mid-century, and 2070-2099 – end-century. The delta method, using a script provided in the AgMIP protocol, was applied in downscaling climate scenarios to each station. Monthly, seasonal (DJF, MAM, JJA and SON) and annual means of station and catchment scale ensembles of minimum, maximum and mean temperature (Tmin, Tmax and Tmean), and rainfall for each of the three periods were computed and compared with 1980-2009 as the baseline period. Temperature is projected to increase, and change in Tmin would be higher than change in Tmax. Tmax in the Catchments would change by 0.7 ^{o}C and 0.8 ^{o}C; 1.3^{o}C and 1.9 ^{o}C; 1.7 ^{o}C and 3.3^{o}C; while Tmin would change by 0.9 ^{o}C and 1.0 ^{o}C; 1.6 ^{o}C and 2.1^{o}C; and 2.0 ^{o}C and 3.8 ^{o}C – for RCP4.5 and RCP8.5 in the early, mid and end-centuries respectively. Increase in temperature would be higher in the cooler and wetter months and seasons (MAM, JJA) than the warmer season (DJF) – which shows a temporal variation in change. While rainfall in the Catchments is projected to increase by 10% and 8%; 15% and 16%; and 20% and 30% – for RCP4.5 and RCP8.5 in the early, mid and end-centuries respectively, the increase would be higher in the drier periods than in the wetter ones. Increase of rainfall alongside increase in temperature could result in increased evaporation to precipitation ratio over the coming years. This in turn creates a likelihood of an increased deficit in local moisture supply for both soil water and surface water flows. Therefore, crop and livestock producers would have to cope with moisture/water deficits through climate smart (soil) water management practices and crop and animal science.

Key words: global warming, climate change

6.1 Introduction

Global warming trends observed over the past centuries and decades have been predicted to increase over the 21st Century. Global surface temperature changes for the end of the 21st century, 2100, will likely exceed 1.5°C relative to 1850 to 1900 (IPCC, 2013). This trend in global warming is predicted to likely increase during the 21^{st} century under all the Representative Concentration Pathways (RCPs). The projected increases would be 0.3–1.7 1C (RCP2.6); 1.1–2.6 1C (RCP4.5); 1.4–3.1 1C (RCP6.0); and 2.6–4.8 1C (RCP8.5) for 2081–2100 compared to 1986–2005 baseline (IPCC, 2013).

The predicted warming will also continue to exhibit interannual-to-decadal variability as well as spatial variability as it will not be regionally uniform. Changes in the global water cycle will also occur in response to global warming, and like temperature, spatial and temporal variations will occur with respect to rainfall. It is projected that contrast in precipitation between wet and dry regions and between wet and dry seasons will increase, although there may be regional exceptions (IPCC, 2013).

Recent studies show that future rainfall and temperature in eastern Africa will vary or depart from present or historical baselines. ICPAC (2016) reported projected changes in annual and seasonal rainfall and temperature in the 2020s, 2030s, 2050s and 2070s under three different socio-economic scenarios compared to 1971-2000 baseline. Based on estimates from general circulation models (GCMs), Shongwe *et al*. (2011) reported a positive shift of rainfall distribution in East Africa during the wet seasons, projected increase in mean precipitation rates and intensity of high rainfall events but for less severe droughts.

Previous studies have tended to focus on larger regions and to overlook the effect of local features such as East Africa's varied topography (Shongwe *et al*., 2011). Understanding the likely response of climate parameters to global warming, is critical in informing development planning and disaster preparedness, especially in a region prone to drought and its consequences such as water scarcity and famine.

6.2 Materials and methods

6.2.1 Study area

This study was conducted in the semi-arid region of Kapir catchment (which covers Lokok and Lokere catchments), connecting downstream to part of Teso sub-region in northeastern Uganda. Karamoja sub-region is part of the Karamoja cluster, an area of land that straddles the borders between south-western Ethiopia, north-western Kenya, south-eastern South Sudan and north-eastern Uganda. The sub-region experiences hot and dry weather characteristics of most semi-arid regions in Eastern Africa. Rainfall in Karamoja sub-region is uneven and unimodal, occurring from March to November, and ranging from < 500 mm per year in eastern Karamoja, 500-800 mm in central Karamoja to 700-1000 mm in west Karamoja and the isolated highlands (Mbogga *et al*., 2014). Mean annual rainfall downstream of the Catchment, in the Teso subregion, is about 1100-1200 mm, distributed between two seasons of March to July and September to November (Kisauzi *et al*., 2012). Temperatures are generally high throughout the year, with an annual average of 28 and 33 °C for minimum and maximum, respectively; leading to high evapotranspiration levels averaging 2072 mm per annum (Mbogga *et al*., 2014). Rainfall variability in the region leads to heterogeneity of landscape resources including availability of pasture and water that influences the pastoral way of life as both a coping and adaptation strategy (Egeru *et al*., 2014).

6.2.2 Downscaling of climate scenarios

This study utilized downscaled station level future temperature and rainfall scenarios obtained from twenty of the latest IPCC climate models (ACCESS1-0, bcc-csm1-1, BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CSIRO-Mk3-6-0, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-CC, HadGEM2-ES, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM, MPI-ESM-LR, MPI-ESM-MR, MRI-CGCM3, and NorESM1-M) embedded in the Agricultural Model Intercomparison and Improvement Project (AgMIP).

The AgMIP simulations follow a set of Representative Agricultural Pathways (RAPs), developed, for consistency with climate modeling, on the basis of the set of SRES emissions scenarios and RCPs used in the IPCC AR4 and AR5, respectively. Representative Concentration Pathways (RCPs), which supersede Special Report on Emissions Scenarios (SRES) projections published in 2000, are four greenhouse gas concentration trajectories adopted by the IPCC for its fifth Assessment Report (AR5) in 2014. These include RCP 2.6; RCP 4.5, RCP 6.0 and RCP 8.5. The four RCPs are based on multi-gas concentration scenarios (Meinshausen *et al*., 2011) and provide a quantitative description of concentrations of the climate change pollutants in the atmosphere over time, as well as their radiative forcing in 2100, spanning from 2.6 to 8.5 W/m2, selected from a wide range of literature (van Vuuren *et al*. 2011). The RCPs have been used to drive climate model simulations planned as part of the World Climate Research Programme's Fifth Coupled Model Intercomparison Project (CMIP5). The naming represents the radiative forcing target level for 2100. RCP 8.5 represents a high emissions scenario, while RCP 4.5 represents a medium mitigation scenario. They were chosen for mean and worst case scenarios in the assessment of the Catchments climate and hydrology.

Based on climate change simulations from an ensemble of general circulation models (GCMs) from the CMIP3 and CMIP5, AgMIP projections are made for three periods under high (A2) and low (B1) SRES emissions scenarios for CMIP3 and RCPs CMIP5 (Rosenzweig *et al.* 2013). The three periods are: 2010–2039 – near-term period (early century); 2040–2069 – Mid-century; and 2070–2099 – End-Century. Target local level ensemble of climate data is then obtained by applying the coarse-scale GCM climate change projections to a high resolution observed (local or station) climate baseline – "the change factor method" (Wilby *et al.* 2004).

The methodology for downscaling climate scenarios to each station was based on the delta method, using a script provided in the AgMIP protocol (Rosenzweig *et al*. 2013 and Hudson and Ruane, 2015). The method involves imposing temperature and precipitation changes from GCMs for the selected projection periods on each location's daily observations baseline period (Ruane *et al*. 2015). That is, the historical time series is adjusted according to changes in climate indicated by comparing a GCM's projection for the future time period against the same GCM's historical period. Using Ag-MERRA as baseline and future climate scenarios for 20 CMIP5 GCMs obtained from the AgMIP website (http://tools.agmip.org/), station level data was obtained using AgMIP Climate Scenario Generation scripts, performed in R statistical software environment (Hudson and Ruane, 2013 and Rosenzweig *et al.* 2015).

6.2.3 Calculation of projected change in rainfall and temperature

Monthly, seasonal (DJF, MAM, JJA and SON) and annual means of station and catchment scale ensembles of minimum and maximum temperature, and rainfall for each of the three periods: early-century; midcentury; and End-Century were computed. Change in means, based on the 1980-2009 baselines was derived as follows:

$$\delta T = T_p - T_b;$$

$$R = \frac{(R_p - R_b)x\ 100}{R_b}$$

Where δTchange in temperature is, $T_p$is the average projected temperature, T_b is the average baseline temperature, R is the percentage change in rainfall, R_p is the average projected rainfall, and $R_b$is the average baseline rainfall.

6.3 Results

6.3.1 Projected change in Maximum temperature in the early and mid-century

In the early-century, annual Tmax is projected to change from the baseline period (1980-2009) by 0.7 ^{o}C for RCP 4.5 in all stations; and by 0.8 ^{o}C in Kaabong and Kotido and 0.9 ^{o}C in Amuria and Moroto for RCP 8.5 (Table 6.1). Average Change in Catchment Tmax is thus projected to be 0.7 ^{o}C and 0.8 ^{o}C for RCP 4.5 and 8.5 scenarios, respectively.

Under the RCP 4.5 scenario, changes in monthly Tmax were generally projected to be high in the months of May, June and July, at 0.8 ^{o}C as seen at the Catchment level. On the other hand, October through December will realize a lesser change, averaging 0.5 ^{o}C at catchment level. The changes are projected to range from 0.4 ^{o}C for RCP 4.5 in December to 0.9 ^{o}C in July in Amuria, and Moroto in June and July. Thus JJA had the largest seasonal change (0.8 ^{o}C), and SON had the smallest at 0.8 ^{o}C and 0.6 ^{o}C respectively.

For RCP 8.5, projected change ranges from 0.5 ^{o}C in in October in Kaabong, to 1.1 ^{o}C in June and July in Amuria, and July in Moroto. The second largest change (1.0 ^{o}C) occurred in April in all stations, and in May in Amuria and Moroto, June in Moroto, July in Kotido, August in Amuria and September in Amuria and Moroto. Thus Amuria and Moroto experienced the largest changes at seasonal and annual temporal scales. Also JJA was the season with the largest change (1.0 ^{o}C), and SON the smallest (0.7 ^{o}C).

Table 6.1: Change in total monthly, seasonal and annual Maximum temperature in early Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	0.6	0.8	0.7	0.8	0.7	0.7	0.6	0.8	0.7	0.8
Feb	0.7	0.8	0.7	0.7	0.7	0.8	0.7	0.8	0.7	0.8
Mar	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.7	0.7
Apr	0.7	1.0	0.7	1.0	0.7	0.9	0.7	1.0	0.7	1.0
May	0.8	1.0	0.7	0.9	0.8	0.9	0.8	1.0	0.8	0.9
Jun	0.8	1.1	0.8	1.0	0.8	0.9	0.9	1.0	0.8	1.0
Jul	0.9	1.1	0.8	0.9	0.8	1.0	0.9	1.1	0.8	1.0
Aug	0.8	1.0	0.7	0.8	0.7	0.8	0.7	0.9	0.7	0.9
Sep	0.7	1.0	0.6	0.9	0.6	0.9	0.6	1.0	0.6	0.9
Oct	0.5	0.7	0.5	0.5	0.5	0.6	0.5	0.7	0.5	0.6
Nov	0.5	0.7	0.5	0.6	0.6	0.6	0.6	0.7	0.5	0.6
Dec	0.4	0.6	0.5	0.7	0.5	0.6	0.5	0.7	0.5	0.7
DJF	0.6	0.8	0.7	0.8	0.6	0.8	0.6	0.8	0.6	0.8
MAM	0.7	0.9	0.7	0.9	0.7	0.8	0.8	0.9	0.7	0.9
JJA	0.8	1.0	0.8	0.9	0.8	0.9	0.8	1.0	0.8	1.0
SON	0.6	0.8	0.5	0.7	0.6	0.7	0.6	0.8	0.6	0.7
Ann	0.7	0.9	0.7	0.8	0.7	0.8	0.7	0.9	0.7	0.8

Projected change in Tmax in the mid-century ranged from 0.5 ^{o}C for RCP 4.5 in September for Kaabong to 1.8 ^{o}C in June for Amuria and Moroto (Table 6.2). For RCP 8.5, change ranged from 1.0^{o}C in September for Kaabong to 2.4 ^{o}C in July for Amuria and May in Moroto.

It is observed that change at Catchment level will be larger around May to July; ranging from 1.4 ^{o}C in July to 1.6 ^{o}C in June for RCP 4.5 and 1.8 ^{o}C in July to 2.3 ^{o}C in May for RCP 8.5. MAM and JJA will experience the biggest change at 1.3 ^{o}C and 1.5 ^{o}C; and 2.0 ^{o}C and 2.1 ^{o}C for RCP 4.5 and RCP 8.5 respectively, at catchment level. November and December will be the coolest months, at 1.1 ^{o}C and 1.2 ^{o}C for RCP 4.5 and 1.6 ^{o}C and 1.4 ^{o}C for RCP 8.5 respectively. Thus, SON will be the coolest season, at 1.2 ^{o}C and 1.7 ^{o}C for RCP 4.5 and 8.5 respectively. Annual change will be 1.3 ^{o}C and 1.7 ^{o}C for RCP 4.5 and RCP 8.5 respectively.

Table 6.2: Change in total monthly, seasonal and annual Maximum temperature in Mid-Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	1.2	1.8	1.5	2.2	1.2	1.9	1.2	1.8	1.3	1.9
Feb	1.2	1.8	1.4	2.0	1.3	1.9	1.2	1.9	1.3	1.9
Mar	1.2	1.8	1.2	1.8	1.3	1.9	1.3	1.9	1.3	1.9
Apr	1.3	2.0	1.2	1.9	1.3	1.9	1.4	2.0	1.3	2.0
May	1.5	2.3	1.3	2.1	1.5	2.3	1.5	2.4	1.5	2.3
Jun	1.8	2.3	1.2	1.8	1.7	2.3	1.8	2.3	1.6	2.2
Jul	1.7	2.4	0.6	1.3	1.6	2.3	1.7	2.3	1.4	2.1
Aug	1.7	2.3	0.6	1.2	1.6	2.1	1.6	2.2	1.4	1.9
Sep	1.7	2.2	0.5	1.0	1.5	2.0	1.6	2.1	1.4	1.8
Oct	1.3	1.9	0.7	1.2	1.3	1.8	1.3	1.8	1.2	1.7
Nov	1.2	1.7	0.9	1.4	1.2	1.6	1.2	1.7	1.1	1.6
Dec	1.1	1.6	0.8	1.2	1.1	1.6	1.1	1.6	1.0	1.5
DJF	1.2	1.8	1.3	1.9	1.3	2.3	1.2	1.8	1.2	1.9
MAM	1.4	2.0	1.3	1.9	1.3	2.0	1.4	2.1	1.3	2.0
JJA	1.7	2.3	0.8	1.4	1.7	2.2	1.7	2.3	1.5	2.1
SON	1.4	1.9	0.7	1.2	1.3	1.8	1.4	1.8	1.2	1.7
Ann	1.4	2.0	1.0	1.6	1.4	2.0	1.4	2.0	1.3	1.9

In the end-century (Table 6.3), December is projected to experience the smallest change in all stations for the RCP 8.5 scenario, ranging from 2.5 ^{o}C in Kaabong to 2.8 ^{o}C in Amuria; and largest in June in all the stations with the exception of Kaabong in May. The change will range from 3.5^{o}C in Kaabong to 4.2 ^{o}C in Amuria and Moroto. For the RCP 4.5 scenario, the change will be smallest in December in all the stations, at 1.3 ^{o}C in all the districts, except in Kaabong where the month with the smallest change will be September (0.8 ^{o}C). The change will be largest in June (2.2 ^{o}C) and July in Amuria (2.2 ^{o}C) and Kotido (2.1 ^{o}C apiece), June in Moroto (2.2 ^{o}C) and in January in Kaabong (2.0 ^{o}C). Overall, at the catchments level, June is expected to experience the largest change (4.0 ^{o}C).

Under RCP 4.5 scenario, SON will experience the smallest change (1.5 ^{o}C), while JJA and MAM will experience the largest change, each 1.8 ^{o}C. SON will also experience the smallest change under RCP 8.5, while JJA is expected to experience the largest change (3.6 ^{o}C). Annual catchment level changes will be 1.7 ^{o}C and 3.3 ^{o}C under RCP 4.5 and 8.5 respectively.

Table 6.3: Change in total monthly, seasonal and annual Maximum temperature in End-Century

	Amuria		Kaabong		Kotido		Moroto		catchments	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	1.5	3.1	2.0	3.5	1.6	3.1	1.5	3.1	1.7	3.2
Feb	1.6	3.2	1.7	3.4	1.6	3.2	1.6	3.3	1.6	3.3
Mar	1.6	3.1	1.5	3.1	1.6	3.1	1.7	3.2	1.6	3.1
Apr	1.8	3.3	1.7	3.2	1.7	3.2	1.8	3.4	1.7	3.3
May	2.0	3.9	1.8	3.6	2.0	3.7	2.1	3.9	2.0	3.8
Jun	2.2	4.2	1.6	3.5	2.1	4.0	2.2	4.2	2.0	4.0
Jul	2.2	4.1	1.1	2.8	2.1	3.8	2.1	4.0	1.9	3.7
Aug	1.9	3.8	0.9	2.5	1.8	3.4	1.9	3.6	1.6	3.3
Sep	1.9	3.7	0.8	2.5	1.7	3.4	1.8	3.6	1.6	3.3
Oct	1.7	3.2	1.1	2.5	1.6	3.0	1.7	3.1	1.5	3.0
Nov	1.6	3.0	1.3	2.6	1.5	2.9	1.5	3.0	1.5	2.9
Dec	1.3	2.8	1.0	2.5	1.4	2.7	1.3	2.7	1.3	2.7
DJF	1.5	3.1	1.7	3.2	1.6	3.1	1.6	3.1	1.6	3.1
MAM	1.8	3.4	1.7	3.3	1.7	3.3	1.9	3.5	1.8	3.4
JJA	2.1	4.0	1.2	2.9	2.0	3.7	2.1	3.9	1.8	3.6
SON	1.7	3.3	1.1	2.5	1.6	3.1	1.6	3.2	1.5	3.0
Ann	1.8	3.5	1.4	3.0	1.7	3.3	1.8	3.4	1.7	3.3

6.3.2 Projected change in minimum temperature

Change in Tmin is projected to be larger than that of Tmax. Respective Catchment level changes in Tmin in early, mid and End-Century will be 0.9 ^{o}C and 1.0; 1.6^{o}C and 2.1; and 2.0 and 3.8 ^{o}C for RCP 4.5 and RCP 8.5 respectively (Table 6.4, 6.5 & 6.6).

In the early century, JJA and DJF are projected to realise the biggest change under RCP 8.5(1.1 ^{o}C each), while SON is expected to have the smallest change (0.9 ^{o}C). This is because December and January are projected to have a relatively larger change at catchment level, averaging 1.0 ^{o}C and 1.1 ^{o}C for RCP 4.5 and RCP 8.5 respectively. Change in annual Tmin will be the same in all the stations, projected to be 0.9 ^{o}C and 1.0 ^{o}C for RCP 4.5 and RCP 8.5 respectively.

In the mid-century, the projected change in Tmin under RCP 8.5 will be largest in JJA (2.4 ^{o}C) and smallest in SON (2.2^{o}C). Under RCP 4.5, with the exception of Kaabong where change in annual Tmin will be smallest (1.1 ^{o}C), the stations are projected to have 1.8 ^{o}C change in temperature. The Change will be more varied under RCP 8.5, ranging from 1.8 ^{o}C in Kaabong to 2.5 ^{o}C in Kotido and Moroto. Under RCP 8.5, October will have the smallest change (2.1^{o}C), while the largest change (2.5 ^{o}C) is projected to occur in January, May, and June. June and July are also projected to have the largest change under RCP 4.5 (1.8 ^{o}C) and October, the smallest change (1.4 ^{o}C).

Table 6.4: Change in total monthly, seasonal and annual minimum temperature in early Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	0.9	1.0	1.0	1.1	1.0	1.1	1.0	1.1	1.0	1.1
Feb	0.9	1.0	0.9	1.0	0.9	1.0	0.9	1.1	0.9	1.0
Mar	0.9	1.0	0.9	1.0	1.0	1.0	1.0	1.0	0.9	1.0
Apr	0.7	1.0	0.8	1.0	0.9	1.0	0.9	1.0	0.8	1.0
May	0.8	1.0	0.8	1.0	0.9	1.0	0.9	1.1	0.9	1.0
Jun	0.9	1.1	0.9	1.0	0.9	1.0	1.0	1.1	0.9	1.1
Jul	0.9	1.1	0.9	1.0	0.9	1.1	1.0	1.1	0.9	1.1
Aug	0.9	1.1	0.8	1.0	0.8	1.0	0.9	1.1	0.9	1.0
Sep	0.8	1.0	0.8	0.9	0.8	1.0	0.8	1.0	0.8	1.0
Oct	0.8	0.9	0.8	0.9	0.8	0.9	0.8	0.9	0.8	0.9
Nov	0.9	1.0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Dec	0.9	1.1	1.0	1.0	1.0	1.1	0.9	1.1	0.9	1.1
DJF	0.9	1.1	0.9	1.1	1.0	1.1	0.9	1.1	0.9	1.1
MAM	0.8	1.0	0.9	1.0	0.9	1.0	0.9	1.0	0.9	1.0
JJA	0.9	1.1	0.9	1.0	0.9	1.0	0.9	1.1	0.9	1.1
SON	0.8	1.0	0.8	0.9	0.8	0.9	0.8	1.0	0.8	0.9
Ann	0.9	1.0	0.9	1.0	0.9	1.0	0.9	1.0	0.9	1.0

At the end-century, Tmin is expected to change by 2.2 ^{o}C under RCP 4.5 in all the stations, with the exception of Kaabong where the change is projected to be smallest (1.5 ^{o}C). The change will however be varied under RCP 8.5, ranging from 3.5 ^{o}C in Kaabong to 4.3 ^{o}C in Kotido and Moroto. SON is projected to have the smallest change for both RCP 4.5 and 8.5, averaging 1.8 ^{o}C and 3.8^{o}C respectively at catchment level, and ranging from 1.1 ^{o}C and 3.0 ^{o}C in Kaabong to 2.0 ^{o}C and 4.0 ^{o}C in Amuria, Kotido and Moroto. The largest change in seasonal Tmin under RCP 8.5 (4.3 ^{o}C) will occur in DJF, while for RCP 4.5 it is projected to occur in MAM and JJA (2.1 ^{o}C).

Table 6.5: Change in total monthly, seasonal and annual minimum temperature in Mid-Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	1.9	2.6	1.1	1.9	2.0	2.7	1.9	2.7	1.7	2.5
Feb	1.8	2.4	1.0	1.8	1.8	2.5	1.8	2.6	1.6	2.3
Mar	1.7	2.3	1.1	1.9	1.8	2.5	1.8	2.5	1.6	2.3
Apr	1.7	2.3	1.3	1.9	1.9	2.5	1.8	2.4	1.7	2.3
May	1.7	2.4	1.5	2.3	1.8	2.6	1.8	2.6	1.7	2.5
Jun	1.9	2.5	1.6	2.3	1.9	2.6	1.9	2.6	1.8	2.5
Jul	1.9	2.5	1.3	2.0	1.9	2.6	1.9	2.6	1.8	2.4
Aug	1.8	2.5	1.1	1.9	1.8	2.5	1.8	2.5	1.6	2.3
Sep	1.8	2.4	0.9	1.5	1.8	2.4	1.8	2.4	1.5	2.2
Oct	1.6	2.3	0.7	1.4	1.7	2.3	1.7	2.3	1.4	2.1
Nov	1.8	2.4	0.8	1.5	1.7	2.5	1.7	2.5	1.5	2.2
Dec	1.7	2.5	0.6	1.5	1.8	2.6	1.7	2.6	1.5	2.3
DJF	1.8	2.5	1.0	1.8	1.9	2.7	1.8	2.6	1.6	2.4
MAM	1.7	2.3	1.3	2.0	1.8	2.5	1.8	2.5	1.7	2.3
JJA	1.9	2.5	1.3	2.1	1.9	2.6	1.9	2.6	1.7	2.4
SON	1.7	2.4	0.8	1.5	1.7	2.4	1.7	2.4	1.5	2.2
Ann	1.8	2.4	1.1	1.8	1.8	2.5	1.8	2.5	1.6	2.3

Table 6.6: Change in total monthly, seasonal and annual minimum temperature in End-Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	2.4	4.5	1.6	3.8	2.4	4.6	2.4	4.6	2.2	4.4
Feb	2.3	4.3	1.5	3.6	2.3	4.4	2.3	4.5	2.1	4.2
Mar	2.2	4.0	1.6	3.5	2.3	4.3	2.3	4.3	2.1	4.0
Apr	2.1	3.9	1.7	3.6	2.2	4.2	2.2	4.2	2.1	4.0
May	2.2	4.1	2.0	4.0	2.3	4.3	2.3	4.3	2.2	4.1
Jun	2.3	4.4	2.0	4.1	2.3	4.5	2.4	4.5	2.2	4.4
Jul	2.3	4.4	1.7	3.7	2.3	4.3	2.3	4.4	2.1	4.2
Aug	2.2	4.2	1.5	3.5	2.1	4.1	2.2	4.2	2.0	4.0
Sep	2.1	4.0	1.2	3.1	2.0	4.0	2.1	4.1	1.8	3.8
Oct	2.0	3.9	1.0	2.9	2.0	4.0	2.0	4.0	1.7	3.7
Nov	2.1	4.0	1.2	3.1	2.1	4.1	2.1	4.1	1.9	3.8
Dec	2.1	4.3	1.0	3.2	2.2	4.4	2.1	4.3	1.9	4.1
DJF	2.3	4.4	1.2	3.6	2.4	4.6	2.3	4.5	2.0	4.3
MAM	2.2	4.0	1.8	3.7	2.3	4.2	2.3	4.2	2.1	4.0
JJA	2.3	4.3	1.7	3.8	2.2	4.3	2.3	4.4	2.1	4.2
SON	2.0	4.0	1.1	3.0	2.0	4.0	2.0	4.0	1.8	3.8
Ann	2.2	4.2	1.5	3.5	2.2	4.3	2.2	4.3	2.0	4.1

6.3.3 Projected change in rainfall

In the early Century, mean total annual rainfall over the Catchment is projected to change by 10 percent and 8 percent under RCP 4.5 and 8.5 scenarios respectively (Table 6.7). The change is projected to be highest in Amuria and Moroto stations under RCP 4.5, by 11 percent and in Moroto under RCP 8.5, by 9 percent. Relative change in annual rainfall will be lowest in Kaabong and Kotido stations, at 9 percent and 6 percent for RCP 4.5 and RCP 8.5 scenarios, respectively; which is lower than the highest relative changes by 3 percentage points.

Table 6.7: Change in total monthly, seasonal and annual rainfall in early Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	39	24	52	26	33	21	34	24	39	24
Feb	28	25	46	48	35	33	34	28	34	32
Mar	11	18	9	17	9	18	10	19	10	18
Apr	7	1	5	0	5	-1	5	0	6	1
May	1	2	3	1	4	1	6	3	3	2
Jun	4	-1	4	-2	6	1	6	2	5	0
Jul	13	7	9	3	10	3	16	7	12	5
Aug	13	8	10	9	8	9	12	11	11	9
Sep	10	4	8	4	7	3	11	6	9	4
Oct	12	13	13	16	13	16	12	16	13	15
Nov	14	15	14	16	12	16	11	17	13	15
Dec	20	14	16	9	18	11	19	14	19	12
DJF	30	23	30	24	24	19	25	19	28	21
MAM	6	5	5	4	5	4	6	5	6	5
JJA	11	5	8	4	8	4	12	7	10	5
SON	12	10	11	11	10	11	12	13	11	11
Ann	11	8	9	6	9	6	11	9	10	8

The projected relative change in Catchment rainfall could nearly double in the mid-century, to increase by 15 percent and 16 percent under RCP 4.5 and RCP 8.5 scenarios respectively (Table 6.8). Further increases from the baseline of 10 percent and 33 percent could occur in the end-century for the respective scenarios (Table 6.9). In the mid-century, Kaabong followed by Moroto are projected to realise the highest relative increase in rainfall of 18 percent and 17 percent respectively, for both RCP 4.5 and RCP 8.5 scenarios. Amuria and Kotido are projected to realise the same percentage relative increase in rainfall, at 16 percent and 14 percent under RCP 4.5 and RCP 8.5 scenarios respectively, in the mid-century.

Smallest and largest projected relative changes in rainfall at monthly and seasonal timescales occurred in different times and scenarios in the stations. In the Early-Century, DJF, the driest season, has been projected to experience the highest relative change in seasonal rainfall over the Catchment; 28 percent and 21 percent under RCP 4.5 and RCP 8.5 respectively. However, the lowest projected relative change in seasonal rainfall over the Catchment occurs in JJA (6 percent under RCP 4.5) and in SON and JJA (5 percent) under RCP 8.5.

Table 6.8: Change in total monthly, seasonal and annual rainfall in Mid-Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	60	71	58	65	49	64	52	71	58	71
Feb	44	62	40	61	46	64	48	65	47	65
Mar	25	32	-4	4	23	30	29	33	24	31
Apr	19	25	20	23	15	20	18	23	18	23
May	4	-1	-9	-12	8	1	9	-1	7	0
Jun	0	0	16	14	4	4	1	1	2	2
Jul	14	5	31	21	12	4	13	6	13	5
Aug	5	8	26	29	6	8	9	10	6	8
Sep	11	11	9	11	8	10	13	13	10	11
Oct	20	17	43	43	27	26	28	26	23	21
Nov	27	29	25	27	27	31	28	31	28	30
Dec	26	35	25	35	24	36	28	37	26	36
DJF	44	57	34	49	34	-2	38	52	40	45
MAM	15	17	3	4	14	14	16	15	15	15
JJA	6	5	25	22	8	5	8	6	7	5
SON	19	18	24	25	20	21	23	23	20	20
Ann	16	16	18	18	14	14	17	17	15	16

Table 6.9: Change in total monthly, seasonal and annual rainfall in End-Century

	Amuria		Kaabong		Kotido		Moroto		Catchment	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Jan	87	107	74	96	71	97	73	98	82	104
Feb	56	91	66	89	65	98	60	93	63	95
Mar	31	57	3	29	30	64	33	68	31	62
Apr	25	39	26	40	23	37	24	39	24	39
May	4	9	-10	-5	7	16	7	16	6	13
Jun	9	9	23	23	12	10	13	10	11	10
Jul	19	20	30	40	8	15	14	17	13	18
Aug	16	26	34	47	13	26	16	34	15	27
Sep	15	21	14	22	14	22	19	25	15	22
Oct	19	33	42	67	26	49	27	48	22	40
Nov	27	53	24	52	27	58	27	57	27	56
Dec	44	77	39	79	40	85	45	86	43	81
DJF	64	93	54	83	51	88	53	86	58	90
MAM	18	32	6	18	18	33	19	36	18	33
JJA	15	20	29	37	11	17	14	21	13	19
SON	20	34	25	44	21	41	24	43	21	38
Ann	21	33	22	35	18	32	21	36	20	33

Projected changes in monthly rainfall vary in all stations and scenarios. In the early Century, under the RCP 4.5 scenario, January is projected to experience the highest change at Catchments level (39 percent), in Amuria (39 percent) and Kaabong (52 percent). However, it is February which is projected to experience the second highest increase in rainfall at the catchment level (28 percent) that will also have the highest increase in Kotido (35 percent). Moroto will experience the same relative change in both January and February (34 percent). The relative change in rainfall in these two months will be higher than the projected change for other months with the closest month registering 19 percent (December) and 18 percent (March) for RCP 4.5 and RCP 8.5 respectively, at Catchment level. Generally, under the early Century, the least relative change (6 percent or less) in monthly rainfall is projected to occur in April, May and June, with no relative change in June under RCP 8.5.

Like in the early – Century, the mid-Century and End-Century monthly rainfall could vary on both temporal and spatial time scales. In the mid-Century, January will experience the highest change in monthly rainfall in both scenarios, ranging from 49 percent in Kotido to 60 percent in Amuria for RCP 5.5; and from 64 percent in Kotido to 71 percent in Amuria and Moroto for RCP 8.5. The relative change will be generally higher in the drier months, rising from October, and peaking in January and February before declining in March and April. May to August are projected to realise the smallest change, with June expected to experience the lowest relative increase in rainfall under RCP 4.5 and May registering no increase under RCP 8.5.

Relative change in monthly rainfall in the End-Century will follow a pattern similar to that in the mid-Century. January will have the highest change in scenarios (83 percent) under RCP 4.5 and 104 percent under RCP 8.5 at Catchment level. With the exception of Kotido where February (98 percent) will realize only 1 percentage higher than January (97percent), January followed by February will have the highest percentage change for both scenarios.

6.4 Discussion

6.4.1 Projected change in temperature

The change in temperature reported in this study is consistent with global warming trends of 1.3°C to 1.7°C by 2050 relative to 1980–1999 under SRES scenarios (IPCC, 2007) and of 0.3°C to 0.7°C for the period 2016–2035 relative to 1986–2005 under RCP scenarios (IPCC, 2013). The change is also consistent with change in Maximum temperatures in the Greater Horn of Africa of 0.5 to 1.5°C under the RCP4.5 and RCP8.5 scenarios compared to the 1971-2000 baseline (ICPAC, 2016).

The results reveal projected temporal variation in temperature change, with warnings higher in the cooler and wetter months and seasons (MAM, JJA) than the warmer season (DJF). This is consistent with ICPAC (2016) that reported higher projected changes in maximum temperatures by 2030 during MAM and JJAS (by 1.0 to 2.5°C compared to the base period) over most parts of the greater Horn of Africa, than in OND – a period of short rains.

Projected change in temperatures in the End-Century is also consistent with projected global-mean surface temperatures (GMST) for 2081–2100, which is projected to 2.6°C (RCP4.5) and 2.6°C to 4.8°C (RCP8.5), relative to 1986–2005 (IPCC 2013). In the greater Horn of Africa, changes in annual maximum temperatures in the 2070s were projected to be 3.5 to 5 °C higher than the 1971-2000 reference period under the RCP8.5, with further warming expected during MAM and JJAS.

ICPAC (2016) also reported projected annual maximum temperatures of 1.5 to 2.5°C higher under the RCP4.5 and 2.5 to 3.5°C higher under the RCP8.5 scenarios over most parts of the GHA by 2050 compared to 1971-2000 baseline. This is also consistent with Otieno and Anyah (2013) who reported a projected approximate temperature increase of 2°C and 2.5-3°C in the GHA by the middle of the 21st century under RCP 4.5 and RCP 8.5 respectively.

Projections show higher change in Tmin than Tmax in all periods, but with similar temporal and spatial variation. This is also consistent with reports by IPCC (2013) that the frequency of warm days and warm nights will increase in most regions, while the frequency of cold days and cold nights will decrease in the next decades. ICPAC (2016) also reported higher changes in minimum temperatures than maximum temperatures but with similar patterns in the Greater Horn of Africa. Annual minimum temperatures were projected to be warmer in almost all the Greater Horn of

Africa region by 1.0 to 3.0°C by 2030 and 2050, and 4 to 5°C by 2070, than during 1971-2000; and warmest during the MAM and JJAS under the RCP 8.5 scenario (ICPAC, 2016).

6.4.2 Projected change in rainfall

Rainfall in the Catchment will increase with temperature. IPCC (2013) projects that long term global precipitation will increase with increased global mean surface temperature at a rate of 1 to 3 percent per °C for scenarios other than RCP2.6. The drier months and seasons (DJF season) are projected to realise higher relative change in rainfall than the wetter months and seasons (JJA, MOM and SON). ICPAC (2016) also reported that over the Greater Horn of Africa, the short rains (OND) are expected to increase over most parts of the region under all the three scenarios (>50 percent), while the long rains (MAM) and JJAS will decrease over most part of the region (10-70 percent), with slight increase (10-25 percent) in MAM rains over the southeastern part of Lake Victoria basin. Hulme *et al*., (2001) suggested that under intermediate warming scenarios, parts of equatorial East Africa will likely experience 5-20 percent increased rainfall from December-February and 5-10 percent decreased rainfall from June- August by 2050.

6.5 Conclusion

Temperature is projected to increase, with larger changes in minimum temperatures increasing more than maximum temperature. Increase in temperature will be higher in the cooler and wetter months and seasons (MAM, JJA) than the warmer season (DJF), signifying a temporal variation in change. Whereas rainfall is projected to increase, the increase will be higher in the drier periods than in the wetter ones, and the increase of rainfall alongside increase in temperature could result in increased evaporation to precipitation ratio over the coming years. This in turn creates a likelihood of an increased deficit in local moisture supply, for both soil water and surface water flows or availability Therefore crop and livestock producers would Soil and water management options would therefore have to cope with such moisture/water deficits through climate smart (soil) water management practices and crop and animal science.

CHAPTER SEVEN

THE IMPACT OF LAND USE AND LAND COVER AND CLIMATE CHANGE ON THE WATER BALANCE OF THE SEMI-ARID LOKERE AND LOKOK CATCHMENTS, NORTHEASTERN UGANDA

Abstract

Changing climatic conditions and land use /cover (LULC) change has become a major concern regarding their impact on already scarce water resources in semi-arid areas of east Africa. The SWAT model was used to evaluate the impact of LULC and climate change on water resources in the Lokok and Lokere Catchments, northeastern Uganda. The simulation was based on 2003 LULC and 1980-2009 Modern Era-Retrospective Analysis for Research and Applications (MERRA)climate data as the baseline. In addition, three projected 2030 and 2050 LULC scenarios and early (2010–2039) and mid-century (1940–2069) ensemble of climate under Representative Concentration Pathway (RCP) 4.5 and 8.5, were obtained from an ensemble of twenty general circulation models (GCMs) using the Agricultural Intercomparison and Improvement Project (AgMIP) delta method protocol. Results showed that evapotranspiration (ET) is the major component of the hydrological budget in the catchments, as over 97 percent of the precipitation received is lost through ET. Surface runoff was the lowest component in the baseline period (0.04 percent), but later attained the highest percentage increase with precipitation up to 708.8 percent in the mid-century RCP 4.5, and 1950 percent under combined pro-farming policy scenarios and mid-century RCP 8.5 rainfall. Return flow was the second highest (0.41 percent), and water yield constituted 0.87 percent of precipitation. Under future climate scenarios with no change in LULC, increase in water yield would range from 79.5 percent under early-century RCP 8.5 to 204.7 percent under mid-century RCP 4.5. However, the increase in water yield would be marginal if only LULC changed, ranging from 5.7 percent to 18.4 percent under business as usual (BAU)2030 and 2050 pro-farming scenarios, where an increase in small scale farming would be high. When LULC and climate change are combined. Increase in water yield would range from 193.7 percent under the 2050 pro-livestock LULC and RCP 8.5 mid-century climate to 223.2 percent under the 2050 pro-farming and RCP 8.5 mid-century climate. Therefore, LULC change could have far more

limited impact on water than climate change. And while the increase in water yield may be limited in volume, it could have significant ecosystem, social and economic benefits if well managed and utilized.

Key words: water resources, east Africa, climate scenario, surface runoff

7.1 Introduction

Climate variability and change, and land use and land cover change, each on its own right, and combined, can result in catastrophic impacts on ecosystems, particularly on water resources and hydrological processes. Rainfall and temperature variability, respectively affect replenishment of moisture in a catchment through precipitation, and the rate of loss of moisture, particularly through evaporation and evapotranspiration. In recent decades, impacts of current anthropogenic climate change on water resources and hydrological processes in Eastern Africa include both frequent flooding due to heavy rainfall, as well as drought conditions (Shongwe *et al*., 2011), leading to drying of water sources.

In addition to climate change, land use and land cover changes lead to alterations in catchment hydrological processes and flow pattern of rivers due to associated changes such as in interception, infiltration rates, and evapotranspiration, as well as distribution of runoff (Lastoria, 2008; Dwarakish and Ganasri 2015 and Anaba *et al*., 2017). Runoff, infiltration, percolation, groundwater recharge and discharge are also affected by soil hydraulic properties which may be modified by land use (Botsford *et al*., 2003 and Manfreda *et al*., 2003). When altered, hydrological processes could result in an increase or reduction of water resources in a given catchment besides becoming channels for transporting water pollutants.

Climate variability and change, and land use and cover change are of increasing concern in Lokok and Lokere catchment which forms the semi-arid part of the larger Kapir catchment, north of Uganda's "cattle corridor" (Mubiru, 2010; Stark, 2011 and Majaliwa *et al*., 2012). Most of the catchment upstream comprises Karamoja sub-region which is semi-arid rangeland with low and highly variable rainfall of about 500mm to 800mm a year (Mubiru, 2010), and faces water scarcity (IUCN-Uganda Office, 2011). Semi-nomadic pastoralism and agro-pastoralism, characterized by extensive livestock production, is therefore the main livelihood activity in the area. Due to its moist riverine areas, the catchment provides refuge for grazing and water, especially during extended dry periods and droughts However, frequent and severe drought being attributed to climate change (Mubiru, 2010 and Stark, 2011) is making water scarcity more acute in the catchment, thus affecting food and forage availability. In addition to changing climatic conditions, land use and land cover change is being experienced in the Karamoja sub-region. Among the factors blamed for the land use and land cover changes in the region are, policy actions aimed at sedentarization of pastoralists to address conflicts caused by cattle rustling between the Uganda's Karimojong and the Pokot community of Kenya (Stark, 2011), as well as promotion of the shift from livestock (grazing) production to crop agriculture, and degazettement of protected areas (Majaliwa *et al.*, 2012). Land use change increases land cover modification which when combined with climate variability and change could aggravate the water scarcity problem by altering hydrological processes in the catchment (Lastoria, 2008).

Given that water is an essential component of a healthy environment and livelihoods that require it to be sustainably managed, an understanding of catchment hydrological dynamics is crucial in aiding management decisions. However, catchment assessment and monitoring require collection of data over an extended spatial and temporal scope given the complexity of hydrological processes in catchment. would. This would be both time and resource intensive. However, models, developed based on several years of research, provide useful tools for representing and understanding the relationship between climate, land use, and hydrological processes (Dwarakish and Ganasri 2015).

Soil and Water Assessment Tool (SWAT) is one of the models that have been widely applied for simulating hydrologic response to climate variability and change, and land use and cover change on catchment water resources. Developed by the United States Department of Agriculture (USDA), Agricultural Research Service (ARS), SWAT is a conceptual, continuous time model for assessing the impact of management on water supplies (flow) and nonpoint source pollution (sediment loads and chemical yields) in watersheds and large river basins (Arnold *et al.*, 1998). SWAT can be implemented using its ArcGIS interface (ArcGIS-SWAT (ArcSWAT)), thus allowing users to leverage the efficient spatial data analysis and application of remote-sensing data that GIS provides (Olivera *et al*., 2006 and Khatami and Khazaei, 2014). ArcSWAT has been successfully applied in a range of catchments including arid and semi-arid catchments of Eastern Africa (Mutiga *et al*., 2011; Dile *et al*., 2013).

In assessing impacts, it is hypothesized that determined land use/cover change results in reduction or increase in catchment surface runoff, lateral runoff, stream flow, groundwater flow and evapotranspiration.

7.2 Materials and Methods

7.2.1 Study area

This study was conducted in Lokok and Lokere catchments which are located in the semi-arid area of the larger Kapir Catchment, connecting downstream to part of Teso sub-region in northeastern Uganda. Karamoja sub-region is part of the Karamoja cluster, an area of land that straddles the borders between south-western Ethiopia, north-western Kenya, south-eastern South Sudan and north-eastern Uganda.

The Karamoja sub-region's topography consists of a plain sloping south-west ward, intermixed with isolated highlands (that include Mt. Moroto, Mt. Iriri, Mt. Kadam, and Mt. Labwor,) in the higher elevated west. The highlands consist of rocks of the crystalline basement complex. Rivers and streams in the catchment originate from the highlands and are mainly ephemeral upstream and perennial in the downstream south-west. The catchment streams are important sources of water in the semi-arid area, especially during the dry season (Mbogga, 2014). Catchment hydrology oscillates with the stochastic climate events in the sub-region. Consequently, most of the rivers in the region are dominated by baseflow components for much of the year with a correlative response pattern to groundwater. Often than not, standing water with slow seepage characteristics is retained in the valley areas by underlying low permeability clay-rich soils of the region (Gavigan *et al*., 2009).

The sub-region experiences hot and dry weather characteristics of most semi-arid regions in Eastern Africa. Rainfall in Karamoja sub-region is uneven and unimodal, occurring from March to November, and ranging from < 500 mm per year in eastern Karamoja, 500-800 mm in central

Karamoja to 700-1000 mm in west Karamoja and the isolated highlands (Mbogga *et al*., 2014). Mean annual rainfall downstream of the Catchment, in the Teso subregion, is about 1100-1200 mm, distributed between two seasons of March to July and September to November (Kisauzi *et al.*, 2012). Temperatures are generally high throughout the year, with an annual average of 28 and 33 °C for minimum and maximum, respectively; leading to high evapotranspiration levels averaging 2072 mm per annum (Mbogga *et al*., 2014). Rainfall variability in the region leads to heterogeneity of landscape resources including the availability of pasture and water that influences the pastoral way of life as both a coping and adaptation strategy (Egeru *et al*., 2014).

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7.2.2 ArcSWAT model description

SWAT (Soil and Water Assessment Tool) is a semi-distributed, physically based and computationally efficient time-continuous model requiring inputs of weather, soil properties, topography, and vegetation and land management practices in the watershed (Arnold *et al*., 2011 and Neitsch *et al*., 2011). ArcSWAT ArcGIS extension provides graphical integration of various spatial data (Winchell *et al*., 2010). SWAT can simulate the hydrological, sediment, and agricultural yields impacts of land use change and management practices in large and complex watersheds with varying soil, land use and management conditions over a long time (Nejadhashemi *et al*. 2011). The model can also use readily available data such as those in the custody of the relevant government agencies, and is computationally efficient and is capable of studying long term impacts. SWAT divides the watershed into a large number of sub-watersheds each of which is in turn sub-divided into hydrological response units (HRUs) based on similar (combination of) land use, soil distribution, and slope.

The SWAT model allows simulation of a high level of spatial detail and is premised on the water balance of a catchment. Water balance is an account of the inputs and outputs of water. In a catchment, it is determined by calculating the input, output, and storage changes of water at the earth's surface (Neitsch *et al*., 2011). SWAT, therefore, simulates processes of the hydrological cycle (Lastoria, 2008) occurring at the earth's surface (Gassman *et al*., 2007). Obtaining accurate predictions with the model requires conformity of the simulated hydrological cycle with realities on the ground. Watershed hydrology simulations is separated into two main divisions (Neitsch *et al*., 2011): the land phase of the hydrological cycle division which controls the amount of water, sediment and pesticide loadings to the main channel in each sub-basin; and the routing phase of the hydrological cycle which deals with their movement through the watershed channel networks to the outlet. The land phase of the hydrological cycle is simulated by applying the water balance equation (Neitsch *et al*., 2011):

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - E_a - W_{seep} \right)$$

Where SW_t is the final soil water content (mm H_2O), SW_o is the initial soil water content on day *i* (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day *i* (mm H_2O), Q_{surf} is the amount of surface runoff on day *i* (mm H_2O), E_a is the amount of evapotranspiration on day *i* (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day *i* (mm H_2O), and Q_{gw} is the amount of return flow on day *i* (mm H_2O).

In the routing phase, the simulated loadings of water, sediment, nutrients and pesticides are routed to the main channel through the stream network of the watershed. This in SWAT is achieved by using Manning's equation to define the rate and velocity of flow; and routing using the variable storage method or the Muskingum river routing method (Neitsch *et al*., 2011). The Muskingum river routing method is suitable in watersheds where there are data limitations. The Muskingum routing equation defines the storage (V_{stored}) in the reach as a linear function of weighted inflow (q_{in}) and outflow (q_{out}) (Lastoria, 2008 and Neitsch *et al*., 2011):

$$V_{stored} = K.q_{out} + K.X.\ (q_{in} + q_{out})$$

Where K is the storage time constant for each reach (s), and X is the weighting factor.

7.2.3 Data / Model Input

Digital Elevation Model: The Digital Elevation Model (DEM) that describes the elevation of any point in a given area at a specific spatial resolution defines the topography (Setegn, 2010). A thirty-meter resolution Digital Elevation Model for Uganda obtained from the Shuttle Radar Topography Mission (SRTM) was used for this study.

Land use and land cover: Land use and cover maps for 1984, 1994, 2003, and 2013 obtained from analysis of images in Chapter 4, were converted into shape files and projected as the DEM.

Soil data: Soils in Karamoja subregion and north-eastern Uganda in general are mainly vertisols, particularly in areas of Moroto, Napak, Abim, and Kotido, with greysols dominating along drainage channels. Luvisols and petric plinthosols are more dominant north of Kotido, in Kaabong (Semalulu and Kaizzi 2013). Following the reconnaissance soil survey for the whole of Uganda between 1958 and 1960 (FAO/UNEP, 1992), Wilson (1959 a&b) plotted soil mapping units for Karamoja. These units were matched with a soil map for the study area clipped from a soil map of Uganda that was obtained from Soil and Terrain (SOTER) dataset at Makerere University College of Agriculture and Environmental Sciences. The soil units were then characterized using Soil Memoires obtained from National Agricultural Research Laboratories (NARL-Kawanda) by identifying approximate equivalent soils in the ArcSWAT database, based on the profiles described in the memoires. The catchment soils were matched on the basis of soil texture – a property of soil which is usually not changed by management and that regulates the whole soil environment (Osman, 2013).

Climate data: Daily AgMERRA climate data, for four locations stations of Amuria, Moroto, Kaabong and Kotido districts, for the 1980-2010 period was used. AgMERRA is one of the reanalyses of weather data produced by numerical weather prediction (NWP) models. The data was obtained from the Agricultural Model Intercomparison and Improvement Project (AgMIP). Only Moroto station data point was within the catchment, however, all were used in the model as adjoining weather stations to provide better aerial weather coverage, for the catchment. This data was used to simulate streamflow for the base period (1980-2010).

In simulating future streamflow scenarios under a changing climate, ensembles of downscaled general circulation models (GCMs) from RCP 4.5 and 8.5 CMIP5 were employed. The downscaling for each of the four stations' weather data was obtained using the delta method and achieved using a script provided in the AgMIP protocol (Rosenzweig *et al*. 2013 and Hudson and Ruane, 2015). Stream flow simulation was undertaken for two periods: 2010–2039 – near-term period (early century); and 2040–2069 – mid-century.

Streamflow data: Streamflow data were obtained for one downstream gauged location (Akokorio), from the Directorate of Water Resources Management (Entebbe, Uganda). The obtained flow data was inspected for gaps. For the period of interest (1st January 1984 t0 31st December 2010), daily streamflow records were missing for nearly eleven continuous years (1st January 1984 to 30th September 1994). There were also gaps in the data, especially from 1st January 1995 to 13th February 1997. Thus, gap filling was performed to obtain daily streamflow data for seven years (1995 to 2001) for calibration; and six years (2003 to 2008) for validation. Average monthly streamflow was computed using the MS-Excel Pivot Table.

7.2.4 ArcSWAT Model setup

ArcSWAT was set up for hydrological processes' simulation in five steps (Winchell *et al*., 2010): data preparation, sub-basin discretization, HRU definition, parameter sensitivity, and uncertainty analysis, calibration, and validation. The spatially distributed data needed for the ArcSWAT interface for prediction of hydrological processes and for calibration purposes include the Digital Elevation Model (DEM), soil data, land use; and weather and river discharge.

The DEM was used to delineate the watershed and to analyze the drainage patterns of the land surface. Watershed and sub-watershed delineation was implemented using the DEM in five steps: DEM setup, stream definition, outlet and inlet definition, watershed outlets selection and definition, and calculation of sub-basin parameters. Sub-basin parameters such as slope gradient, slope length of the terrain, and the stream network characteristics such as channel slope, length, and width were derived from the DEM. The DEM was set up by adding it onto ArcSWAT and manually defining a mask around the area of interest for DEM-based stream definition. ArcSWAT uses DEM in terrain processing to define these parameters and delineate the watershed.

Land use maps were reclassified into SWAT land cover/ plant types, in the "crop" and "urban" tables of the "SWAT2012" database, required by the model and linked to a user table with land-use code (Winchell *et al*. (2010). The reclassified land use and cover maps (Table 7.1) were then overlaid to determine hydrological response units (HRUs).

Table 7.1: Reclassified Land use and land cover in SWAT model setup

Catchment land cover /Land use	SWAT Land cover/ plant code (ICNUM)	SWAT Land cover/ plant four–letter code (CPNM)	SWAT Name/ Description	Area (%)
Built-up areas	1	URML	Residential-Med/Low Density	0.12
Bushland	16	RNGB	Range-Brush	21.43
Grassland	15	RNGE	Range-Grasses	58.10
Small scale farming	1	AGRL	Agricultural Land-Generic	13.75
Wetland	11	WETN	Wetlands-Non-Forested	1.94
Woodland	16	FRSD	Forest-Deciduous	4.65

7.2.5 Model uncertainty, sensitivity and performance

Model uncertainties often remain a concern due to spatial heterogeneity of catchments and a large number of input parameters (Abbaspour, 2018 and Kumar *et al*., 2017). This leads to under or over-simulation of hydrological processes. Vigilant calibration and uncertainty analysis is therefore crucial if model outputs are to provide a fair representation of the natural water balance of any given catchment.

In this study, these analyses were carried out using the semi-automated Sequential Uncertainty Fitting 2 (SUFI-2) procedure in SWAT Calibration Uncertainty Procedure (SWAT-CUP), a computer-based program linked to SWAT for model calibration (Abbaspour, 2015). SUFI-2 algorithm is a stochastic calibration that expresses model errors and uncertainty as arrays of parameter values, thus accounting for all sources of errors (Mehan *et al*., 2017). Besides being semi-automated, thus allowing user control by applying local knowledge of the catchment and hydrological expertise in the definition of parameters and their ranges (Abbaspour, 2015), SUFI-2 has been reported to perform better than the fully automated Parameter Solution (ParaSol) and GLUE by producing a better statistical evaluation of parameters (Shivhare *et al*., 2018). The model was calibrated for a monthly time step for a seven-year period (1995-2001) and validated using a six-year period (2003-2008). The Nash-Sutcliffe efficiency (NSE) and R^2 coefficients were used to determine the performance of the model (Gassman *et al*. (2007).

7.2.5.1 Calibration

The calibration was guided by a protocol proposed by Abbaspour (2018). The protocol, which has been drawn based on experience and review of findings of previous studies on SWAT, aims to reduce uncertainty due to poor parameterization and misrepresentation of catchments' structure.

Uncalibrated model simulation for a twelve-year period (1990-2001) was obtained using the default SWAT parameters setting. A five-year (1990-1994) warm-up period, which allowed the model to initialize processes and reach dynamic equilibrium (Daggupati *et al*., 2015) was applied. The uncalibrated simulated streamflow was plotted with observed data in SWAT-CUP. The uncalibrated model poorly simulated catchment streamflow and thus required careful calibration.

A pre-calibration run and fitting of driving variable (rainfall) parameters and of those that generate water in the catchment model structure were undertaken (Table 7.2). Pre-calibration run also helped to exercise the modeler's knowledge of the catchment (Moriasi *et al*., 2012). As a first step, the ICN calculation method was changed from Soil Moisture method to Plant ET method and PET Method was changed from Penman/Monteith to Hargreaves, as the model exhibited overestimation of streamflow. This reduced the simulated flow before any parameters were adjusted.

Obtaining the best parameters by calibration (optimizing an objective function) with measured data begins with selecting the appropriate set of parameters for sensitivity analysis. The set of parameters for sensitivity analysis (Table 7.3) were selected based on previous studies indicating that they influence streamflow response (e.g. Arnold *et al.*, 2012; Anaba *et al.*, 2017; Mehan *et al.*, 2017; and Abbaspour, 2018). Equally important is the definition of the range of parameter values that denote the range of uncertainty (Mehan *et al*., 2017). Range of parameter values was defined by examining the default values that had been applied in the uncalibrated simulation and considering ranges that were likely to aid increase in peak flow. For example, CN2 and ESCO value ranges were defined to aid model fitting of high and low values respectively, to increase peak flow (Abbaspour, 2018).

Table 7.2: Fitted parameters during pre-calibration

Parameter	**Description**	**Impact on simulation When value increased**	**Range of model values**	**Mathematical Operation**	**Value applied**
CN2	Initial SCS runoff curve number for moisture condition **II**	Increases surface runoff	35-98	Relative	0.64
sol_z	Soil depth	0-3500	0-3500	Relative	0.64
sol_k	Saturated hydraulic conductivity	0-2000	0-2000	Relative	0.1
SOL_AWC	Soil available water capacity	0-1	0-1	Relative	5
Canmx	Maximum canopy storage	Reduces infiltration and surface runoff but increases evapotranspiration	0-100	Relative	70
ESCO	Soil evaporation compensation factor	Decreases evaporation	0-1	Relative	0.5
surlag	Surface runoff lag time	holds less water in storage	0.05-24	Relative	8

Previous studies present relatively varying views on model performance evaluation statistics. While traditionally, coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE) statistics are used, with values above 0.5 indicating good performing models (Arnold *et al*., 2012), Moriasi *et al.* (2007) recommended NSE, percent bias (PBIAS), and the ratio of the root mean square error (RMSE) to the standard deviation of measured data (RSR). Respective satisfactory model statistics for the latter two are within ±25 and less than 0.70 (Moriasi *et al*., 2007). Gupta *et al.* (2009) however criticize the NSE for being problematic in calibration due to interaction among its components, that is, "the correlation, the bias, and a measure of relative variability in the simulated and observed values" (p.81), that must be balanced to maximize it. Because the interplay between variability and correlation in NSE could result in an underestimation of the variability in the flows, the Kling–Gupta efficiency (KGE) statistic decomposes model performance into correlation, bias and variability terms and seeks to separately (multi-objectively) maximize them (Gupta *et al*., 2009 and Kling *et al*., 2012). Like NSE, KGE′ values range between $-\infty$ and 1, where a value of 1 indicates a perfect simulation of the observed data. The coefficient of determination (R^2), NSE, PBIAS, RSR, and KGE were all used to evaluate the model.

Table 7.3: Results of sensitive analysis and fitted parameter values of the flow calibration fitted using SUFI2

Parameter Name	Description	Fitting method applied	t-Stat	P-Value	Fitted	Range
REVAPMN.gw	Threshold depth of water in the shallow aquifer for “revap” or percolation to the deep aquifer	Replace	0.012	0.990	475.650	450-600
ALPHA_BNK.rte	Base flow alpha factor for bank storage	Replace	0.056	0.955	0.241	-0.52
CH_N2.rte	Manning’s ‘N’ value for the main channel.	Replace	0.089	0.929	0.081	0.02-0.2
CN2.mgt	Initial SCS runoff curve number for moisture condition **II**	Relative	0.155	0.877	-0.140	-0.32
SLSUBBSN.hru	Average slope length	Relative	-0.671	0.502	0.052	-0.11
CANMX.hru	Maximum canopy storage	Replace	0.957	0.339	71.080	50-90
SURLAG.bsn	Surface runoff lag time	Replace	-1.037	0.300	12.210	5-15
GW_DELAY.gw	Ground water delay	Replace	1.217	0.224	35.432	28-36
ALPHA_BF.gw	Base flow factor	Replace	-1.262	0.208	0.161	0.1-0.7
CH_K2.rte	Specific hydraulic conductivity in main channel alluvium	Replace	-1.407	0.160	108.118	64-150
SLSUBBSN.hru	Average slope length	Relative	1.823	0.069	0.066	0.02-0.1
GW_REVAP.gw	Groundwater "revap" coefficient	Replace	4.565	0.000	0.052	-0.16
GWQMN.gw	Threshold water depth in shallow aquifer for required for return flow	Replace	6.073	0.000	1387.300	900-2000
ESCO.hru	Soil evaporation compensation factor	Replace	-8.519	0.000	0.583	0.25-0.7

7.2.5.2 Uncertainty analysis

Hydrological models face uncertainty in predictions arising from three main sources: model structure, input, and parameters (Abbaspour, 2015). Uncertainty from model structure arises from assumptions adopted to simplify the modelling of the desired process, exclusion of processes occurring in the watershed whether known or unknown to the modeler and processes included in the conceptual model that are not utilized by the modeler. Factors that could give rise to uncertainty in any given catchment include wetlands, dams, water abstraction, surface, and groundwater interaction and wind erosion. Input and parameter uncertainty arises from error in input data and error in non-uniqueness of sets of model parameters (Singh *et al*., 2014 and Abbaspour, 2015).

Uncertain analysis in SWAT-CUP's SUFI-2 algorithm, which applies p-factor and r-factor statistics to quantify the fit between simulated and observed streamflow was used in this study (Abbaspour *et al*., 2004).

The p-factor is the percentage of observed data bracketed by the 95 percent prediction uncertainty (95PPU). The 95PPU is uncertainty in model output expressed as a 95 percent probability distribution. It is calculated at the 2.5 and 97.5 percentiles of the cumulative distribution of output (simulated) variable obtained through the propagation of parameter uncertainty, using Latin hypercube sampling, normally with between two and five interactions in the SUFI-2 algorithm (Abbaspour *et al*., 2004 and Abbaspour, 2015). Model good of fit is assessed using the p-factor and the average distance $\underline{d}$ between the upper and the lower 95PPU can be determined from (Abbaspour, 2007):

$$\underline{d} = \frac{1}{k}\sum_{l=1}^{k} \quad (X_u - X_L)_l$$

where k is the number of observed data points. However $\underline{d}$ is more reasonably measured as r-factor expressed as:

$$r = \frac{\underline{d}_x}{\sigma_x}$$

Where σ_x is the standard deviation of the measured variable, x.

Values for *P-factor* ranges between 0 and 100 percent, while that of *R-factor* ranges between 0 and infinity, with respective values of 1 and zero representing a simulation that completely agrees with measured data (Abbaspour, 2015). Thus the strength of the calibration is seen from the degree of departure from the ideal values.

The task in calibration is to bracket the largest possible data points within the 95PPU, however, this also increases the distance between the upper and lower limits. In SUFI2, reasonable values of these two factors are obtained, by iterating simulations, by assuming a large parameter uncertainty within a physically reasonable range to allow more data to fall within the 95PPU. This uncertainty is then decreased in subsequent steps while monitoring the P factor and r factor. Preceding parameter ranges are updated with smaller ranges by calculating the sensitivity matrix and a covariance matrix, at 95 percent confidence intervals of the parameters, and a correlation matrix (Singh *et al.*, 2014). A number of iterations, usually less than 5, are made to obtain an acceptable p-factor and r-factor in addition to other measures such as r^2 and NSE. Abbaspour (2015) suggests *values greater than* 70 percent and around 1, for p-factor and r-factor respectively. Singh *et al*. (2014) observe that 80–100 percent of the observed data should be bracketed by the 95PPU when data is of good quality while 50 percent may be sufficient for poor quality data.

7.2.6 Analysis of model outputs

The parametric ordinary least square regression method was used to assess the trend of annual streamflow over the 30 years, for each scenario. The significance of the linear model was tested at a probability of 0.05 (Helsel and Hirsch, 2002 and von Storch and Zwiers, 2003).

The sensitivity of the water balance components to climate and land cover change was calculated as percentage relative change of surface runoff (SURQ), lateral flow (LAT_Q), groundwater discharge/return flow (GWQ), recharge to the deep aquifer, actual evapotranspiration (ET) and water yield, in each scenario from the corresponding component baseline.

7.3 Results

7.3.1 Model performance

Figures 7.1 and 7.2 show the performance of the model during calibration and validation, respectively. The model performed well as it's R^2, NSE, and KGE for both calibration and validation exceeded 0.5, with values of above 0.6. Model RSR, being 0.49 was also well within the desire=d value of less than 0.7 (Table 7.4). Whereas the model underestimated streamflow during calibration, it slightly overestimated it in the validation but remained well within the threshold value of ±25. Although the model exhibited large uncertainty for both calibration and validation simulations, given the values of p-factor and r-factor were less than desired respective values of above 70 percent and around 1 for good quality data, it was considered to be sufficiently calibrated to estimate the catchments' hydrological processes. This was because the p-factor values of 0.5 and 0.58 for calibration and validation respectively met a threshold of 0.5 percent, which may be sufficient where observation data quality may be low (Singh *et al*., 2014).

Table 7.4: Streamflow calibration and validation results

Variable	p-factor	r-factor	R2	NSE	PBIAS	RSR	KGE
Calibration	0.80	1.75	0.78	0.75	19.6	0.50	0.76
Validation	0.58	3.17	0.73	0.69	-1.5	0.55	0.84

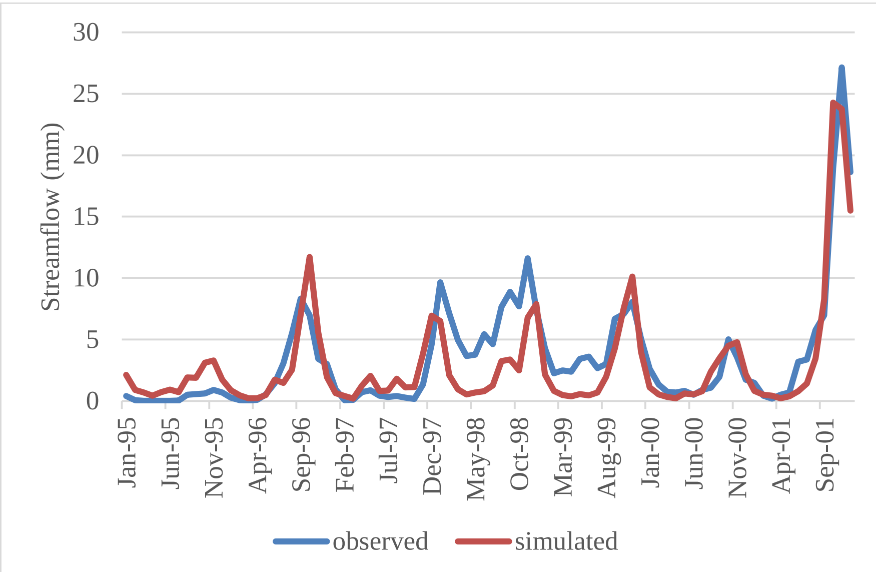

Figure 7.1: Model performance in the calibration period (1995-2001)

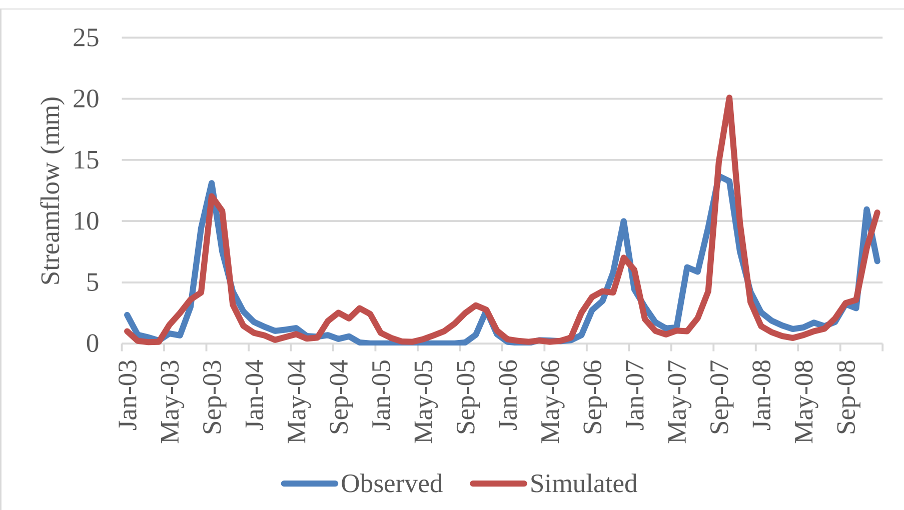

Figure 7.2: Model performance in the validation period (2003-2008)

7.3.2 The Catchments' water balance in the base period (1980-2009)

The hydrological process was simulated for the base period (1980-2009) to determine the value of each component in the water balance of the catchments. Most of the water (97.2 percent) was lost through evapotranspiration and runoff (0.04 percent) accounted for the lowest amount of the precipitation received (Figure 7.3). Return flow (groundwater discharge) was the highest contributor to water yield, with just 0.41 percent of the Catchments' water balance.

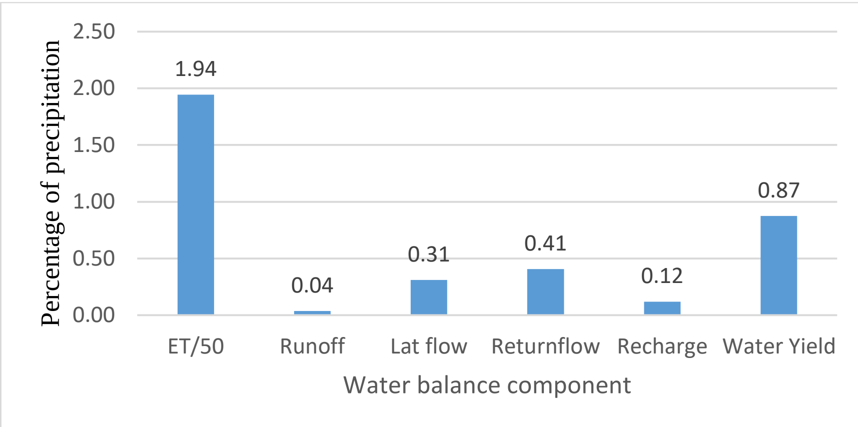

Figure 7.3: Simulated water balance of Lokok and Lokere Catchments as a percentage of precipitation, for the 1980-2009 period (ET/50 is evapotranspiration divided by 50, to fit the graph)

7.3.3 Effect of climate change on discharge

Table 7.5 shows the simulated discharge under future climate (temperature and precipitation) scenarios compared with the baseline period (1980–2009), with no change in land use and land cover (2003). Results showed a very large percentage increase in the water balance components as rainfall increased.

Table 7.5: Simulated discharge for Lokok and Lokere catchments under future climate (temperature and precipitation) scenarios

Climate scenarios	PCP	ET	Runoff	Lat flow	Return flow	Recharge	Water Yield
RCP4.5E	17.1	15.6	411.8	23.2	246.6	68.6	150.3
RCP8.5E	14.4	13.7	264.7	17.3	121.3	39.0	79.5
RCP4.5M	22.5	20.5	708.8	32.4	323.3	85.7	204.7
RCP8.5M	22.8	22.3	685.3	27.6	84.8	30.5	83.7

PCP is precipitation, ET is evapotranspiration, RCP is representative concentration pathways 4.5 and 8.5 in the early-century (E) and mid-century (M)

The highest increase would occur in the mid-century under RCP 4.5, where runoff could increase sevenfold (708.8 percent). Runoff could have the highest percentage increase in all scenarios and periods, ranging from 264.7 percent under RCP 8.5E in the early century to 708.8 percent in the mid-century RCP 4.5M. An increase in discharge would be higher under RCP 4.5 than RCP 8.5 in both early and mid-century.

7.3.4 Impact of land use and land cover change on streamflow

Table 7.6 shows the percentage change in the simulated discharges for the land cover in 2030 and 2050 for each of the policy scenarios of BAU, pro-farming and pro-livestock, with no change in climate factors. Results showed that a negligible decrease in evapotranspiration (-0.1 and -0.2 percent) but a relatively high increase in return flow would occur, ranging from 12.4 percent under the BAU scenario in 2030 to 36.8 percent in the pro-farming policy scenario in 2050. Water yield would increase more in the pro-farming policy scenario, where the area under small scale farming has increased and grassland is reduced, by approximately the same percentage in 2030 and 2050, than in any other. Most of the increase in water yield in the pro-farming policy scenarios would come from return flow, and it would increase by more than double the increase in the other scenarios. Surface runoff would increase by 14.7 percent in the BAU and pro-livestock scenarios where the percentage area under grassland is large but only 2.9 percent in a pro-farming scenario where the area under grassland is low and cultivated land has increased.

Table 7.6: simulated discharge for Lokok and Lokere catchments under future LULC scenarios (2030 and 2050)

LULC scenario	PCP	ET	Runoff	Lat flow	Return flow	Recharge	Water Yield
BAU30	0	-0.1	14.7	-3.3	12.4	3.8	5.7
BAU50	0	-0.1	14.7	3.7	16.0	4.8	10.0
FARM30	0	-0.2	2.9	-0.4	36.2	9.5	18.1
FARM50	0	-0.2	2.9	-0.4	36.8	9.5	18.4
LIVE30	0	-0.1	14.7	3.3	13.2	4.8	8.6
LIVE50	0	-0.1	14.7	3.7	13.8	4.8	9.0

LULC is land use/land cover, BAU30 is LULC under business as usual (BAU) policy scenario by the year 2030, LIVE30 is LULUC under pro-livestock policy scenario by the year 2030, and FARM30 is LULC under pro-farming policy scenario by the years 2030

7.3.5 Future scenarios of streamflow in the Catchments

Table 7.7 presents simulated water balance components under future scenarios of land use/cover, and climate for the early century (2010-2039 climate, and 2030 LULC) and mid-century (2040-2069 climate, and 2050 LULC). While ET would increase by a relatively small percentage (from 3.5 to 15.5 in all combined scenarios of LULC in 2030 and early-century climate), the percentage increase in water yield would be large (from 87.5 percent in the BAU and RCP 8.5 to 170.7 percent in the Pro-Farming Policy scenario and RCP 4.5). The same pattern would occur with combined

2050 LULC and mid-century scenarios, where an increase of 22.5 - 22.9 percent in rainfall would lead to an increase of 19.2 to 21.1 percent in ET, and a very large increase in water yield, ranging from 193.7 to 223.2 percent.

As seen in the effect of climate change, the surface runoff would increase more than any other water balance component, and twice the average return flow which is in second place. The increase in surface runoff would range from 264.7 percent under combined 2030 pro-farming and RCP 8.5 early-century (where an increase in rainfall would be relatively low and percentage area under small scaling farming large) to 476.5 percent under BAU30 and RCP 4.5E and LIVE30 and RCP 4.5E combinations (where the increase in rainfall would be relatively high and percentage area under small scaling farming small).

This pattern would also occur when the mid-century climate is combined with 2050 LULC scenarios (Table 7.8). However, the percentage change in components of the water balance would be higher than in the early century. Water yield would range from 193.7 percent under the 2050 pro-livestock and RCP 8.5 mid-century climate to 223.2 percent under the 2050 pro-farming and RCP 8.5 mid-century climate scenario. Like water yield, surface runoff which would have the highest percentage increase (up to 1950 percent under the 2050 pro-farming and RCP 8.5 mid-century climate), would realise the highest percentage increase. Surface runoff and water yield would generally be higher under pro-farming policy scenarios than under the pro-livestock scenarios.

Table 7.7: Simulated discharge under early-century climate scenario and 2030 land use/cover scenario

Scenario	PCP	ET	Surface Runoff	Lat flow	Return flow	Recharge	Water Yield
BAU30-4.5E	17.1	15.5	476.5	25.7	264.0	72.4	162.7
BAU30-8.5E	14.4	13.6	311.8	13.2	136.2	41.9	87.5
FARM30-4.5E	17.1	15.3	405.9	22.8	288.5	78.1	170.7
FARM30-8.5E	14.4	13.5	264.7	17.3	157.9	46.7	97.5
LIVE30-4.5E	17.1	15.5	476.5	26.5	266.3	72.4	164.0
LIVE30-8.5E	14.4	13.6	311.8	20.6	137.6	41.9	90.7

PCP is precipitation, ET is evapotranspiration, RCP is representative concentration pathways 4.5 and 8.5 in the early-century (E), LULU is, BAU30 is land use/cover (LULC) under business as usual (BAU) policy scenario by the year 2030, LIVE30 is LULUC under pro-livestock policy scenario by the year 2030, and FARM30 is LULC under pro-farming policy scenario by the years 2030

Table 7.8: Simulated discharge under early-century climate scenario and 2050 land use/cover scenario

	PCP	ET	Runoff	Lat flow	Return flow	Recharge	Water Yield
BAU50-4.5M	22.5	20.5	794.1	36.0	345.5	90.5	220.7
BAU50-8.5M	22.9	21.1	847.1	36.4	293.8	79.0	197.7
FARM50-4.5M	22.5	20.4	691.2	32.0	362.1	96.2	223.2
FARM50-8.5M	22.9	20.8	1950.0	30.5	244.7	72.4	220.7
LIVE50-4.5M	22.5	19.2	167.6	35.7	382.9	144.8	217.6
LIVE50-8.5M	22.9	19.9	194.1	36.0	332.6	131.4	193.7

PCP is precipitation, ET is evapotranspiration, RCP is representative concentration pathways 4.5 and 8.5 in the mid-century (M), LULU is, BAU50 is land use/cover (LULC) under business as usual (BAU) policy scenario by the year 2050, LIVE50 is LULUC under pro-livestock policy scenario by the year 2050, and FARM50 is LULC under pro-farming policy scenario by the years 2050

The results also show a generally higher increase in the water balance components under RCP 4.5, where rainfall would be higher, than under RCP8.5, regardless of the LULC scenario. Surface runoff would increase more than any other component, nearly twice more than return flow, which would realize the second most increase. The lateral flow would realise the lowest increase.

7.4 Discussion

The SWAT model was successfully calibrated and used to evaluate the combined Lokok and Lokere Catchments. Elsewhere, the Model has also been successfully calibrated, validated, and applied elsewhere in Eastern Africa (Guzha *et al*., 2018) including in the arid and semi-arid Gilgel Abay River Catchment of the Upper Blue Nile Basin in Ethiopia (Dile *et al*. 2013); the upper Mara River Basin in Kenya (Mango *et al*., 2011a&b); and the Blue Nile River in Ethiopia and Sudan (Sead *et al*. 2010). This study is, therefore, a further confirmation that the model can be used in the analysis and evaluation of the implications of LULC change, climate change, and management practices on water resources in the semi-arid catchment of East Africa, and Uganda’s semi-arid Karamoja sub-region.

The model simulated that ET accounted for 97 percent of the mean annual precipitation received in the Catchments in the base period (1980-2009). This result is consistent with reports that ET in dryland ecosystems usually accounts for greater than 90 (Huxman *et al*., 2005) and even greater than 95 percent (Lu *et al*. (2011) of, or approximately equal to (Kurc and Small, 2004), precipitation. Kurc and Small (2004) explain that ET is believed to be limited by soil moisture most of the time in dryland ecosystems as precipitation is much less than PET in these areas. The result of this study affirms ET as an important water balance component that further decides the water productivity in any given catchment (Bhatt and Hossain, 2019).

Consistent with Wilcox *et al*. (2003), groundwater recharge accounted for the lowest proportion of precipitation received as the water remaining after evapotranspiration remained as runoff (surface runoff, lateral flow, and return flow). Surface runoff was the lowest component in the baseline period while return flow was the highest. However, in the scenarios where precipitation increased, surface runoff became the highest water balance component. Given that the infiltration rate equals surface water input rate when the latter is less than infiltration capacity (Tarboton, 2003), surface runoff was probably low in the baseline period when rainfall was relatively low because much of the precipitation infiltrated into the soil. The increase in surface runoff in periods when rainfall is high could also be explained by an exceedance in the infiltration capacity of the soils when there is an input of water into the ground (Tarboton, 2003). Suarez et a. (2015) reported a strong correlation between wet conditions and direct runoff in the semi-arid Kaap Catchment of South Africa; as surface runoff and lateral flow are the dominant component of streamflow in wet months and years (Okello *et al*., 2018).

While the values of surface runoff, lateral flow, and return flow may be low, small differences in surface runoff and deep percolation beyond the root zone, which contributes to lateral flow, groundwater recharge, and return flow, can have significant ecological, hydrological, or socioeconomic effects (Huxman *et al*., 2005).

A relatively low percentage surface runoff and high return flow under Pro-farming scenarios where the area under small scale farming increased, compared to their percentages under pro-livestock and BAU scenarios where the area under grassland was relatively large is probably because tilling of the land increases water infiltration rates. Mašíček *et al*. (2012) reported faster infiltration and a higher accumulative infiltration in arable land compared to permanent grassland. Gol and Yilmaz (2017) also reported that among three land-use types/land cover, the highest infiltration rate occurred in cultivated land, followed by forest land, and least in grassland.

The higher percentage increase in water yield under a combined change in LULC and climate than when the changes are isolated are consistent with reports by Ahiablame *et al*. (2017) that indicated up to 60 percent change in streamflow under combined conditions compared to up to 18 percent and 41 percent under changed LUCU and climate respectively. Dile *et al*. (2013) reported that climate change may cause a decrease of between -40% to -50% in mean monthly flow volume during 2010-2040, but may increase by more than double (over 200 percent) during 2070-2100 compared to a baseline period of 1990-2001, as rainfall decreased and increased in respective periods. Therefore, the simulations in this study are in agreement with other studies which also show that climate has a higher hydrological impact in a catchment than LULC, as more change in streamflow and/or water yield is realized with change in climate than LULC (e.g Li *et al*., 2009; Mekonnen1 *et al.*, 2017; Marhaento *et al.,* 2018 and Puno *et al*., 2019).

7.5 Conclusion

The water balance of Lokok and Lokere Catchments was simulated using 2003 LULC and 1980-2009 MERRA climate data for the baseline period. Simulations were also made using 2030 and 2050 LULC scenarios, with an early-century (2010-2039) and mid-century (2040-2069) ensemble of climate data respectively, under RCP 4.5 and 8.5. Evapotranspiration is a major consumer of precipitation, accounting for over 97 percent of received precipitation in the catchments. Because the values of surface runoff, lateral flow, return flow, and groundwater recharge are so small, their changes in percentage terms are too large. Surface runoff is the lowest water balance component in the catchments, however, could realise the highest percentage increase if precipitation increases; while return flow is the second highest. Further, surface runoff and high return flow are likely to increase as more land is converted into small scale farming compared to when there is more grassland. Given the high ET, promotion of sustainable land management practices aimed at water conservation is critical in sustaining productivity in semi-arid environments. Overall, the study shows that climate change may result in an annual increase in flow volume/ water yield in the catchment and that land use and land cover change will have a far much-limited impact on water than climate change. Therefore, efforts aimed at sustainable ecosystems and livelihoods should focus on climate change mitigation and adaptation as changes in climatic parameters are the main divers of hydrological processes that determine productivity and water availability

CHAPTER EIGHT

GENERAL DISCUSSION, CONCLUSION AND RECOMMENDATIONS

8.1 General Discussion

The study assessed the impact of LULC and climate change on surface water resources of Lokok and Lokere Catchments by evaluating the contribution of each to stream flow. The model simulated that ET accounted for 97 percent of precipitation received in the Catchments in the base period (1980-2009) – a result which is consistent with reports that ET in dryland ecosystems usually accounts for greater than 90 (Huxman *et al*., 2005 and Lu *et al*, 2011) or approximately equal to (Kurc and Small, 2004) precipitation received. ET is known to increase with high temperatures (Snyder *et al.*, 2011) and yet annual air temperature (Tmean, Tmax and Tmin) in the Catchments rose significantly in the 1980-2009 period and is projected to continue to rise. Of more concern is that Tmin rose faster than Tmax and if this continues as projected, will heighten water loss throughout the day. As ET is an important water balance component which further decides the water productivity in any given catchment (Bhatt and Hossain, 2019), increased temperatures will negatively impact water resources and crops.

After evapotranspiration, water in the Catchments largely remained as runoff (surface runoff, lateral flow and return flow). Therefore, ground water recharge accounted for the lowest proportion of precipitation received, and this finding is expected in dryland catchments (Wilcox *et al.,* 2003). Surface runoff was the lowest component in the baseline period while return flow was the highest, however, in the scenarios where precipitation increased, surface runoff became the highest water balance component.

Given that the infiltration rate equals the surface water input rate when the latter is less than infiltration capacity (Tarboton, 2003) surface runoff is probably low in the baseline period when rainfall was relatively low because much of the precipitation infiltrated into the soil. The increase in surface runoff in periods when rainfall is high could also be explained by an exceedance in the infiltration capacity of the soils when there is input of water into the ground (Tarboton, 2003).

Suarez et a. (2015) reported a strong correlation between wet conditions and direct runoff in the semi-arid Kaap Catchment of South Africa; as surface runoff and lateral flow are the dominant component of streamflow in wet months and years (Okello *et al*., 2018).

A relatively low percentage surface runoff and high return flow under Pro-farming scenarios where area under small-scale farming increased, compared to their percentages under pro-livestock and BAU scenarios where area -grassland was relatively large is probably because tilling of the land increases infiltration rates. Mašíček *et al*. (2012) reported faster infiltration and a higher accumulative infiltration in arable land compared to permanent grassland. Gol and Yilmaz (2017) also reported that among three land use/cover types, the highest infiltration rate occurred in cultivated land, followed by forest land and least in grassland. But the relatively low changes in the increase of water balance parameters suggests that cropping would be more of a concern when rainfall variability affects its productivity than its impact on the water balance in the catchment. It should however be noted that while the values of surface runoff, lateral flow and return flow may be low, small differences in surface runoff and deep percolation beyond the root zone – which contributes to lateral flow, ground water recharge and return flow – can have significant ecological, hydrological, or socioeconomic effects (Huxman *et al.*, 2005).

The higher percentage increase in water yield under combined change in LULC and climate than when the changes are isolated are consist with reports by Ahiablame *et al.* (2017) that up to 60 percent change in streamflow under combined conditions compared to up to 18 percent and 41 percent under changed LUCU and climate respectively. Dile *et al*. 2013 reported that climate change may cause a decrease of between -40% to -50% in mean monthly flow volume during 2010-2040 but may increase by more than the double (over 200 percent) during 2070-2100 compared to a baseline period of 1990-2001, as rainfall decreased and increased in respective periods. Therefore, simulations in this study are in agreement with other reports which also show that climate has a higher hydrological impact in a catchment than LULC, as much more change in streamflow and/or water yield is realized with a change in climate than LULC (e.g Li *et al.*, 2009; Mekonnen1 *et al* 2017; Marhaento *et al.*, 2018 and Puno *et al*., 2019).

However, variability of rainfall and temperature that greatly influence surface water (stream flow) in catchments shows temporal and spatial differences that would continue into the future. Annual Tmean increased significantly and also seasonally in all seasons (at 0.02-0.04 ^{o}C per year), but not in SON in Kaabong and Kotido. Temperatures were more variable in the first one and half decades of the study period, when temperatures were lower; and in the latter period when temperatures were higher. Temperatures generally began rising in a steady manner in 1994 from below average level, until positive shifts in trends largely occurred after 2000, with non-random variability occurring after 2002. Amuria station showed a more distinct pattern, particularly from that of Kotido station, while Moroto and Kaabong intermittently showed varied or similar patterns with other stations. Tmax, Tmin and Tmean were "extremely hot" in all the stations in 2002 (with a random shift) and in 2009.

Further, rainfall was higher in Amuria; and despite not being significant at the catchment level, increase in total annual rainfall over the 1980 and 2013 period was significant in Kotido and Moroto. Drought occurrence and inter-annual variability, was higher in the 1980-1989 decade, that registered extreme drought (1984 and 1993), with the 1984 drought associated with the strong ENSO event of 1983–1987 which led to intense drought in the Sahel region (Okonkwo *et al*. (2014). It therefore suggests seasonal and spatial availability of water in soils and streams of the catchment that would support mobile herding.

Given that small scale farming would increase in the medium and long term under all policy scenarios, and that reliance on cropping could increase vulnerability of the population to climate variability in the catchment and the greater semi-arid Karamoja region (Aklilu, 2016) where herding has been both a culture and a coping mechanism, strategies that improve both crop and livestock production could be more beneficial to population. Such strategies could cover farm, crop science, and feed and pasture management and catchment water management practices (Ben-Gal *et al*., 2006 and Adugna and Aster, 2007; Tilahun *et al*., 2017).

The application of strategies for improved crop and livestock production require the sustainable management and use of woodlands, bushland and wetlands; in order to leverage seasonal and interannual changes in water and pasture resource availability in semi-arid lands (Scoones, 1991). This way, more could be gained from the projected relatively higher change in rainfall, especially in the usually drier months and seasons.

8.2 Conclusion

The study assessed how a change in land use and land cover (LULC) and climate impacts on the water resources of Lokere and Lokok Catchments located largely in the semi-arid Karamoja subregion and partly (downstream) in the Teso sub-region of Uganda. The study was motivated by the growing global concern over the impact of climate change coupled with LULC change on freshwater ecosystems and productivity, particularly in arid and semi-arid areas. This is particularly relevant for the Lokere and Lokok Catchments where a change in land use and cover has been attributed to sedentarisation of traditionally mobile pastoralists, and promotion of alternative livelihoods to pastoralism. These factors are believed to work in concert with the increasing frequency of drought and flooding associated with climate change to exacerbate the situation. This study considered historical, present, and plausible future impacts of change in LULC and climate on the water balance of the Catchments.

LULC for 1984, 1994, 2003, and 2013 were established through unsupervised and supervised classification of satellite images and three plausible future trajectories – the BAU, pro-livestock policy, and pro-farming policy – scenarios of LULC were developed, using GIS tools. The LULC maps were cross-compared for change detection. The results reveal that there is a substantial change in land use and cover in the Lokere and Lokok Catchments, as the population seeks for alternative livelihoods to mobile herding, leading especially to increased small-scale farming. Key LULC changes include conversions of woodlands and bushlands into small-scale farmlands, with degradation of woodland and bushlands contributing to increasing areas under grassland. The changes are likely to continue as population and settlement increase. Thus small-scale farming would increase in all LULU scenarios to the year 2030 and 2050, suggesting the continuation of the long tradition of agro-pastoralism of the inhabitants even in the presence of policy shifts to particularly promote livestock rearing. However, pro-farming policies would, in both the 2030 and 2050 modeling periods, result in a reduction of grassland as small-scale farming substantially increases (doubling the 2003 land area in 2050). The decline of woodlands, bushland, and degradation of land has the potential to make the inherent water shortage worse in the Lokere and Lokok Catchments and Karamoja sub-region in general, with likely adverse impacts on livelihoods.

The study also assessed trends and variability of rainfall and temperature over the 1980-2009 period, and their projected change based on an ensemble of station (district) level climate scenarios for three periods (2010–2039, 2040–2069, and 2070-2099 or early, mid and end-century respectively), downscaled using the delta method from twenty of the latest IPCC climate models embedded in the Agricultural Model Intercomparison and Improvement Project (AgMIP). The study established that temperatures over Lokere and Lokok Catchments are significantly increasing with time. The results reveal that temperatures are most variable during MAM as rainfall sets in and more stable in JJA, the period of rainfall peak. The Tmin was found to be rising faster than Tmax, especially during the rainy season, with the former rising significantly at monthly, seasonal and annual temporal scales. However, Tmax is increasing and more variable than Tmin during the dry season. These trends would continue into the early, mid, and end-century periods as a change in Tmin would be larger than the change in Tmax under RCP 4.5 and 8.5 considered in this study.

An increase in rainfall has spatial and temporal differences, with a relative increase lowest in the wetter Amuria location. Total annual rainfall significantly increased only in Kotido and Moroto, while October rains significantly increased in all the stations, except Amuria, resulting in a significant increase in SON rainfall in the stations. In addition, there was a significant increase of January rainfall in only Kaabong. Although there was a rise in average Catchment rainfall, the increase was not significant. Like temperature, rainfall is projected to increase, the increase would be higher in the drier periods than in the wetter ones.

There is high inter-annual variability in rainfall over the Catchments, the highest being from 1980-1989 when three (four in Amuria) drought events occurred, and the lowest occurring from 2000-2009. Rainfall variability is also highest during the onset period of MAM, which may result in uncertainty and indecision by farmers concerning the timing of planting. The variable SRA across the stations depicts a spatial variability of rainfall over the catchments.

Simulation of the water balance of Lokok and Lokere Catchments based on 2003 LULC and 1980-2009 MERRA climate data has shown that evapotranspiration is a major consumer of precipitation, accounting for over 97 percent of received precipitation in the catchments. The values of surface runoff, lateral flow, return flow and groundwater recharge are so small, as a result, their changes in percentage terms are too large. Although surface runoff is the lowest water balance component, it could record the highest percentage change if precipitation increased. Further, surface runoff and high return flow would occur under Pro-farming scenarios where the area under small-scale farming has increased, compared to under pro-livestock and BAU scenarios where the area under grassland is relatively large. While water yield increased with an increase in rainfall, the higher percentage increase would occur under a combined change in LULC and climate. Overall, the study shows that climate change may result in an annual increase in flow volume/ water yield in the catchment and that land use and land cover change will have a far much-limited impact on water than climate change.

8.3 Recommendations

The following recommendations arise from the key results of this study:

a) Agro-pastoralism constitutes the primary use of land or livelihood of the people in the Catchments and the broader Karamoja subregion. Given the increasing climate variability, extensive livestock production, which is well adapted to the inherent extreme climatic events experienced in semi-arid areas, remains viable in the study area, and therefore crop cultivation should just be promoted as a complementary livelihood activity.

b) Given that key transitions in the land use and land cover change in the catchments are attributed to the conversion of woodlands and bushlands into small scale farming, the government and development agencies should focus their attention on awareness creation and engaging the communities on sustainable land management practices to ensure both environmental and livelihood security.

c) Because rainfall has a spatial variability in the Catchments, it is crucial to consider characterizing vulnerability and adaptation options within the different sites in the Catchment.

d) Regulated change of LULC to farming could be beneficial by increasing water yield through increased infiltration. Therefore, soil and water management practices should be promoted along with crop farming so as to enhance water yield in the Catchments and continue to provide an alternative source of livelihood to pastoralism.

e) While the projected increase in rainfall, given variability in the Catchments could result in increased flooding, the projected increase in water yield presents an opportunity for rainwater harvesting and appropriate damming to provide water for livestock and farming.

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Appendix I: QuestionQuestio guide for keyk informant interview

Part 1: Land use

1. What is the traditional land use in this district/area?

   Is the land use changing?

   ----

2. Whichich specific changes have you observed over the years?

   ----

3. What are the key reasons for/cause of this change?

Part 2: Climate variability and Change

4. What were the patterns of rainfall and temperature:?

a) 50 years ago,

   ----

b) 30 years ago, and

   ----

c) 10 years ago?

   ----

5. How are these patterns today?

   ----

6. How have these patterns changed?

Part 3: Impact on Water resources

7. What are the major water resources?

   ----

8. How important is Lokok river system

a) economically,

   ----

b) socially/ culturally and

   ----

c) ecologically)

   ----

9. How has water availability in this river/sources been changing?

----

10. What are the cause of the changes?

----

11. How has land use/cover change influenced this change in water availability?

----

12. How has climate variability/change influenced this change in water availability?

----

13. What has been the effect of these changes?

----

14. Who are the most affected?

APPENDIX II: QUESTION GUIDE FOR FOCUS GROUP DISCUSSION

Land use/cover change

1. What are the major land uses in this area?

----

2. What major shift in land use occurred in your locality in the past years[Reduction (-), increase (+), no change (0)]?

Shift (e.g Conservation - Grazing	10 years a go to now		20-10 years ago		50 to 20 years ago	
	Area	Quality	Area	Quality	Area	Quality

3. What are the new land uses that have been adopted by the people of this area?

----

4. Which land uses have increased/reduced?

----

5. What are the major factors that affect your decision related to land use or management in order of importance (explain)? And what is the difference in these factors between dry/wet/normal years?

----

6. Describe land lost or additional land gained12 during the last 10, 20 and 50 years associated factors?

----

7. What are the major changes in land use (area + quality) and management you noted in communal properties over the last 10, 20, 50 years and the institutional changes that go along with these?

----

8. Are there external factors that are out of your control? Describe and explain:

----

9. What are the challenges faced by the existing land uses?

----

10. Do you predict any future challenges for the existing land uses?

----

11. Which land uses do you think will increase in future (2020 and 2050)?

Climate variability and change

12. Have you noticed changes in (i) flooding, (ii) rainfall, (iii) drought (*monga*), (vi) storms, (vii) river bank erosion, (vii) temperature in the last few years?

----

13. If yes, ask for each of the changes –

----

14. How is it (are they) different from original situation?

----

15. When did you first notice the change (year, if possible) and Where?

----

16. What do you think are the main causes or reasons for the change?

APPENDIX III: GUIDELINES FOR PARTICIPATORY MAPPING

A1 paper sheet will be provided, the purpose of map explained, lead map making person chosen among participants and time for map making agreed. All participants will be given drawing pens/markers/pencils and can add to drawings made by lead persons who draws as they discuss the elements drawned. Symbols are agreed for each element drawn. A tape recorder will be used and all gadgets will be shown and their purpose explained to participants. After mapping, one or two participants will guide and identification of major features on map on the ground and their points recorded using GIS.

Major elements to be included will include major roads, major land uses, water points and streams, major settlements/camps, hazard prone areas.

1. On the sheet, draw the existing major roads, rivers/streams, and major features known in this sub-county
2. Now, where are major current land uses?
3. Now show areas where land use shifts have occurred in the last 10 years, 20 years and 50, years.
4. Let's explain why these shifts have occurred
5. Where are the current water points?
6. Which are seasonal/perennial?
7. Which areas had water points that have disappeared/ are new/reduced/increased?
8. What factors are responsible for these changes/
9. Which areas are prone to hazards (flooding, etc.)?
10. How frequently do these occur and have they increased or reduced in the past days?

APPENDIX IV: SEASONAL CALENDAR GUIDE

Guidance notes:

1. This activity will take approximately 1 hour and 15 minutes including discussion: 30 minutes for the calendar, and 45 minutes for the discussion. On large sheets of paper, the months of the year will be marked off on the horizontal axis. The participated will be briefed that that the purpose is to develop a calendar to show key events and activities that occur during

2. The will be asked to list seasons, events including extreme events, conditions, etc., and arrange these along the vertical axis.

3. When the key events have been listed, they will be plotted based on their timing in the table based on agreement among the participants.

4. Note will be taken of the any events for which the group has difficulty deciding on timing.

Land use Seasonal Calendar

Land use activities	***Jan***	***Feb***	***Mar***	***Apr***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***	***Nov***	***Dec***
2010s												
2000s												
1990s,												
1980s												
1970s,												

Climatic seasonal calendar

Events	***Jan***	***Feb***	***Mar***	***Apr***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***	***Nov***	***Dec***
2010s												
2000s												
1990s,												
1980s												
1970s,												

APPENDIX V: HISTORICAL EVENT USED TO GUIDE LAND USE/COVER CHANGE DISCUSSION DURING THE 1984 – 2013 PERIOD

Decade	District	Historical event	
		In Ngakaramojong	In English
2000-2013	Napak	Akuru Amuseveni	The years of disarmament under President Yoweri Kaguta Museveni
	Kotido	Ekaru ka Apoloris	The year Apoloris was killed
	Napak	Nyakari Atomia	The years of disarmament
1990-2000	Kaboong	Ekaru-Akobalanga	
	Kotido	Ekaru ngolo alokalomuuny	The year the Turkana from neigburing Kenya undertook a fierce raid.
	Napak	Nakabalanga	They year Iteso (people of neighboring Teso) repulsed the Karimojong from Obalanga village land where the latter had temporaily settled in search for water and pasture.
1980-1990	Napak	Ekaru Kaakoro –	Hear of the great famine (1980)
	Kotido	Ekaru ngolo Akolera/Lomulen	The year of Cholera outbreak
	Napak	Kakoro/Eron	Hear of the great famine (1980)
1970-1980	Napak	Ekaru-Ka aruruma	The year Amin “undressed” people
	Kotido	Ekaru ngolo alain	The time Amin came into power
	Napak	Aruruma	The year Amin “undressed” people