Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Social and Educational Sciences
Department of Geography

Isaac Fred Nandala

Land Use and Land Cover Changes (1985-2023) from Multiple Drivers in Kikuube District, Western Uganda

Master's thesis in Natural Resources Management - Geography
Supervisor: Ass. Prof. Martina Calovi
Co-supervisor: Dr. Charlotte Anne Nakakaawa - Jjunju
June 2023

NTNU
Norwegian University of Science and Technology

Isaac Fred Nandala

Land Use and Land Cover Changes (1985-2023) from Multiple Drivers in Kikuube District, Western Uganda

Master’s thesis in Natural Resources Management - Geography
Supervisor: Ass. Prof. Martina Calovi
Co-supervisor: Dr. Charlotte Anne Nakakaawa - Jjunju
June 2023

Norwegian University of Science and Technology
Faculty of Social and Educational Sciences
Department of Geography

NTNU
Norwegian University of
Science and Technology

Isaac Fred Nandala

LAND USE AND LAND COVER CHANGES (1985-2023) FROM MULTIPLE DRIVERS IN KIKUUBE DISTRICT, WESTERN UGANDA

Master of science in Natural resources Management-Geography

Academic supervisors: Martina Calovi and Charlotte A. Nakakaawa-Jjunju

Department of Geography

Norwegian University of Science and Technology

Trondheim, June 2023

NTNU – Trondheim
Norwegian University of
Science and Technology

ABSTRACT

Land use and land cover changes in nature are complex and are an outcome of land use practices in space and time. This study quantified land cover changes and the mechanisms in which land use practices interacted to contributed to land cover change in Kikuube district, western Uganda for a period of 38 years (1985-2023). Thus, understanding land use/land cover changes is vital in understanding the dynamic and complex global environmental change and sustainable land management. The maximum likelihood classifier supervised classification algorithm and the post classification categorical change detection method was used to quantify land use/land cover change patterns based on remotely sensed Landsat imagery for 1985, 1995, 2005, 2015 and 2023 using ArcGIS Pro software. A review of literature on historical developments in Kikuube district were also used to understand the nature of changes. Findings revealed that the largest decline rates across the study period were in woodlands at 0.24%, low stocked tropical high forests at 0.12%, plantation forests at 0.09%, and well stocked tropical high forest at 0.05%. The largest rate of increase per annum were in subsistence farmlands at 0.35%, commercial farmlands at 0.14%, and wetlands at 0.05%. Therefore, changes between natural and human induced land cover types were through afforestation, reforestation, deforestation and degradation for agricultural expansion, infrastructure development. It was also observed that LULC changes were largely outside protected areas shaped by terrain, population demographics and policy changes for oil exploration and development activities, refugees' influx, and sugar cane growing expansion. On the other hand, NDVI min, max values (-0.027, 0.44 to -0.069, 0.5) revealed an increase in vegetation across the study period. A key contribution of this study was twofold; Firstly, LULC changes from major activities and how they interact across space and time and finally LULC changes before commercially viable oil reserves were declared. It is recommended that further research should focus on household perceived drivers of change and their implications of land use/land cover changes in Kikuube district.

DEDICATION

To my mum Jennifer N. Nandala; my late Dad Peter Nandala; and Sister Martha Liz Nafuna

ACKNOWLEDGEMENT

My deepest appreciation goes to my supervisors Ass. Prof. Martina Calovi and Dr. Charlotte Anne Nakakaawa-Jjunju of the Department of Geography, NTNU who through numerous meetings, email exchanges and comments have tirelessly provided guidance throughout my masters' thesis journey.

Additionally, I also extend my appreciation to the Uganda Projects Team led by Prof. Hilde Refstie, Department of Geography, NTNU through insightful discussions, presentations and constructive feedback which triggered critical thinking during development and progression of my thesis. Furthermore, I would like to thank Dr. Michale Ogbe, whose discussions in 2021 led to the initiation and interest in research concept founded on remote sensing.

I would like to thank the entire leadership of the NTNU CostClim project (Collaborative Action for Strengthening Training Capacities in Climate Risk and Natural Resource Management) under the Norwegian Agency for International Cooperation and Quality Enhancement in Higher Education (DIKU) from which I received a full Masters' scholarship at NTNU. Special mention and appreciation is extended to Prof. Haakon Lein and Dr. Charlotte Anne Nakakaawa-Jjunju who I have directly engaged with more often on the project.

During field work, I would like to thank the institutions: Kikuube district local government, the National Forestry Authority, and Uganda wildlife Authority from which valuable formal engagements contributed to a successful fieldwork. I also worked with excellent research assistants; Mr. Denis Lukato and Mr. Samuel Okurut. With their technical expertise (such as loading map data using Garmin base camp), dedication, and hard work, the data collection process was completed despite the field challenges encountered.

Finally, I'm indebted to the friends and 'family' in Norway who in a special way have provided moral, spiritual, and social support that has contribution to completion of my Masters' degree despite their busy schedules; of these, a special mention of Dr. Sarah K. Mwandha, Mr. Robert Mwandha, the Jjunju family, Ms. Ritah Kigonya, Mr. Emmanuel Viga that may God bless and fulfil your desires.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

ACRONYMS

CFR	Central Forest Reserve
EACOP	East African Crude Oil Pipeline
GIS	Geographic Information System
GPS	Global Positioning System
LaSRC	Land Surface Reflectance Code
LEDAPS	The Landsat Ecosystem Disturbance Adaptive Processing System
LULC	Land use and Land Cover Change
NBSLCS	National Biomass Study Classification System
NDVI	Normalized Difference Vegetation Index
NFA	National Forestry Authority
PAU	Petroleum Authority of Uganda
PSA	Production Sharing Agreements
UWA	Uganda Wildlife Authority

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Land use and Land cover changes (LULCC) directly impact on the global climate, biodiversity, ecosystem service provisions, human societies, and the sustainable utilization of natural resources (Liu et al., 2022). LULCC are thus complex in nature and require several methods of analysis to understand drivers of change across time and space (Reid et al., 2000). Geist & Lambin, (2002) and Lambin et al., (2001) have studied extensively the drivers of global land use change as an outcome of natural and socio-economic aspects in space and time. LULCC can not only be caused by differences in climate, soil properties, topography, and availability of natural resources but also infrastructure extension, wood extraction, agricultural expansion influenced by population growth, economic growth, new technologies, social and cultural arrangements, policy, and institutional instruments. LULC changes in a given area can be better understood with an analysis of historical processes associated with drivers of change (Msoffe, 2010).

Geographical Information Systems (GIS) and remote sensing are tools that have been used to assess Spatio-temporal LULC changes. Change detection between LULC types in research helps understand and monitor growth of urban centres, forest degradation, deforestation (Tempfli et al., 2009). Landsat is among the most widely used land remote sensing source of geospatial data for it's global, synoptic, and repetitive collection of multispectral imagery used in detection, differentiation, and monitoring of landscapes over time (Wulder et al., 2022).

1.2 Statement of the problem

Environmental and human dynamics and their interactions have the greatest influence on changes in land use/land cover. Changes can be either beneficial or detrimental to human wellbeing and welfare and occur at spatial and temporal scales (Briassoulis, 2020; Kusiima, et al., 2022; Lambin et al., 2003). Negative impacts of land use/land cover change (LULCC) have been the primary focus in land use research such as converting forest to agricultural land and/or urban use (Briassoulis, 2020).

Global land use/land cover changes recorded for the past 300 years indicate that negative impacts continue to increase at unprecedented rates (Briassoulis, 2020). The most notable impacts are biodiversity loss, climate change, desertification, and pollution (Meyer & Turner, 1994). Consequences of such impacts can be short-term affecting especially food security, human health, and vulnerability to disasters. In the long term, earth viability from global environmental change. Human activities have largely been the main cause of these changes especially in magnitude and severity. (Lambin et al., 2001; Song et al., 2018).

In sub-Saharan Africa, the main human drivers of LULCC are over exploitation of natural resources, agricultural expansion and unplanned urbanization (Lambin et al., 2003). Natural resource extraction drives conversion of forest cover through deforestation and/or forest degradation and reduced agricultural area. Agricultural extensification drives conversion of forest cover and increased area for agriculture, while urbanization drives conversion of forest cover and agricultural land (Black & Sessay, 1997; Salemi, 2021). The changes have been known to be indirectly caused by the growing population and the need for economic growth (Lambin et al., 2001). Changes in land use and land cover thus result from complex interactions of drivers originating from both anthropogenic and natural forces across space and time (Hoyos et al., 2018).

The Albertine region of Uganda is a biodiversity hotspot supporting key populations of birds, tree and mammal species in Africa in and outside several protected areas (Plumptre et al., 2007). Major activities have also been documented in the Albertine region such as infrastructural development for oil exploration and development following the discovery of significant oil deposits since first reported in the 1920's (Anderson & Browne, 2011), and agricultural expansion for commercial sugarcane growing (Bahati et al., 2022). Several LULC change studies conducted in Albertine region have focused on how single drivers cause LULC (Blerk et al., 2021; Ddamulira, 2021; Dowhaniuk et al., 2018; Kusiima, Egeru, Namaalwa, Byakagaba, Mfitumukiza, & Mukwaya, 2022; Mwavu & Witkowski, 2008; Ssekandi et al., 2017; Twongyirwe, 2015). Additionally, studies on LULC associated with oil development and its impacts have focussed on 2006 when oil deposits were declared to be of commercial value (Dowhaniuk et al., 2018; PAU, 2022). This study will also quantify LULC associated with oil exploration before 2006 since oil deposits were first reported in the 1920's (Anderson & Browne, 2011; PAU, 2022). The influence of land use practices from oil exploration and development activities, largescale sugarcane farming, and refugee populations on land cover changes in Kikuube district is the primary focus of this study.

Understanding spatial-temporal land use and land cover change is vital in responding to the dynamic and complex global environmental change that is having diverse effects on the integrity of most landscapes. (Tewabe & Fentahun, 2020). Therefore, this study aims at quantifying the spatial-temporal land use/land cover changes from multiple drivers using remotely sensed Landsat imagery in Kikuube district, in the Albertine region of Uganda, from 1985 to 2023

1.3 Objectives of the study

The main aim of the study is to investigate the drivers of land use and land cover changes in Kikuube district, Western Uganda, over a period of 38 years.

1.3.1 Specific objectives

The study is guided by the following specific objectives.

i. **Quantify the spatial-temporal** land use/landcover changes for the periods 1985-1995, 1995-2005, 2005-2015 and 2015-2023 in Kikuube district.
ii. Analyse the **trends, nature, and extent** of land use/land cover for 1985, 1995, 2005 and 2023 in Kikuube district.
iii. Identify the **major drivers** of land-use/landcover change between 1985 and 2023 at decadal intervals in Kikuube district.

1.4 Research questions

What spatial/temporal changes have occurred in land use and land cover between 1985-1995, 1995-2005, 2005-2015 and 2015-2023 in Kikuube district?

What is the nature and extent of land use/land cover in 1985, 1995, 2005 and 2023 Kikuube district?

What are the primary drivers of land use/land cover change between 1985 and 2023 in Kikuube district?

1.5 Justification of the study

The study aims to quantify spatial-temporal changes from oil exploration and development, commercial sugarcane expansion and refugee population dynamics in Kikuube district. The key contributions of this study are (1) improve understanding of how multiple drivers interact over space and time; and (2) to quantify LULC trends and changes that occurred before commercial oil deposits were declared in Uganda (1985-2006).

1.6 Thesis structure

This thesis consists of six chapters.

Chapter one provides a background to this study, including general information about land use trends from the global to the local context. It also highlights the drivers of land use change in the study. This follows the formulation of the research problem to be investigated. In additional, I present the research objectives, research questions and justification for the study.

Chapter 2 reviews literature on land use and land cover change including definitions, studies done in the Albertine region. Additionally, a comprehensive theoretical review of drivers of land use and land cover change was presented. Finally, a review of legislation related to major activities (oil exploration and development, commercial farming and refugees) in the Albertine region are presented.

Chapter 3 introduces the study area and includes the location, climate and topography, land tenure, economic activities, and population dynamics. The chapter also consists of a methodology section highlighting satellite imagery data acquisition, imagery pre-processing for radiometric and geometric correction, image classification, accuracy assessment of the classified maps and change detection computation. Fieldwork description for ground truthing accuracy assessment points randomly generated for the classified maps and associated ancillary data is described.

Chapter four presents the results from the study in line with research objectives. The chapter presents accuracy assessments results to validate the use of quantitative data generated from the maps. The generated maps are 1985, 1995, 2005, 2015 and 2023; the nature, extent, trends, land use and land cover changes, transition matrix, rates of change and NDVI indices for each classified map were computed.

Chapter five is a comprehensive discussion of the trends, extent of land use and land cover in Kikuube district, land use and land cover changes, and the annual rate of change based on previous studies. The historical and theoretical underpinning of these findings are further discussed and how they are related to oil development, refugee population dynamics and commercial agriculture in Kikuube district.

Chapter six summarizes the main findings from the study, discusses the application of research findings and proposes recommendations for further research within land use and land cover change.

CHAPTER TWO

LITERATURE REVIEW, THEORY AND HISTORICAL FRAMEWORK

This chapter presents the theoretical underpinnings of land use/land cover change and is comprises of four main sections. The first section presents a general introduction with mainly definitions of land use and land cover, which have been used in research. The second section presents the land use/land cover framework. The third section presents the use of remote sensing techniques in land use/land cover change analysis. The last section presents the historical and policy development of oil development, refugee population dynamics and commercial agriculture.

2.1 Introduction of key concepts in this study

2.1.1 Land use and land cover

Nedd et al., (2021) made a comprehensive review of land use and land cover definitions that have been used in academia. The key concepts communicated across the definitions are discussed in this chapter.

Land cover refers to the observed biophysical state of the earth's surface and immediate subsurface (Turner et al., 1995). Land cover involves categorising and quantifying the surface vegetation, water, and earth materials (Meyer & Turner, 1994, 5). Debates on whether water surfaces, bare rock and or bare soil are part land cover remain. Bare rock or bare soil on land surface usually describe land itself. However, they have been categorised under land cover (Di Gregorio, 2005). Land cover also originally referred only to vegetation types on the land surface; the scope thus widened to include the physical environment, such as surface and ground-water, soils, and biodiversity; and human structures such as buildings, roads, or pavements (Briassoulis, 2020, 15).

Land use is the "purpose for which land is used" or the manipulation of the biophysical attributes of the land (Turner et al., 1995). The Food and Agricultural Organization (FAO) also defines land use as the human arrangements, activities and inputs that produce, change, or maintain a land cover type (Di Gregorio, 2005). Skole, (1994) defined land use as "the human employment of a land-cover type; the means by which human activity appropriate the results of net primary production as determined by a complex of socio-economic factors". The definitions thus establish a link between land cover, and human impacts on land as presented in *Table 1*.

Table 1: The relationship between land use and land cover highlights the uses of different types of land cover (Source: Briassoulis, 2020)

Type of Land cover	Type of land use
Forest	Natural forest, Timber production, Recreation, Mixed use (Timber production and recreation)
Grassland	Natural area, Pastures, Recreation, Mixed use (pasture and recreation)
Agricultural land	Annual crops, Perennial crops (Orchards, groves), Recreation, tourism, Mixed uses
Built-up Land	City, Village, Archaeological site, Industrial area, Tourism development, residential area, commercial area, Transportation, mixed uses.

2.1.2 Land use change and land cover change

Change in Land use and Land cover in literature has been understood and conceptualised from simplistic to broader and complex ways. The simplistic meaning of land use and land cover change refers to quantitative changes in the areal extent (increase or decrease) of a given type of land use and land cover. The amount of change detected depends on the scale. The higher the spatial scale, the larger the changes detected in an area. In broader terms, 'conversion' and 'modification' have been found in scientific literature to describe land cover change (Skole, 1994, 438; Turner et al., 1995). Land cover *conversion* refers to a change from one cover type to another such as grassland to agriculture. Land cover *modification* involves alterations of structure or function of a land cover type through changes in productivity, biomass, or phenology (Skole, 1994, 438).

Land cover changes are caused by natural and anthropogenic processes. Natural processes such as climatic variations, volcanic eruptions, or sea level changes occur at relatively slower rates. However, anthropogenic processes have more significant influence of land cover changes both in the present and recent past such as the need of land for production or settlement (Turner et al., 1995, 27). Meyer & Turner (1996) noted that land use alters land cover by 1) conversion to a different category type; 2) modification without changing its state; and 3) maintaining a state resilient to natural changes (Meyer & Turner, 1996, 238).

Land use change may also involve either conversion from one type of use to another or modification of a land use type (Skole, 1994). Modification of a land use type may involve alterations and or changes in the intensity of this use such as changes from low-income to high-income residential areas, changes of suburban forests from their natural state to recreation uses (Briassoulis, 2020). For example, different forms of agricultural land use can include intensification, extensification, marginalization and abandonment (Clark & Jones, 1997).

Land cover change contributes to significant environmental impacts and global change thus an examination needed on how land use is linked to changes in land cover at different spatial-temporal scales. A suitable spatial-temporal scale for land use and land cover change analysis is essential to identify land use and land cover types of interest, drivers and processes affecting change. At a local scale, decisions by communities and landowners on land use may not produce significant land cover change. Still, they may accumulate across space and time to make substantial land cover changes at higher spatial levels. For example, agricultural land conversion to urban uses results from the individual landowners' decision to convert their farmland to non-farm uses. Land use changes are more qualitative at a local scale but become quantitative with time. For example, gradual and incremental changes in the types of crops grown at the farm scale or in the quality of land management may result in abandoned agricultural land or degraded farmland (Briassoulis, 2020).

2.1.3 Remote Sensing for land use and land cover change analysis

The term "remote sensing" was first coined in the 1960s by Evelyn Pruitt of the US office of Naval research to refer to indirect or non-contact measurements. In satellite applications, remote sensing depends on reflected or emitted electromagnetic radiation from the earth to detect Earth surface changes (Emery & Camps, 2017). The collected geospatial data can be used to assess the status, mapping, monitoring, and forecasting changes on the earth's surface (Tempfli et al., 2009).

Overview of the Landsat program satellites.

Landsat is among the most extensive and well-known collections of space based, moderate resolution land remote sensing data source since 1972. The images produced are repetitive, synoptic and cover the global scale. Initially known as the Earth Resources Satellite program (1966), Landsat 1, 2 and 3 used the NIMBUS program mounted with a four-band multispectral scanner (MSS) and a three spectral-band (green, red, near-infrared) return beam vidicon (RBV) camera to provide a high-quality calibrated television-like image were launched into the Earth's orbit. They were later renamed Landsat in 1975 (Emery & Camps, 2017; Williams et al., 2006).

In 1985, the Earth Observation Satellite Company (EOSAT) developed Landsat 4 and 5 with the Thematic Mapper (TM). The TM instrument added the thermal infrared (IR) channel to the existing MSS channels. EOSAT also developed Landsat 6 and 7 with an improved design and sensor called the Enhanced Thematic Mapper Plus (ETM+). In 1993, Landsat 6 was lost due to launch failure which later increased image costs. The satellite developed problems with the scan system which led to implementing a scan line corrector in 2003. In September 2021, Landsat 7 was deactivated (Emery & Camps, 2017).

In 2013, Landsat 8 launched by NASA and USGS carries the Operational Land Imager (OLI) for improved land surface measurements and the Thermal Infrared Sensor (TIRS) for improved land surface temperature measurements in two thermal bands. The images have a 15 m panchromatic and a 30 m multispectral resolution along a 185 km swath (Emery & Camps, 2017). In September 2021, Landsat 9 launched by NASA and the USGS carries two science instruments: the OLI-2 and the TIRS-2 with moderate spatial resolution of 15 m, 30 m, and 100 m depending upon the spectral band. Through careful calibration of the Landsat archive, scientists have confirmed that multiple Landsat missions in the Landsat program can be used to detect earth landscape changes (Lulla et al., 2021).

2.2 Conceptual Framework for drivers of land use and land cover change

Bio-physical and socio-economic drivers can be linked to land use change. Bio-physical drivers are processes of the natural environment, such as variations in weather and climate, soil type, topography, availability of natural resources etc. Socio-economic drivers are the demographic, social, economic, political, and institutional forces shaping land use decisions such as population change, technological change, industrial change, family, markets, public sector, policies and rules, values, norms, property regimes, community organization, etc (Briassoulis, 2020).

Turner et al., (1995) developed a framework that links bio-physical and socio-economic drivers in a land use/land cover system as shown in *Figure 1*. Biophysical drivers do not directly cause land use change but may influence decisions made by landowners. A feedback mechanism may be created in which new land cover changes result from land use decisions.

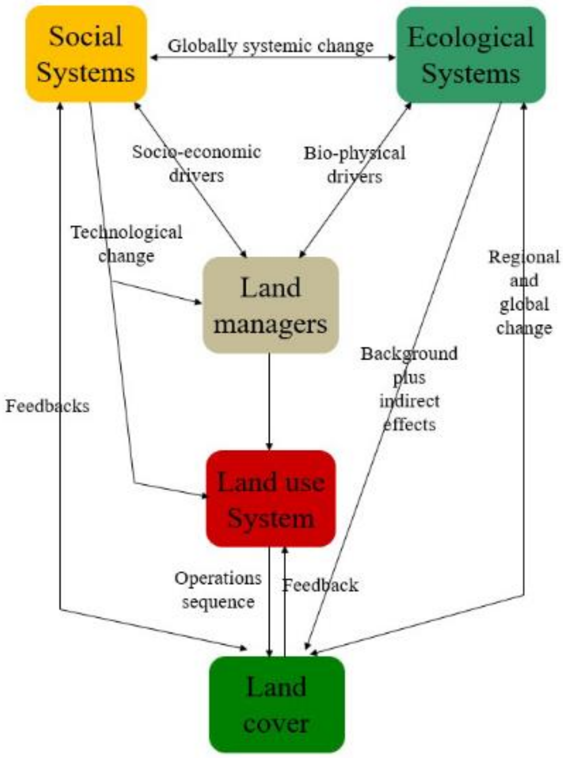


Figure 1: Relationship between Land use, Land cover and biophysical and socio-economic drivers. Source: (Turner et al., 1995)

Geist & Lambin, (2002) identified proximate and underlying drivers as causes of land use change in a study on tropical deforestation as shown in *Figure 2*. Underlying drivers are categorised into human driving forces and human mitigating forces. Human driving forces are fundamental societal forces that result in land use change by linking humans to nature such as population change, technological change, cultural and socio-economic arrangements. Human mitigating forces are societal forces that result in land use change by regulating or altering human driving forces such as local and international regulation, market structures, technological innovations and informal societal norms and values (Moser 1996, 244). Proximate drivers are the "aggregate final activities that result from the interplay of human driving and mitigating forces to directly cause environmental transformations, either through the use of natural resources (e.g. as input to agriculture, mining activities, or as raw material for industrial production), through the use of space, or the output of waste (solid waste, emissions, pollution, etc.)" (Moser 1996, 244-245). Additional examples of proximate drivers are deforestation, site abandonment, largescale farming by conversion of large tracts of grassland, urbanization (Meyer & Turner 1994, 5; Skole 1994, 438). Agricultural expansion through permanent cultivation, shifting cultivation, colonization agriculture is the leading cause of tropical land use change; shifting cultivation is mainly through slash-and-burn agriculture. Wood extraction is prevalently through harvesting for fuelwood and poles for household use specific to Africa. Infrastructural development especially road construction is a key contributor to land use change (Geist & Lambin, 2002).

For underlying factors, economic factors are the leading cause through market failures, market growth of key products and services, low domestic costs for land, labour leading to poverty- and capital-driven deforestation (Rudel & Roper, 1997). Institutional factors through policies, land tenure arrangements, policy failures and property influence the trends in land use and land cover change. Technological factors influence land use change by determining the degree of agricultural intensification and extensification. Cultural and social factors reflect economic and policy interests through attitudes, values, and public concern. Demographic factors intervene most when new populations through in-migration colonise less populated areas (Geist & Lambin, 2002). Quantification of these factors can aid in determining the most frequent drivers of land use and land cover change. Proximate drivers cause land cover change by realising human goals of land use (Geist & Lambin, 2002; Meyer & Turner, 1994).

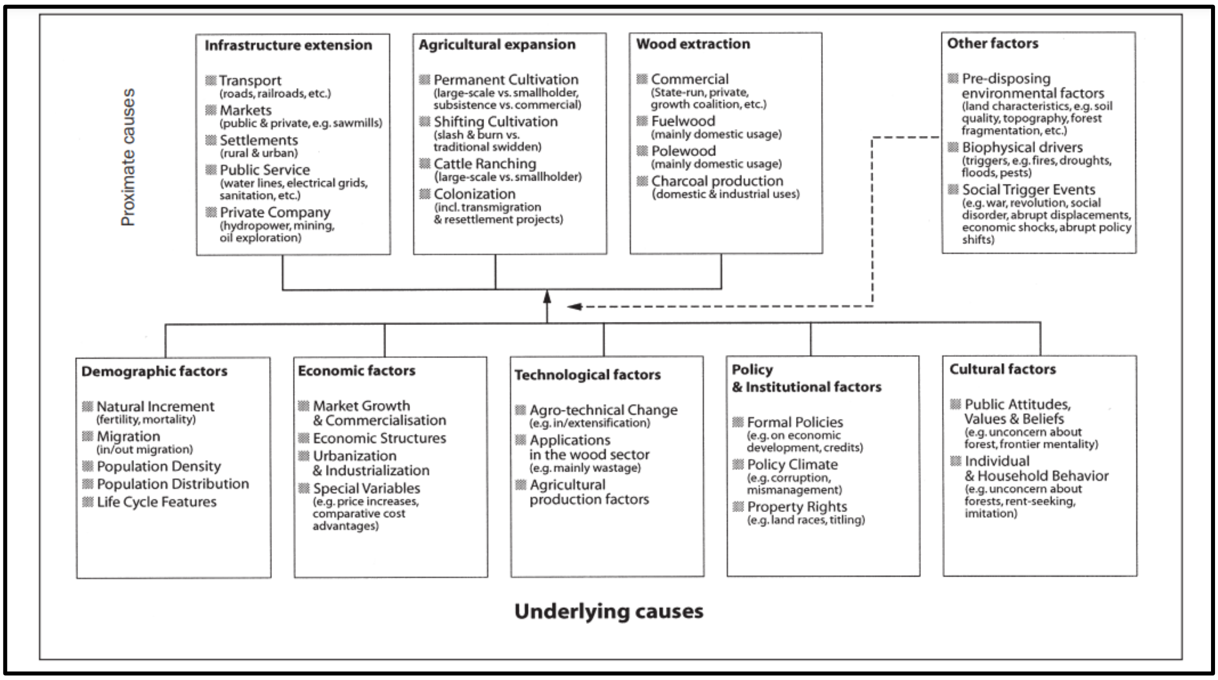


Figure 2: Linkages between underlying drivers and proximate drivers of land use and land cover change illustrates how multiple drivers interact to cause land use and land cover change. Source: (Geist & Lambin, 2002)

2.3 Land use land cover change studies in the Albertine region

Several studies on LULCC in the Albertine region that have focused on the drivers and the associated impacts. Kusiima et al., (2022) used supervised classification of Landsat Imagery to quantify decadal landscape spatio-temporal dynamics between 1990 and 2020 for the Bugoma-Budongo landscape of which Kikuube district is part and highlighted commercial agriculture from sugarcane growing and oil exploration activities as significant drivers of change from which predictions would be made using the Business-as-Usual scenario. Ddamulira, (2021) reported a 34% deforestation rate in Hoima district in relation to land use changes from oil development by quantifying land use change before (1984-2006) and after (2007-2019) oil policy development using the Global Forest Watch for web mapping and LandTrendr of the Google Earth Engine for change detection. Population growth, expansion of subsistence agriculture and oil sector infrastructure were the main drivers of change. In a study on land use change around forest areas, Twongyirwe, (2015) revealed that forest cover declined/reduced significantly outside gazetted forests by up to 90% for forest corridors. The most significant drivers of change were sugarcane farming and subsistence agriculture expansion. In another study by Twongyirwe et al., (2022) on projected land use changes under oil extraction and status quo scenarios revealed an increase in sugarcane growing at the expense of small-scale farming mainly attributed to unclear land tenure and the aggressive out-grower sugar cane growing schemes.

In their study Ssekandi et al., (2017) focused on how post-eviction resettlement from oil exploration areas causes LULCC in Uganda with Buliisa and Hoima districts as case study areas between 2002-2005 and 2005-2015 using supervised classification of Landsat imagery. The results indicated a decline in woodland area and an increase in the area for settlements and farmland. Land use changes were attributed to government's lack of a resettlement plan during the eviction process. Blerk et al., (2021) studied the refugee population dynamics and environmental change in response to the 2016 and 2019 refugee influxes in Kyangwali refugee settlement and quantified LULCC between 2015 and 2021 using supervised classification of sentinel-2 multi spectral images. The results revealed a decline in woodland area, and an increase in farmland area into Kyangwali refugee settlement. Proximate drivers were mainly agricultural expansion, fuelwood extraction, insecure land tenure and resource access rights and limited institutional capacity by the government to implement policies and guidelines. Land use and cover changes between 1988 and 2002 assessed around Budongo forest reserve revealed a 17-fold increase in sugarcane cultivation, a decline in forest and woodland cover.

These were attributed to agricultural expansion, increasing human population, large scale refugee influx, unclear land tenure and political interference in forest management (Mwavu & Witkowski, 2008).

A national-level study by Nakakaawa et al., (2011) revealed that most land use and land cover changes occur systematically around forests in Uganda. The key physical and socioeconomic drivers of forest land use change identified were protection status, market access, poverty, slope, soil quality and presence of water courses. Among these, increase in slope decreased the probability of degradation.

2.4 Historical and policy framework governing oil resources, refugees, and commercial agriculture in Uganda

2.4.1 Refugees in Uganda; History, legislation, and population trends

The UNHCR 1951 refugee convention defines a refugee as "someone who is unable or unwilling to return to their country of origin usually due to the well-founded fear of being persecuted for reasons of race, religion, nationality, membership of a particular social group, or political opinion" (UNHCR, 1951). The term refugee is used to include displaced persons who may fall outside the legal definition in the convention when they either flee from their countries as a result of war or are forcefully displaced within their country (UNHCR, 1951). The 1969 Organisation of African Unity (OAU) Convention, governing the specific aspects of refugee problems in Africa, expanded the definition to apply to persons facing external aggression, foreign domination or disruption of public order forcing them to leave their country of origin (UNHCR, 1992).

Uganda currently hosts over 1.5 million refugees; the largest refugee population in Africa with most refugees coming from South Sudan, Somalia, Burundi, and the Democratic Republic of Congo (DRC) (UNHCR, 2022a). The Refugee Act (2006), provides refugees the right to employment and freedom of movement and may move from rural settlements to urban centres thus contributing to land use change through urbanization. Additionally, refugees in rural settlements are given plots of land to cultivate food crops, own property, and access social services. This approach also integrates and extends services to the host community. The 2010 refugee regulations had further implications on land use by refugees in which free access to land for cultivation and pasturing without selling the land within refugee settlements. However, refugees outside refugee settlements can also acquire land on leasehold tenure (World Bank Group, 2016). This highlights that refugees contribute to land use decisions thus contributing to land use change processes. Refugee integration in national planning was realised through the Settlement Transformative Agenda for refugees into the National Development Plan II, 2015/16-2019/20.

Colonial and post-Independence period

Under colonial rule, Uganda hosted 7,000 polish refugees displaced by the second world war at Nyabyeya, western Uganda; and Koja, eastern Uganda. The refugees were later resettled in Britain, Australia, and Canada. As a British protectorate, the 1951 UN Convention on refugees was ratified by Britain on behalf of her colonies. However, as an independent state, Uganda ratified the convention in 1976. In 1955, the country hosted refugees from the Anglo-Egyptian condominium of the Sudan. In 1959, conflicts from neighbouring colonies struggling for independence from colonial rule displaced up to 78,000 refugees into Uganda; examples of the conflicts included the Mau-Mau conflict in Kenya, the assassination of Lumumba in Zaire (currently the DRC), the Rwandan civil war of 1959, and Sudan (Mulumba, 2014). In 1960, most refugees received from Rwanda and the DRC were settled in the newly established Kyangwali refugee settlement in the now Kikuube district, Uganda (UNHCR, 2022a).

1971 to 1985

In 1972, Uganda's President Idi-Amin expelled Ugandan citizens of Asian origin. In 1976, most refugee settlements in West Nile and Northern Uganda were opened following the creation of the determination of refugee status committee upon ratification of the 1951UN convention on refugees (Betts, 2021). Following Idi-Amin's overthrow in 1980, Ugandans in the West Nile and Madi region fled to Sudan, Kenya, and Tanzania. The government of Uganda and the Lord's Resistance Army conflict in Northern Uganda and the Luwero Triangle resulted to both refugees out of Uganda and many internally displaced in Uganda (Mulumba, 2014).

1986 to date, self-reliance strategy and the refugee law

Since 1986, Uganda became more stable to receive refugees from other countries that by 1994, more than 300,000 refugees were hosted that fled the conflict in South Sudan of which 60,000 refugees were resettled in Kyangwali refugee settlement in addition to the 4,700 Rwandan refugees at the time (Foote et al., 1993; Lomo et al., 2001). Following the after math of the genocide in 1994, most Rwandan refugees were repatriated to a stable Rwanda reducing the refugee population in Uganda from 84,000 to a few thousand. In 1999, Uganda developed and adopted the Self-Reliance Strategy for refugee-hosting areas (SRS) to empower refugees and host communities to be self-reliant and ensure integration of social services to both refugees and host communities. Refugees accessed public social services such as education, health service and plots of land were allocated within settlements for homesteads and subsistence farming and access to education, health services. (Betts, 2021). In 2006, a refugee law, the 2006 refugee act was passed by the parliament of Uganda to formally provide refugees the right to work and freedom of movement (The Refugee Act, 2006). The 2010, Refugees Regulations were passed to manage refugee integration through registration applications, host community integration, inclusion of refugees in local, regional and national development planning, right of movement, land ownership, and citizenship (Omata & Kaplan, 2013). Following the laws and policies, the refugee populations were reduced from 200,000 to 75,000 between 2006 and 2007. The refugee population was then maintained at manageable numbers until the 2015 refugee influx from both South Sudan and the DRC exponentially increasing the overall refugee population to about 1.2 million in Uganda, and with Kyangwali refugee settlement population doubled (UNHCR, 2021). In 2015, the government of Uganda passed the ReHoPE (the Refugee and Host Community Empowerment) Strategy to attract financial support to manage the new influx in line with the 2015/16 refugee influx in Europe. However, in 2018 systemic corruption, fraud, and improper contract award in the office of the Prime minister (OPM) and UNHCR Kampala failed the strategy's objectives. In 2019, the CRRF (the Comprehensive Refugee Response Framework) strategy was adopted to expand the scope to a global scale to promote refugee self-reliance through access of labour markets (Betts, 2021).The population trends for refugees in Uganda between 1985 and 2023 are summarised in *Figure 3* and *Figure 4* for Kyangwali refugee settlement.

Several refugee settlements in Uganda have been established to manage and administer aid to refugees. includeclude Nakivale and Oruchinga settlements in Mbarara district; Kyaka II settlement in Kabarole district; Kyangwali settlement in Kikuube district (formerly Hoima district); Rhino camp and Imvepi settlements in Arua district; Kali and Parolinya, Moyo district; Acholpii settlement in Kitgum district; Adjumani district has 24 settlements which include; Alere I, Alere II, Arra, Baratuku, Biyaya, Elema, Ibibiaworo; Keyo I, Keyo II, Keyo III, Magburu, Mongola, Nyeu, Nyumanzi I, Nyumanzi II, Oliji, Ukusijioni, Ramogi, Robidire, Umwiya, Uhirijoni, Obilikogo, Kolididi, Maaji. A small population of urban refugees are settled in Kampala City. In 2021, Uganda temporarily resettled about 2,000 refugees from Afghanistan.

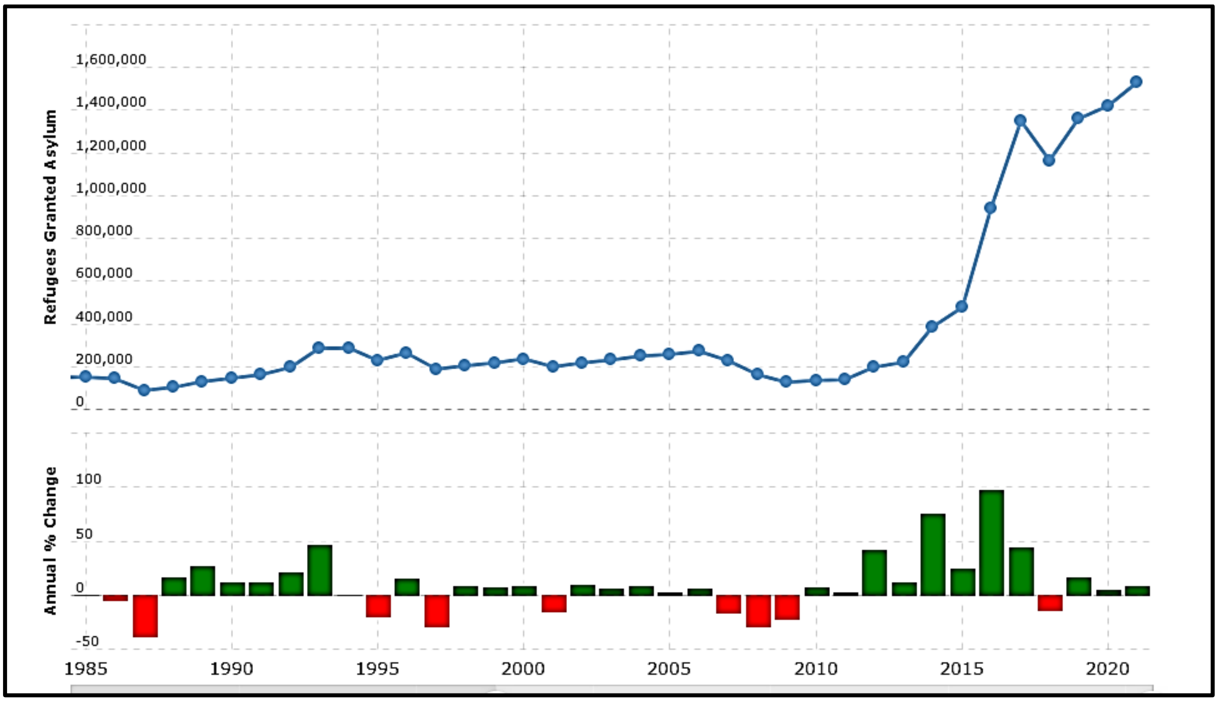


Figure 3: Historical refugee population trend and annual percentage population change in Uganda between 1985 and 2021. Source: (Betts, 2021; World Bank, 2023)

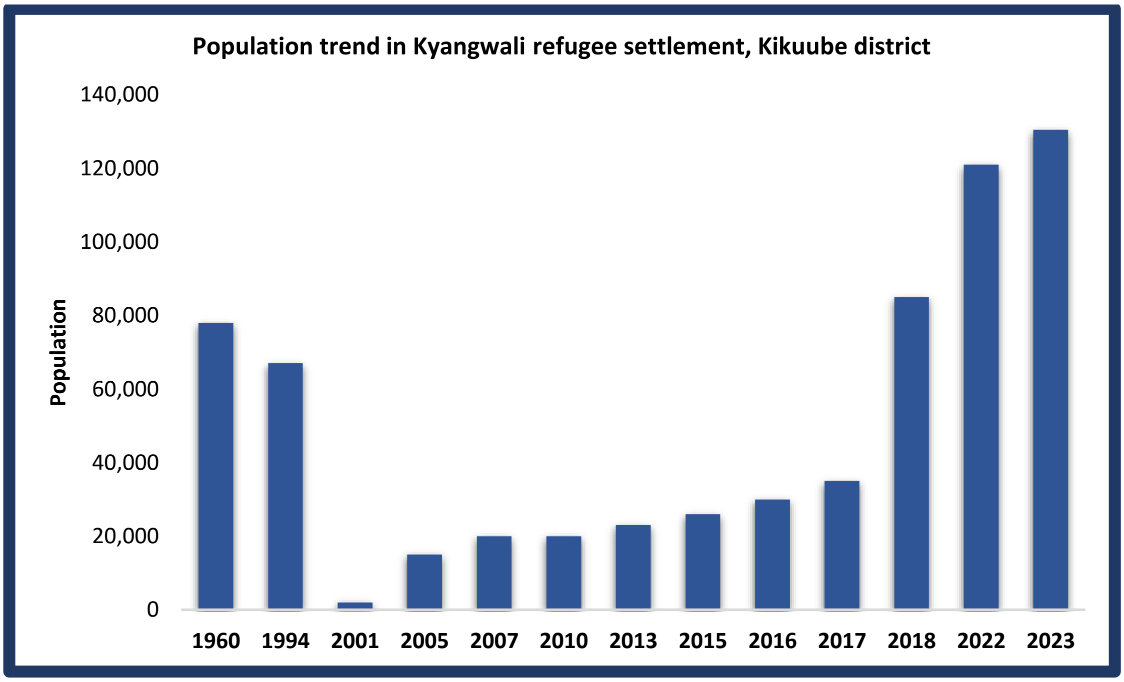


Figure 4: Population trend in Kyangwali refugee settlement. Retrieved from;(Betts, 2021; Gianvenuti et al., 2020)

2.4.2 Oil development in Uganda; History and legislation

Oil development undergoes three broad stages: upstream, midstream, and downstream stages. The upstream stage also referred to as the oil prospecting and exploration is the stage in which seismic surveys are conducted to identify areas with oil reservoirs. Exploration drilling follows to confirm seismic survey findings and to determine reservoir oil properties. Appraisal drilling is done to determine the production potential for each identified oil reservoir (National Oil and Gas Policy for Uganda, 2008). Land use and land cover changes associated with upstream activities are largely modification of the physical landscape from road construction, permanent and temporary camps, and other infrastructure. Social impacts are mainly caused by in-migration, displacement and resettlement of affected communities, changes in values and local customs caused by new cultures from new people in the project area (Ibem-Ezera, 2010; Johnson, 2007).

The midstream stage is the second stage that involves development, production, and transportation of oil resources to designated point locations usually through pipelines from a central processing facility to a refinery. Production involves processing and refining of crude oil and gas into final products. Infrastructure development associated with this stage includes oil refineries, road construction, airports, storage facilities, pipelines among others. Deforestation and forest degradation, social change, pollution are associated Land use and land cover change drivers and impacts of midstream activities (CSCO, 2017; Ibem-Ezera, 2010).

The downstream stage is the final stage in oil development which largely involves distribution and marketing of the final products to both local and international markets. This state also includes all decommissioning and site restoration activities (Ibem-Ezera, 2010). Long-term physical and social impacts on the landscape can result from cumulative midstream and upstream activities (Johnson, 2007; MEMD, 2017).

The earliest record of oil in Uganda dates to the 1870s when Emin Pasha, a German physician, found oil sips in Western Uganda. The record was confirmed, and ownership declared by Captain Frederick Lugard, a British colonial administrator of the Imperial British East Africa Company (Guweddeko F, 2000). In 1913, World War I halted exploration at Kibiro oil seep by the British East African syndicate licensed by the British colonial administration. However, exploration resumed in the early 1920s by Britt & Sydney, Chijols Oil, and Grog & Tanner British oil companies who had limited success due to ‘financial constraints. In the late 1920s, the Geological Survey of Uganda confirmed the presence of oil and gas seeps in Western

Uganda. The British government and the Anglo-Persian oil company then agreed oil prospecting and production through a joint venture project. Part of the agreement was the construction of an oil pipeline from Lake Albert to Wakiso district, Uganda. The great depression deterred the implementation. In 1938, test wells drilled by the Johannesburg based African-European Investment company in the Semliki basin found promising prospects for oil especially the Butiaba Waki B-1 well. In 1957, the Colonial legislative council passed the Petroleum Act (Guweddeko F, 2000; Kashambuzi, 2010).

Following Uganda's independence from colonial rule in 1962, the Ugandan government granted exploration rights to Shell Oil and Kirkwall Associates and Collin Oil and Gas companies. In 1980, financial support from the World Bank supported the government of Uganda to conduct aerial magnetic surveys of the Albertine Graben. Three sub-basins were discovered to have significant oil deposits (Kashambuzi, 2010).

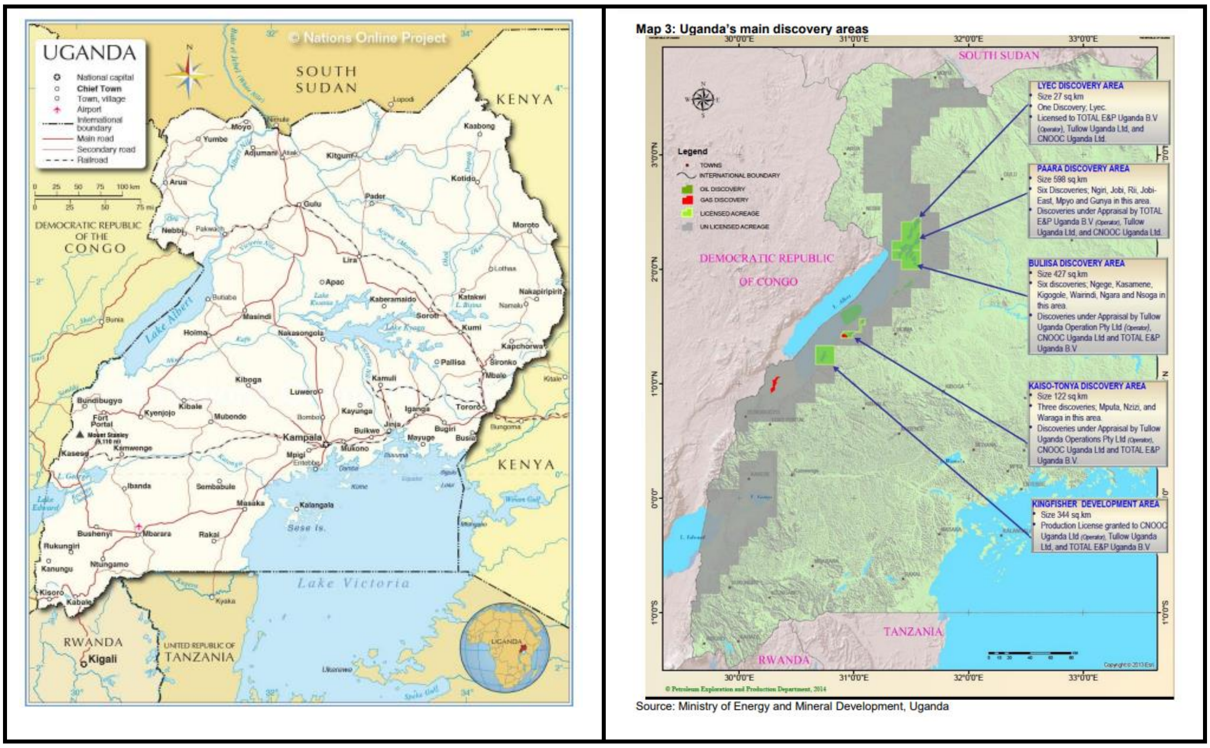


Figure 5: The location of oil and gas exploration areas in Uganda. The study area lies in Exploration area 2 and 3. Source: (Patey, 2015; PEPD, 2015)

In 1985, the Petroleum (Exploration and Production) Act was enacted and led to the establishment of the Petroleum Unit in the Geological Survey and Mines department. In 1986, President Museveni halted further oil exploration negotiations until local technical capacity was built and strengthened (Kashambuzi, 2010). In 1990, the governments of Uganda and Zaire (now DRC) signed an agreement of cooperation for exploration and exploitation of common fields (PAU, 2022).

In 1991, the Ugandan government and Petrofina, a Belgium company, signed a production sharing agreement (PSA) for two years and granted the company exploration rights over the Albertine region. Petrofina's license was not renewed upon failure to meet the PSA obligations. In 1997, the government of Uganda signed another PSA with Heritage Oil and Gas Ltd company, granting the company exploration rights over the current Exploration Area 3 that covers the Semliki basin and the Southern part of Lake Albert (PAU, 2022). In 1998, Heritage Oil and Gas Ltd conducted the first seismic survey in the Albertine graben yielding significant oil deposits. In 2001, the government of Uganda signed a PSA with Hardman Petroleum and Energy Africa Ltd, granting each a 50% stake in exploration rights for Exploration Area 2 (Northern Lake Albert) as shown in *Figure 5.* Heritage sold its stake to Energy Africa for Exploration area 3. Between 2002 and 2004, two out of three wells drilled by Heritage Oil and Gas Ltd showed evidence of oil and gas deposits but had limited clarity on quantities sufficient for commercial production; the remaining well had methane contaminated with carbon dioxide. In 2004, Tullow Oil PLC bought exploration rights from Energy Africa to take over its 50% stake in Exploration Area 2 and 3. Heritage Oil and Gas Ltd was awarded a 50% working interest in Exploration Areas 1 (Pakwach) and 3A. In 2005, the government of Uganda signed a PSA with Neptune Petroleum (Uganda) Ltd granting them exploration rights over Exploration Area 5 (Rhino Camp Basin, West Nile). Hardman Resources drilled the Mputa-1 well and found significant quantities of oil and gas in Exploration area 2. In 2006, The Uganda government received financial support from the government of Norway to develop and strengthen its policy and regulatory framework and build institutional and technical capacity for petroleum resources in Uganda. In the same year, multiple successful discoveries confirmed presence of commercial oil quantities in Uganda notably in Exploration Area 2; the Waraga-1, Mputa-2, and Nziz-1 wells were drilled to find oil and gas; Exploration Area 3, Kingfisher-1 well also found oil and gas (Kashambuzi, 2010; PAU, 2022).

In 2007, Tullow Oil PLC bought Hardman Resources' 100% stake in Exploration area 2 and 50% stake in Exploration area 3. The government of Uganda also signed a PSA with Dominion Petroleum granting them exploration rights over Exploration area 4B (south and northeast of Lake Edward). Tullow Oil PLC confirmed oil and gas presence in Nzizi-1, Nzizi-2, and Mputa-3 wells in Exploration area 2 and the Kingfisher well in Exploration area 3. In 2008, the National oil and gas policy was passed with financial support from the government of Norway. In the same year, the civil Society Coalition in oil and gas (CSCO), a loose network of member organizations established to coordinate civil society and advocacy efforts to promote governance of oil and gas resources in Uganda. Tullow Oil PLC found significant oil and gas deposits in Taiti-1, Ngege-1, Karuka-1, Kasamene-1, Kigogole-1 wells. Heritage Oil and Gas Ltd succeeded in the Exploration 1 wells (Ngiri-1, Jobi-1, Rii-1) and exploration area 3 wells (Kingfischer-2/2A and Kingfischer-3/3A). In 2009, Tullow oil PLC discovered significant oil and gas deposits in seven of the eight wells in exploration area 2. In 2010, a feasibility study report for the oil refinery project was submit to the government of Uganda by UK consultant Foster Wheeler. Tullow Oil PLC discovered oil and gas deposits in additional 8 wells in exploration area 2. Heritage Oil and Gas Ltd discovered deposits in two wells of Exploration Area 1 and none for Neptune in Exploration area 5 (PAU, 2022).

In 2012, communal land disputes were reported around Waraga-1 well with pastoralists settling around the oil well for access to water and grazing land. The government of Uganda signed two PSA with Tullow Oil PLC for exploration area 1 and the Kanywataba prospect in Ntoroko district. In 2013, the Petroleum (Exploration, Development, Production) Act, 2012 and the Petroleum (Refining, Conversion, Transmission and Midstream Storage) Act, 2013 were signed into law. In the same year, CNOOC was granted a production license for the Kingfisher well 1A in Hoima district now Kikuube district. In 2014, the government of Uganda signed a Memorandum of Understanding with joint venture partners Total, CNOOC and Tullow to commercialize petroleum resources in Uganda. By the end of 2014, Uganda's oil resources had reached an estimated 6.5 billion barrels and 530 acres of land in Buseruka subcounty, Hoima district had been secured for the oil refinery project. Over 200 families faced eviction from land said to be for the construction of a petroleum waste management facility in Rwamutonga, Hoima district. The Hoima-Kaiso-Tonya Critical Oil Road was completed (PAU, 2022).

In 2015, the Petroleum Directorate was established in the Ministry of Energy and Mineral development responsible for making policy and monitoring petroleum resources in Uganda; EnviroServ International completed construction of an oil waste treatment plant in Nyamasonga, Hoima district. In 2016, eight production licenses were granted to joint Venture oil companies in Exploration areas 1 (Ngiri, Jobi-Rii and Gunya) and 2 (Mputa-Nzizi-Waraga, Kasemene-Wahrindi, Kigogole-Ngara, Nsoga and Ngege oil fields). In 2017, the Intergovernmental Agreement between the governments of Uganda and Tanzania for the construction of the 1,445 km crude oil pipeline from Hoima, Uganda to Tanga, Tanzania was reached making it the longest electrically heated pipeline in the World. Signing of the agreement-initiated negotiations for the signing of the Host Government Agreements, Shareholders' Agreements and Financing Agreements. An Agreement between the government of Uganda and the Albertine Graben Refinery Consortium a merger of Yaatra Ventures LLC, Intra-Continent Asset Holdings, Saipem Spa, General Electric and JK Minerals Africa was reached for design, procurement, and construction of the oil refinery (PAU, 2022).

In 2020, Tullow Oil sold 100% of its stake to Total for 575 million USD. In 2021, the Host Government Agreement, Tariff and Transportation Agreement, Shareholders Agreement were signed between the governments of Uganda and Tanzania which legally enabled oil companies start the construction of the East African Crude oil pipeline (EACOP). In the same year, the government of Uganda approved a resettlement action plan for the EACOP project (PAU, 2022).

2.4.3 Commercial sugarcane growing in Uganda; History and legislation.

Uganda's agricultural sector is the largest contribution to Uganda's economy contribution 25% to the country GDP and the main source of livelihood more than 70% of the population (Osapiri, 2021). Sugarcane growing is among the most important cash crops in Uganda together with coffee, tea, and cotton. Between 2000 and 2020, sugarcane production increased from 1.5 million metric tonnes (MT) to 5.8 million MT with land area under sugarcane increasing from approximately 20,000ha to over 80,000ha (Mbowa et al., 2022).

Sugarcane growing in Uganda dates to the early 1920s. Sugarcane plantations were first established by Vithaldas Haridas & Company managed by Muljibhai Madhvani and the Sugar Corporation of Uganda Limited managed by the Mehta Group in Eastern Uganda (Kasozi, 1994; Mamdani, 1987). From the early 2000s, large-scale plantations have been established including Kinyara sugar works limited in Masindi with majority shares owned by Rai Group, Atiak sugar factor in Amuru district, Amuru Sugar Works in Amuru district, Hoima Sugar limited in Kikuube district. Hoima sugar Ltd was incorporated in 2016 plans but has encountered challenges associated with land grabbing, internal displacement, and public outcry over the acquisition of 22 square miles of land by lease within the Bugoma central forest reserve landscape (Bahati et al., 2022).

The legislation in Uganda controlling sugar production and marketing has evolved. The first law was the Sugar (control) Act 1938 (cap.34) to control the export and production of sugar through regulation of issuance of sugar export licenses, restriction on the quantity of sugar held in stock and sets quotas for sugar that can be exported in exemption to East African countries (Osapiri, 2021). The rapid growth in sugar production and processing by largescale scale between 2005 and 2014 led to the growth of out-grower schemes. The accruing challenges led to the formulation of the 2010 National Sugar policy followed by the 2020 Sugar Act. The 2020 Sugar Act led to the creation of the National Sugar Board, creation of marketing zones, the regulation of cane prices. However, debates on whether the law adequately protects out-growers remain unresolved (Mbowa et al., 2022).

The growth in the cane milling capacity increased demand for sugar attracting more farmers to grow sugarcane as out-growers whose supply augments mill capacity for processing (Mbowa et al., 2022). Prioritization of the Ugandan government to promote commercial agriculture for job creation and inclusive development has availed legal incentives for actors involved. Such incentives include largescale land acquisition through leasehold, access to loans, capital incentives etc.(Osapiri, 2021)

Member countries int the East African Community (EAC) can seek waivers on sugar imports from member countries during sugar shortages. Uganda has the largest domestic supply in East Africa, with 5,500 tonnes and is the only member country with a domestic sugar surplus to meet shortages in neighbouring countries (Bahati et al., 2022). Conflict-prone DRC and South Sudan rely on the Uganda market. In 2017, Kenya, Tanzania and Rwanda had a sugar shortage of 543,000, 200,000 and 70,000 tonnes respectively. The high market demand promotes monopolistic tendencies of price fixing and marginalization of landowners (Martiniello, 2021).

Out-growers supplement sugar production supplies to sugar companies for sugarcane production. However, sugar companies have a monopoly over the sugar cane prices of mature plantations of out-growers. Additionally, marginalization through uneven competition between sugar companies and out-grower schemes have been seen to destroy traditional livelihoods in Uganda. Additionally, communities near sugar cane plantations have been documented to be poorer in the form of land exchanged for loans, a form of land ‘grabbing’ (Martiniello & Azambuja, 2019). Furthermore, the most dominant form of labour are migrant and seasonal workers who are paid low wages, working in poor health and safety conditions. This increases footprint on the increasing population on the environment (Dubb et al., 2017).

CHAPTER THREE

STUDY AREA AND METHODOLOGY

This chapter is comprised of two broad sections: The study area and methodology. The study area section fully describes the area including the location, socio-economic environment, population dynamics, protected areas, and other biophysical attributes. The methodology section addresses the methods, issues and challenges related to data acquisition, image pre-processing, image classification and change detection and vegetation analysis. A description of the entire research process is also presented from the initial concept development, the fieldwork planning process, field work execution and challenges faced during fieldwork.

3.1 Study area

3.1.1 Location

The study focused on Kikuube District, lying in the Albertine Graben, mid-western region of Uganda as shown in *Figure 6*. The district borders Hoima district to the North, Kyankwanzi District to the East, Kagadi, Kakumiro, and Ntoroko Districts to the South. The district stretches to the national boundary with the Democratic Republic of Congo to the West. The district covers a land area of 2,097 km^2 with a population density of 171 people per sq. km. The district was established in 2018 from part of the Hoima district through government district decentralization (Bahati et al., 2022; Uganda Bureau of Statistics, 2017). The district is largely known for oil development activities in the Kingfisher development area, Nzizi and Mputa licensing areas, largescale sugar cane plantations owned by Hoima Sugar Ltd, Kisaru and Bugambe tea estates, Bugoma and Wambabya central forest reserves, Kabwoya wildlife reserve, and Kyangwali refugee settlement (Blerk et al., 2021).

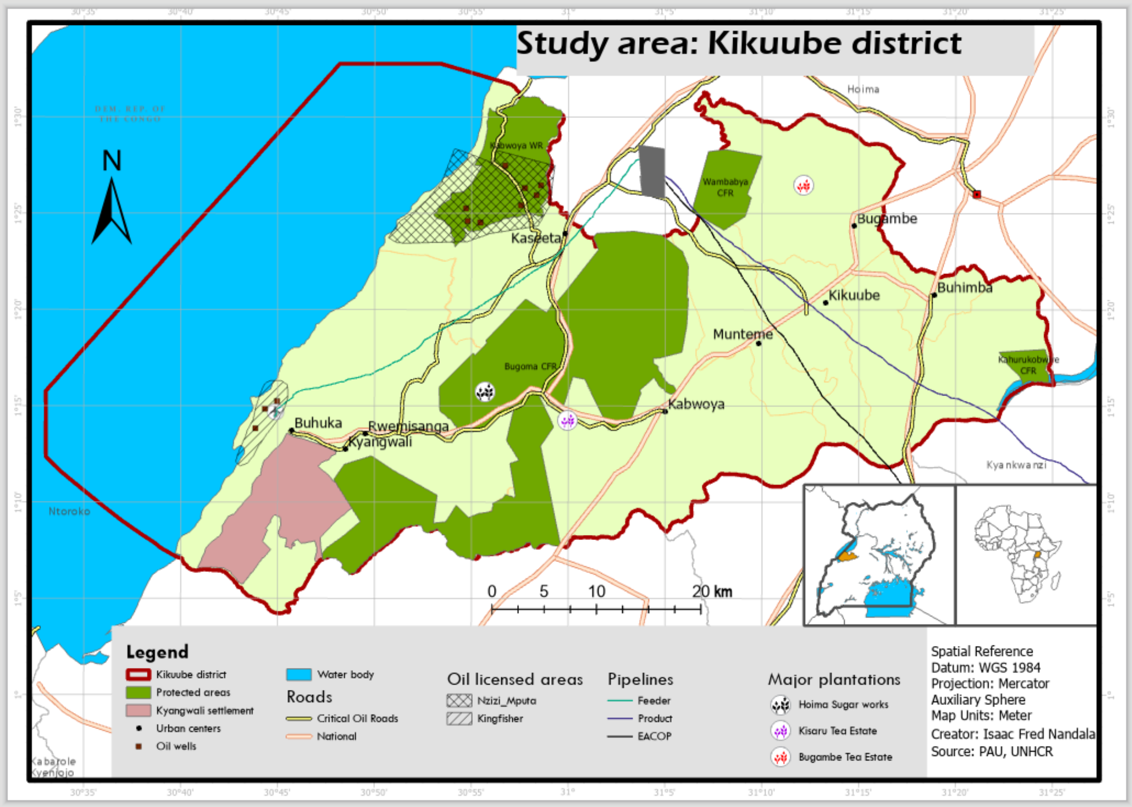


Figure 6: Study area showing protected areas, Kyangwali refugee settlement, oil licensed areas, oil wells, major plantations, major roads, and urban centres (Author, 2023)

3.1.2 Climate and topography

The climate of Kikuube district varies significantly along the topography gradient from the rift valley floor next to Lake Albert, the escarpment, and the raised topography towards the East as shown in *Figure 7*. The rift valley floor lies in the rain shadow of both the escarpment and Mt. Rwenzori, the highest peak in Uganda and thus the driest and hottest receiving an annual average rainfall of about 900 mm in the district. Areas over the escarpment receive rainfall up to 1,400 mm per annum. There are two rainfall seasons, one between March and May and one between September and December (CNOOC Uganda, 2019).

Minimum monthly temperatures vary between 17.5 and 21.1 degrees Celsius. Maximum monthly temperatures are usually recorded in March (29 degree Celsius) and November (27 degrees Celsius) (CNOOC Uganda, 2019).

Figure 7: The escarpment close to lake Albert shows sharp changes in topography in Kikuube district. This influences the average rainfall and temperature in the floodplain and top of the escarpment. Photo taken by Author, 2023.

The topography of Kikuube district varies greatly from the shores of Lake Albert to the East as shown in *Figure 8*. The surface of Lake Albert is at an average elevation of 615 metres above seas level. The top of the Escarpment is at an elevation of about 930 metres above sea level. The eastern part of the district is mostly flat with broad and flat-topped hills varying between 950 to 1,428 metres above sea level (CNOOC Uganda, 2019).

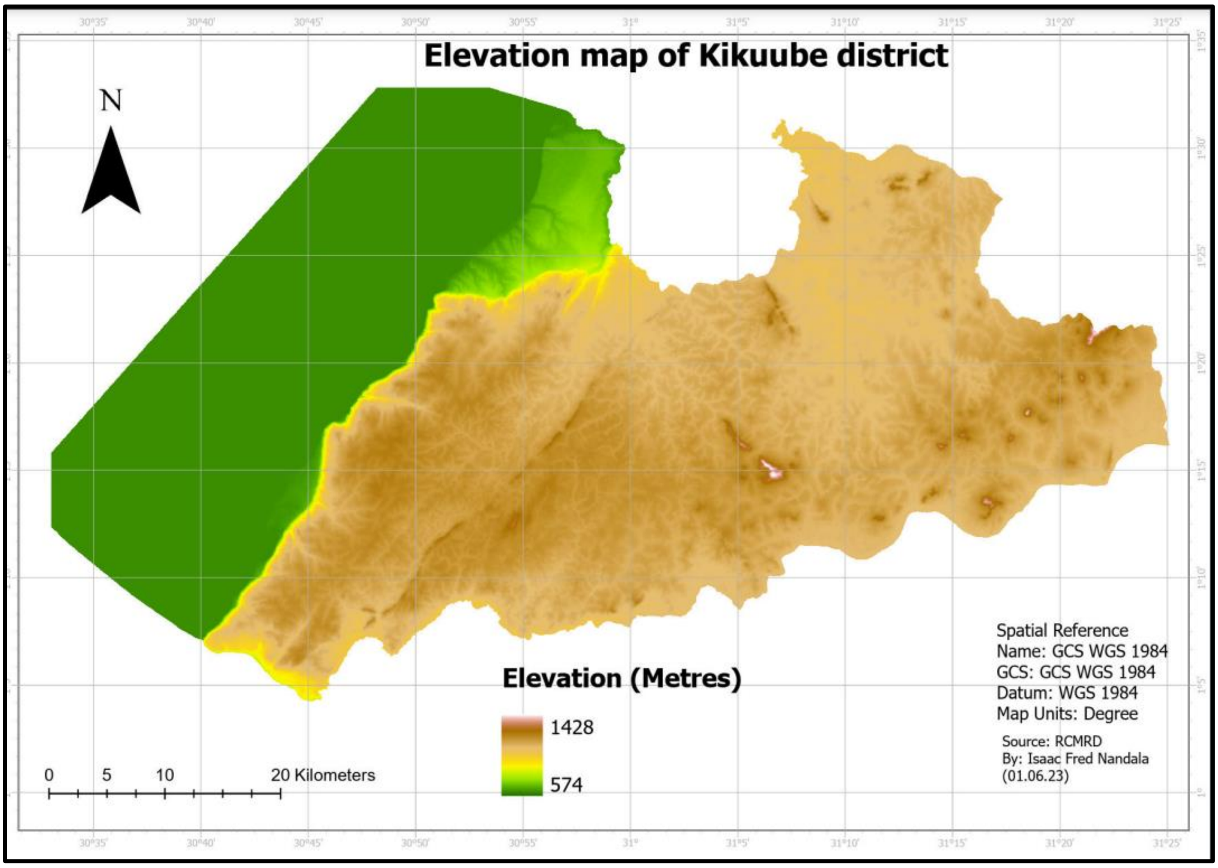


Figure 8: The elevation differences of Kikuube district are greatly influenced by the escarpment and Lake Albert; The lowest elevation is Lake Albert (in green); low elevation is associated with the rift valley floor close to Lake Albert and curved by the escarpment (Yellow line); The highest elevation starts from the top of the escarpment towards the east of the district (Source: Author, 2023).

3.1.3 Land tenure and land use

According to the 1998 Land Act, there are four forms of land tenure: customary, freehold, leasehold and mailo. Customary, freehold, and leasehold tenure are common in Kikuube district. Historically, the large part of the district was part of a wildlife reserve. The reserve was degazetted in 2001, resulting in land either communally or individually owned (Hunt, 2004; Uganda Wildlife Authority, 2023). To minimize land conflicts related to communal land, Buhuka Communal Land Association was formally approved by the Ministry of Lands, Housing and Urban Development on behalf of five villages; Nsonga, Kyabasambu, Kyakapere, Nsunzu and Kiina (CNOOC Uganda, 2019). Conflicts, and evictions related to land ownership have been common in the district especially since oil and gas production was commercialized.

Land use in the district is over 80% for agriculture, through subsistence and commercial farming. The major economic activities observed around towns/rural growth centres are small-scale business activities and services. Fishing, livestock grazing is common around Lake Albert (CNOOC Uganda, 2019).

3.1.4 Population density, in migration and refugee influx

The April 2023 population census revealed that Kikuube district has a total population of 376,600 persons on a district land area of 2,097 km^2 with about 89.5% of the district population living in rural areas. Kyangwali refugee settlement has a total refugee population of 130,461 settling on an estimated 90 km^2 land area. The refugee population as a proportion of the host district population is 26% composed of about 96.5% refugees from the DRC, 2.9% from South Sudan, with the rest from Rwanda, Burundi, and Somalia (Kikuube district Local government, 2023; Omata & Kaplan, 2013; UNHCR, 2023). Between 2014 and 2020 the population of Kikuube district increased from 267,455 to 358,700 indicating an annual population growth rate of about 5%. (Uganda Bureau of Statistics, 2017).

In 2016, ethnic tensions in the DRC's Ituri province resulted in a refugee influx into Kyangwali refugee settlement, the refugee population doubled from 36,713 to 68,703 between December 2017 and March 2018. Furthermore, about 70,000 refugees have fled to Uganda from the DRC since the beginning of 2018 fleeing from violence in the Ituri province, DRC (Blerk et al., 2021; CNOOC Uganda, 2019). The refugee population had reached 125,039 by January 2021; peaked at 136,570 by February 2022 and later reduced to 124,430 by August 2022. The proportion of the refugee population in the Kikuube district increased from 12% in 2014 to 25% in 2021 (UNHCR, 2021, 2022b). Small businesses and subsistence agriculture are the primary sources of livelihood in Kikuube district. *Figure 9* shows the Kyangwali refugee settlements' main business centre (Kasonga) that booms with local businesses and subsistence farming practiced on plots of land allocated to each refugee household.

In-migration into Kikuube district is mainly from migrant labour to work in Hoima sugar Ltd plantations, Kisaru and Bugambe tea estates and oil infrastructural development activities (Bahati et al., 2022; Blerk et al., 2021).

Figure 9: Kyangwali refugee settlement; The photo to the left (N1° 11.295' E30° 46.970') shows the high-density local trading center booming with local business at Kasonga and the photo to the right (01.2075 N, 030.7821 E) shows subsistence farmland system where each household is allocated land for food cultivation in Kyangwali refugee settlement Photos taken by Author, 2023

3.1.5 Socio-economic environment

Subsistence farming

Agriculture through subsistence farming and small-scale commercial farming are the district's main economic activities with farmers predominantly growing beans, maize, rice, cocoa, coffee, and tobacco. Agriculture is the largest livelihood option supporting about 90% of the population contributing about 71% of the district's local revenue as shown in *Figure 10* (CNOOC Uganda, 2019). Fishing is another key economic activity practiced largely in the sub-counties of Kabwoya, and Kyangwali close to Lake Albert that covers about 2,268 km^2 with the most diverse fish fauna species for example Tilapia, Nile Perch, Ngaa, Ngasa, Lanya and Male (Uganda Investment Authority, 2019).

Recently, there was an influx of cattle keepers from as far as Tanzania and Kasese areas, leading to a tremendous increase of cattle in Buhuka flats mainly in search for water and pasture within the open grassland (CNOOC Uganda, 2019).

a) (N1° 14' 49.8" E31° 05' 02.7") b) (N1° 21' 36.3" E30° 57' 01.6")

Figure 10: Local trade at a) Kabwoya trading centre (Photo to the left: N1° 14' 49.8" E31° 05' 02.7") provides alternative livelihood in Kikuube district. and b) a garden of maize and beans mixed farming (Photo to the right: N1° 21' 36.3" E30° 57' 01.6"); a form of subsistence agriculture which is the most dominant source of livelihood in Kikuube district. Photos taken by the Author, 2023.

Commercial agriculture

The main commercially grown crops in Kikuube district are sugarcane and tea. The main ventures are Hoima sugar Ltd for sugarcane and Agricultural Enterprises Ltd managing Bugambe and Kisaru tea estates for production with supplies augmented by both sugarcane and tea out growers. Bugambe tea estate located in Bugambe sub-county was established in 1960 on 1,644 acres as a government of Uganda initiative to diversify the agricultural sector from cotton and coffee and to stimulate development in the region. Kisaru tea estate originally part of Bugambe tea estate became an independent estate in 2020 producing about 1.59 million kilograms of tea per annum. Between 2010 and 2020, the estate area has more than doubled from 83 to 177 hectares (McLeod Russel Uganda, 2020).

Sugarcane is grown commercially by Hoima Sugar Ltd located in Kiziramfumbi subcounty, Kikuube district. Hoima Sugar Ltd is a medium-sized sugar company owned by Rai Holdings, which is a family-owned group with a 70% shareholding in Kinyara Sugar Works located in Masindi District (Bahati et al., 2022). The sugar company was launched by the Ugandan president Y.K. Museveni in May 2016 (Kivabulaya, 2016). In 2016, the factory had registered about 450 out growers and by 2020 the number rose exponentially to about 3,500 out growers covering 163 villages in Kikuube and Hoima districts accounting for 65% of the supply (Jjingo, 2020).

In 2020, the national environment authority of Uganda granted Hoima Sugar Ltd a license to develop 13 out of the 22 square miles of land and recommended the preservation of the remaining land which is part of the wetlands and close to Bugoma forest. The land was leased from Bunyoro Kitara kingdom (The Independent, 2023). However, there are pending court cases related to forceful eviction of 398 households and over 4,000 locals from over 1,300 hectares of land for sugar cane growing leased to Hoima sugar Ltd in Kijayo village, Kiziramfumbi sub county, Kikuube district (Bahati et al., 2022). *Figure 11* shows tea and sugar cane plantations identified during fieldwork.

a) Kisaru Tea estate (N1° 15.040' E30° 59.274') b) Private sugarcane plantation (N1° 18.286' E31° 12.341')

Figure 11: Kisaru Tea estate (left) and Sugarcane out growers are among the dominant forms of commercial agriculture in Kikuube district. Photos taken by Author, 2023

Oil exploration and development

Kikuube district is currently undertaking major midstream oil developments. CNOOC Uganda Ltd, (2019) notes that most midstream activities have been implemented in the Kingfisher development area located in Buhuka parish, Kyangwali subcounty. The infrastructure developed includes a petroleum central processing facility, the drilling camp, the permanent camp, and plans are in place to construct the 46 km feeder pipeline that traverses 24 villages in Buhuka, Butoole and Kyangwali parishes in Kyangwali subcounty to the oil refinery in Buseruka subcounty, Hoima district. Some of the oil exploration and development infrastructure developments during field work are shown in *Figure 12*.

Major upstream development activities are almost complete with commercial oil and gas deposits first discovered in the late 1990s by Heritage Oil and Gas Ltd. The three major licensed areas with oil discoveries are; the Kingfisher (5 oil wells); Mputa (5 oil wells); and

Nzizi (3 Natural gas wells) (MEMD, 2017; PEPD, 2015). Local benefits from oil development are mainly livelihood diversification through employment and improved income-generating activities from project infrastructure from cash compensation and resettlements (Aboda et al., 2022). On the other hand, land acquisition, household displacement, livelihood displacement and in-migration have been challenges associated with the oil development project (Ogwang & Vanclay, 2019). Direct and indirect impacts from the oil project footprint will likely drive land use and land cover change.

a) Kingfisher oil field; Central processing facility at Buhuka flats near Lake Albert (N1° 14' 06.6" E30° 45' 24.6")

b) Mputa oil well pad located in Kabwoya wildlife reserve (N1° 25.469' E30° 57.572')

c) Oil pipeline route through Kabwoya wildlife reserve (N1° 26.512' E30° 57.322')

d) High density settlement at Buhuka flats (N1° 14' 06.6" E30° 45' 24.6")

Figure 12: Some of the oil exploration activities in Kikuube district include a) Central processing facility at Buhuka flats under the Kingfisher licensed area; b) an oil well pad in the Mputa licensed area; c) Water intake pipeline routes within Kabwoya wildlife reserve and d) A high density Buhuka flats flood plain near lake Albert where active oil development takes place. All photos taken by Author, 2023

3.1.6 Protected areas

Bugoma Central Forest reserve

Bugoma central forest reserve is a protected medium altitude semi-deciduous forest with high biodiversity managed by the National Forestry Authority. About 257 trees and shrub species have been recorded in the forest with seven endemic species to the region, 12 globally threatened and 14 are on the IUCN Redlist (Plumptre et al., 2007). The forest is a vital source of River Nguse and Rutowa and significantly supports the populations of the Eastern Chimpanzee, Nathan's Francolin, numerous endemic birds, and butterflies. The major drivers of change in the forest are mainly deforestation, encroachment, fuelwood collection, charcoal burning largely from growing settlements and subsistence farming from immigration and an increasing population at the forest edges. More recently, commercial agriculture from sugarcane growing is becoming a major threat (CNOOC Uganda, 2019).

Kabwoya wildlife reserve

The reserve covers an area of 87 square kilometres in the rift valley plain curved by the escarpment to the East, Lake Albert to the west. The area dates to the early 1960s when the Uganda Game department declared it a Controlled Hunting Area until 2002 when it was gazetted as a Wildlife reserve with important populations are: the Uganda Kob, Buffalo, and Hartebeest. Several oil wells have been drilled within the reserve within the Nzizi-Mputa licensed areas (Uganda Wildlife Authority, 2023).

3.2 Methodology

3.2.1 Research process

The research concept development for this study started from a general interest of using a GIS based methodology for my master's thesis which I had always longed for ever since I got introduced to remote sensing and GIS basics during my Bachelor (Forestry) studies at Makerere University, in Uganda. The specific focus on land use and land cover changes broadly stemmed from the individual mapping project in the GIS and data capture methodology course where I mapped Land use changes in Uganda for 1996, 2004, 2012 and 2020 using the global landcover data downloaded from the European Space Agency (ESA) Climate Change Initiative (CCI) Copernicus Climate Change Service (C3S) Climate Data Store (CDS) in

NetCDF formats inspired by a research article from Ampim et al., (2021). However, further proposal development of this study was through review of published literature and guidance from my supervisors which led to the adjustment of the scope of study from an initially broad scope of the Albertine region to the narrow Kyangwali refugee settlement and then finally broadened to Kikuube district. Land use and land cover change analysis required an enormous amount of time learning supervised classification process using ArcGIS software. Additionally, presentations and feedback from the research seminar and Uganda projects team meetings provided constructive feedback which informed the study design.

This study focused on the nature, trends, and extent of land use/land cover changes from multiple drivers in Kikuube district. The primary method used in this study is remote sensing and geographical information system using ArcGIS Pro software, a powerful tool for visualization, management, analysis of geospatial data. Land use changes between 1985 to 2023 were analysed using five (5) moderate, 30 m resolution Landsat images downloaded from the open access United States Geological Survey (USGS) earth explorer website (https://earthexplorer.usgs.gov/). The analysis was performed using Landsat 5 thematic mapper for 1985 and 1995 images, Landsat 7 extended thematic mapper plus for the 2005 image and Landsat 8 operational land imager for the 2015 and 2023 using maximum likelihood classifier supervised classification algorithm. Changes in vegetation caused by seasonal and phenological changes were accounted for using the normalized difference vegetation index (NDVI). Secondary data based on a literature review was used to identify likely primary multiple drivers of land use/land cover change in Kikuube district.

3.2.2 Satellite imagery processing for land use/land cover change analysis

LULC analysis for this study involved the following steps: image acquisition, image pre-processing, classification scheme development, image classification, ground truthing and accuracy assessment, and change detection analysis. *Figure 13* shows the LULC change mapping methodology flow chart employed in this study as modified from Kirimi et al., (2018). Satellite images were pre-processed to improve their spectral signatures. This mainly involved cloud removal and gap filling. Supervised classification based on the maximum likelihood classifier was used to generate land classes. Through an accuracy assessment, randomly generated accuracy assessment points were ground-truthed against the generated classes in the classified maps to calculate the classification error. Finally, the categorical change detection method was used to generate spatio-temporal changes of the study area.

ArcGIS Pro 3.0.0 is a licensed software developed by ESRI and students at NTNU have rights to use the software through their NTNU institutional account. A single user project geodatabase was created and linked to a project folder. The most appropriate projected co-ordinate system for Kikuube district in the geodatabase is the WGS 1984 UTM Zone 36N that ensures map projection and alignment with all other spatial data.

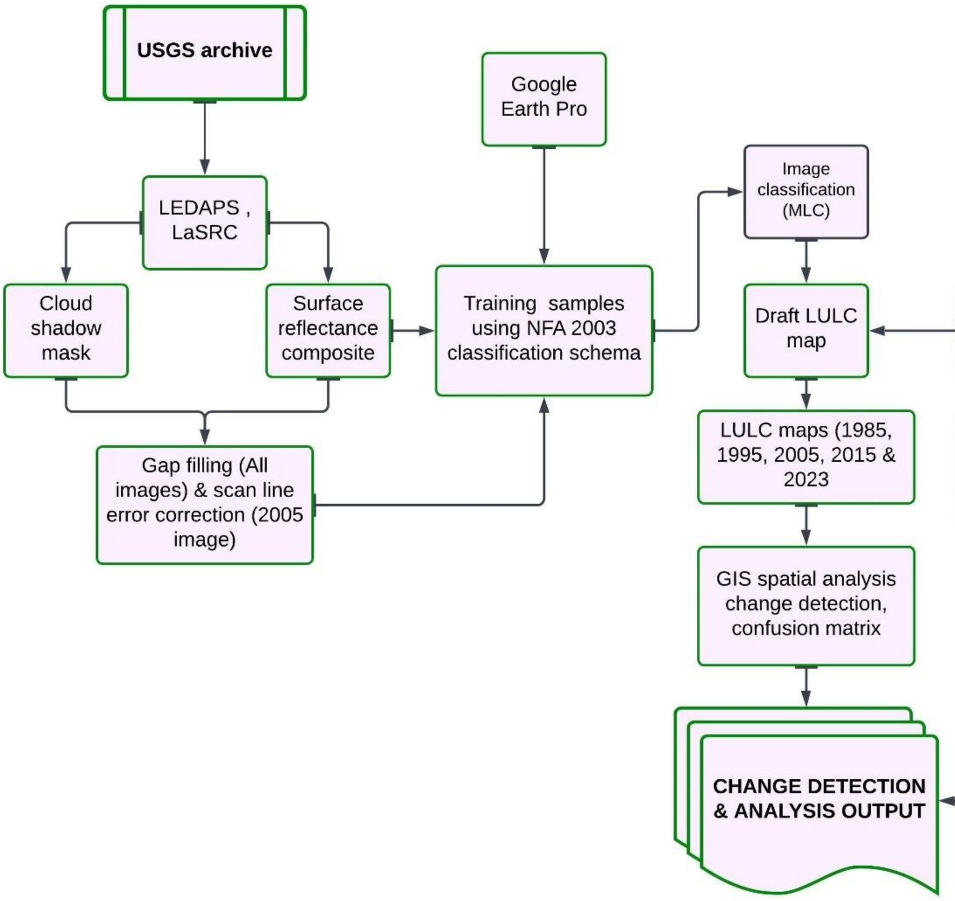


Figure 13: Schematic flow of the classification process for land use/land cover change analysis modified from Kirimi et al., (2018). (Author, 2023)

3.2.3 Selection of satellite imagery

Ten Landsat images were downloaded from the open access USGS Earth explorer website for the period between 1985 and 2023 *(Table 2)*. Each year of analysis (1985, 1995, 2005, 2015 and 2023) had two images selected in different Landsat paths 172 and 173 and row 059 to cover the entire study area. The images were all selected from the dry season (December-April) to ensure compatibility during analysis and to increase the likelihood of having images with low (10% or less) cloud cover (Feng et al., 2015). The images were also obtained from different sensors (Landsat 4 TM, Landsat 7 ETM+ & Landsat 8 OLI) but with similar spectral resolution of 30 m.

Table 2: Satellite Imagery data sources used for the analysis of LULC in the study area retrieved from USGS Landsat archive.

Year	Acquisition date	Image (Landsat product ID)	Season	Satellite	Cloud cover (%)
2023	07/01/2023 14/01/2023	LC08_L2SP_172059_20230107_20230111_02_T1 LC08_L2SP_173059_20230114_20230130_02_T1	Dry	Landsat8	0.06 6.97
2015	01/01/2015 08/01/2015	LC08_L2SP_172059_20150101_20200910_02_T1 LC08_L2SP_173059_20150108_20200910_02_T1	Dry	Landsat8	0.72 0.11
2005	03/04/2005 05/02/2005	LE07_L2SP_172059_20050403_20200914_02_T1 LE07_L2SP_173059_20050205_20200914_02_T1	Dry	Landsat7	5 4
1995	27/02/1995 17/01/1995	LT05_L2SP_172059_19950227_20200912_02_T1 LT05_L2SP_173059_19950117_20200912_02_T1	Dry	Landsat5	0.00 10
1985	14/01/1985 04/12/1984	LT05_L2SP_172059_19850114_20200918_02_T1 LT05_L2SP_173059_19841204_20200918_02_T1	Dry	Landsat5	1.00 58

Landsat images were prioritized because different Landsat missions (Landsat 5, Land sat 7 and Landsat 8) can be integrated for multi-temporal analysis (Tempfli et al., 2009). Additionally, there is a rich image database over the study area sufficient to address the objectives of this study. The imagery time periods chosen for this analysis cover a decade time step and corresponded to major driving factors of LULCC (oil development, refugee influx and commercial agriculture) as revealed in some literature (Mwavu & Witkowski, 2008; Twongyirwe et al., 2015) and shown in the timeline in *Figure 14*. With 1985 as a baseline year, the earliest low cloud satellite Landsat imagery over the study area, changes for 1995, 2005, 2015 and 2023 were evaluated. The main drivers of change interact interchangeably throughout the study period with some becoming more pronounced than others. Population, economic and policy changes in Kikuube district and Uganda can influence the interaction of these drivers across time and space.

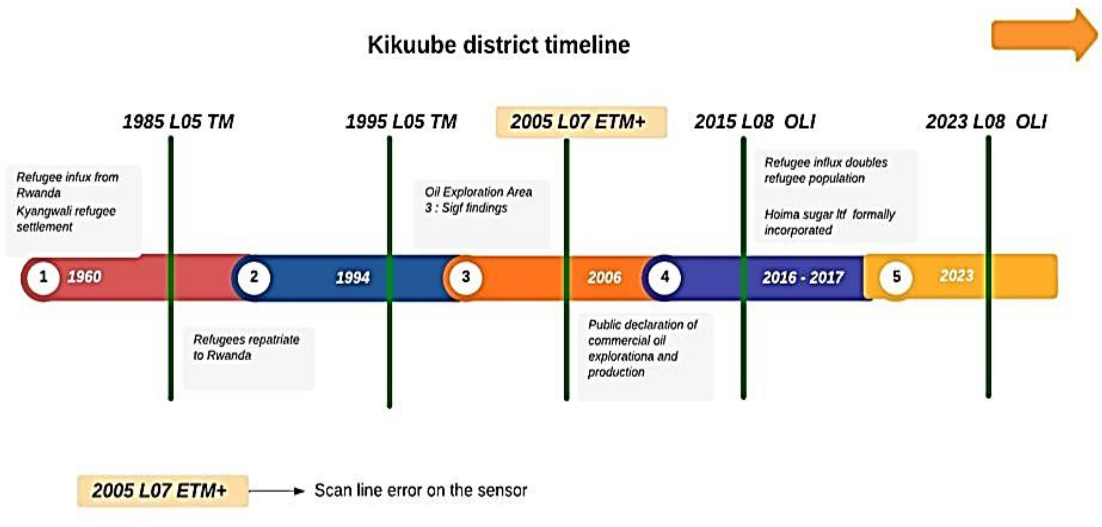


Figure 14:The timeline shows relationship between satellite imagery and major drivers of land use/land cover change in Kikuube district; With 1985 as a baseline to 2023, changes in refugee populations, significant findings from oil exploration efforts and increase in commercial agriculture informed choice of satellite imagery (Author, 2023)

The properties of Landsat sensors and raw imagery produced in this study included Landsat 5 TM imagery that consists of seven (7) spectral bands with a spatial resolution of 30m for bands 1 to 5 and 7. Spatial resolution for band 6 (thermal infrared) is 120 m but is resampled to 30-m/pixels. The Landsat 7 ETM+ image consists of eight (8) spectral bands. Bands 1 to 7 have a spatial resolution of 30 m while band 8 (panchromatic) has 15 m. Finally, the two Landsat 8 OLI/TIRS images consist of nine spectral bands. Bands 1 to 7 and 9 have a spatial resolution of 30 m; band 8 (panchromatic) is 15 m and thermal bands 10 and 11 at 100 m. Approximate scene size for all Landsat 5,7 and 8 imagery is 170 km north-south by 183 km east-west. Band characteristics for Landsat 4-5 TM, 7 ETM+ and 8 OLI/TIRs mission properties as shown in in Appendix ***1*** (USGS, n.d.).

3.2.4 Image pre-processing

Radiometric calibration and atmospheric correction

Remotely sensed imagery for this study had radiometric and geometric errors which were eliminated or reduced to enhance image quality for its true surface reflectance (Tempfli et al., 2009). Radiometric errors are attributed to variations in atmospheric conditions such as clouds; geometric errors are attributed to variations in the sensor view angle and scan line errors (Townshend et al., 1991). All the downloaded imagery scenes for this analysis are Landsat collection 2 level 2 science products. The Landsat image products were pre-processed in the USGS data base using two atmospheric correction algorithms and uncertainty analyses: The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) that generated surface reflectance imagery by atmospheric correction of Landsat TM and Landsat ETM+ digital numbers (Schmidt et al., 2013); and the Land Surface Reflectance Code (LaSRC) algorithm that corrected Landsat 8 OLI/TIRs collection 1 data to produce top of atmosphere surface reflectance products (Masek et al., 2006).

A single projected geodatabase was created in ArcGIS Pro software. The projection coordinate system (WGS 1984 UTM 36N) was set. The downloaded imagery data was imported to the geodatabase. The shapefile for Kikuube district necessitated use to two adjacent Landsat scenes for each year which were mosaicked in the software. Kikuube district shapefile was retrieved from LWF-Uganda[1]. The mosaicking process involved merging two overlapping image scenes into one entity (a mosaic) as shown in *Figure 15*. The Landsat image covering the larger portion of the study area was prioritized to fill the overlapping pixels using the mosaic function in ArcGIS Pro.

Figure 15: Mosaicking two dry season 1985 Landsat imagery from different scenes covering study area using the mosaic tool in ArcGIS Pro. (Author, 2023).

Further pre-processing of downloaded images involved cloud removal for all images and scan line error correction for 2005 Landsat 7 ETM+ images only. Cloud removal was performed using the mask raster function that identifies clouds and shadows which include all pixel values and NoData values that do not belong to land and water class using the embedded

[1] Shapefile source: https://www.arcgis.com/home/item.html?id=97fbfcc7d3734d0ea677f165b6122cb7

QA mask as shown in *Figure 16*. A cloud free output raster was produced using the Clip and Remap functions.

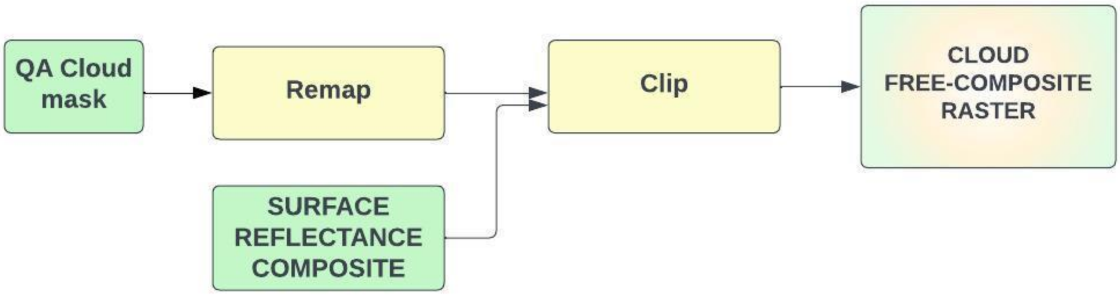


Figure 16: Cloud removal using the QA mask layer and the surface reflectance layer were remapped and clipped to produce an output having land and water surface reflectance hence cloud removal (Author, 2023)

Cloud and shadow free pixels in the raster image contain No data values. Scan lines in 2005 image mosaic are left with No data pixels which require to be filled with surface reflectance data pixels. The No data pixel values were then filled with spectral data using the Raster Calculator function in ArcGIS Pro. This function follows the Geostatistical Neighbourhood Similar Pixel Interpolator proposed by Chen et al., (2011), which assumes that neighbourhood pixels close to gaps share similar spectral characteristics and temporal patterns with no data pixels found in gaps. This method produces the high accuracy for filled spectral signatures for heterogenous areas which fits the largest portion of the study area (Yin et al., 2017). The mean value of a specified number of neighbouring rectangular pixels closest to the gaps was calculated and filled into the gaps (Zhu et al., 2012). The function used to fill gaps is shown in Equation 1. The input and output raster imagery are presented in *Figure 17*.

Equation 1

$$Ro = Con(IsNull(Ri), FocalStatistics(Ri, NbrRectangle(x, y, "CELL"), "MEAN", "DATA"), Ri)$$

Ro is the output raster, Ri is the input raster, x, y is the cell size calculated to fill no data values.

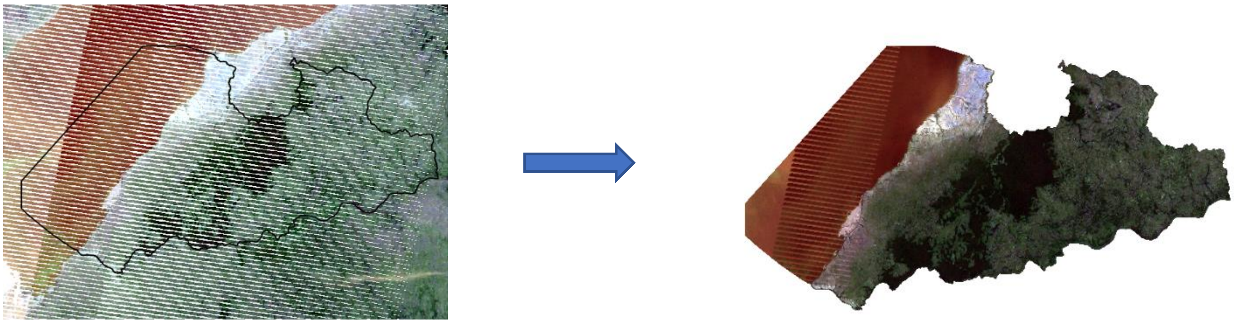


Figure 17: Gap filing of the 2005 Landsat 7 ETM+ image mosaic to correct for the scanline error and No data values from cloud removal (Left) and a corrected final image (right) ready for classification (Author 2023)

Image sub setting involved extracting imagery for the study area which reduces the processing time during classification. The buffer mask tool in ArcGIS Pro was used to execute this function.

3.2.5 Supervised statistical classification.

Several supervised classification algorithms for land use change have been used in the research realm (Tempfli et al., 2009). Supervised classification is the type of classification in which the user collects training samples of the land cover classes (training data) and the classification software determines each class by what it resembles most in the training signatures to perform the classification using a defined algorithm (Maciej Serda et al., 2009). The algorithm used for this study was the Maximum Likelihood Classifier due to its shorter processing time while achieving high accuracy (MohanRajan et al., 2020). The Maximum likelihood classifier algorithm assigns pixels to the class with the highest probability of being a member of the class using generated training samples. The algorithm assumes that the data for each band is normally distributed; each class has a normal distribution in a multivariate space (Coppin et al., 2004; Tempfli et al., 2009). The challenge of using this classifier is the possible difficulty in distinguishing the pixels that come from different land cover classes but have very similar spectral properties resulting into the ‘salt and pepper’ effect (Mustapha et al., 2010). This was evidenced especially while differentiating built-up from bare surface land cover for this study where both land cover showed more similar spectral properties. The challenge was managed by extracting training samples using Google Earth Pro as a reference as a guide to identify differentiate land classes with similar spectral properties.

The classification system adopted for this study is the Uganda National Biomass Study Classification System (NBSLCS) developed by National Forestry Authority (NFA), Uganda (NBS, 2003). The classification system has been used in several studies in Uganda such as by Kusiima, Egeru, Namaalwa, Byakagaba, Mfitumukiza, & Mukwaya, (2022) and Opedes et al., (2022). There are 13 land classes that the author reclassified into 12 classes by merging broad leaved and coniferous plantations to plantation forest with the remaining classes maintained as shown in *Table 3*. Broad leaved plantations such as eucalyptus and coniferous plantations such as pine are usually planted in proximity and produce more less similar spectral properties during classification. The reclassified classes were used to create a classification schema for use in the classification process. The different land cover classes as they appeared during the field work are presented in *Figure 18* and *Figure 19*.

Table 3: Reclassified Land cover classes used in this study.

Original classes (NBSLCS)		Description	Reclassified classes by Author	Number of samples used for training
1.	Broad leaved plantation	Broad leaved trees	Plantation Forest-PF (1,2)	47
2	Coniferous plantation	Needle leaved trees		
3	Tropical High Forest well stocked	Closed multi-storied trees	Tropical High Forest well stocked (THF-WS)	28
4	Tropical high forest low stock	Open high trees	Tropical high forest low stock (THF-LS)	20
5	Woodland	Closed trees, open trees, generally open trees, very open trees, woody areas	Woodland (WD)	39
6	Bush	Closed, Open or very open shrubs	Shrubland (SH)	65
7	Grassland	Graminoids and herbaceous areas	Grassland (GS)	23
8	Wetland	Permanently wet Graminoids and herbaceous areas	Wetland (WT)	33
9	Small scale farmland	Shrub and herbaceous crops on small fields.	Subsistence farmland (SF)	65
10	Commercial farmland	Shrub or herbaceous crops on medium or large size fields	Commercial farmland (CA)	69
11	Built up area	Artificial surfaces-Urban. Airport, refugee camp	Built up area (BU)	29
12	Open Water	Standing and flowing water and water dams	Open Water (OW)	4
13	Impediments	Bare soil and bare rocks, quarry	Bare surface (BS)	16

Source: Modified from the Uganda biomass study, 2003 classification scheme (NBS, 2003)

Plantation forest (N1° 21' 00.5" E30° 56' 38.3")

Tropical high forest-well stocked (N1° 13' 52.2" E31° 02' 21.6")

Tropical high forest-low stocked (N1° 19' 26.6" E30° 59' 29.3")


Woodland (N1° 22' 21.3" E30° 58' 04.9")

Shrubland (N1° 26' 52.9" E30° 57' 03.9")

Grassland (N1° 28' 32.9" E30° 56' 21.1")

Figure 18: a) Selected photographic view of the land use and land cover in the study area during field work. All photos taken by author between 17th-22nd April 2023.

Subsistence farmland (N1° 21' 36.3" E30° 57' 01.6")

Commercial agriculture (N1° 18.286' E31° 12.341')

Open water (N1° 14' 25.0" E30° 44' 06.4")

Wetland (N1° 19' 33.1" E31° 11' 45.3")

Built up (N1° 14' 06.6" E30° 45' 24.6")

Bare surface (N1° 28' 32.9" E30° 56' 21.1")

Figure 19: b) Selected photographic view of the land use and land cover in the study area during field work. All photos taken by author between 17th-22nd April 2023.

Training samples were created by training the classifier to assign pixels to a given class. The polygon training samples were based on both Google Earth Pro and the different band combinations for Landsat 5 TM, Land 7 ETM+ and Landsat 8 OLI that highlighted distinct features in the image. *Table 4* shows the most relevant band combinations used in this study. As many samples as possible were collected to ensure higher accuracy of the classification model. The training sites were merged to generate average signatures for each class. The classification wizard in ArcGIS pro was used to perform the pixel based maximum likelihood supervised classification. Each of the raster's pixel value of the imagery corresponds to a land cover class.

Table 4: Band combinations used for image classification. Combinations highlighted distinct features representing designated land classes.

Features	**Landsat 5 and 7 (RGB)**	**Landsat 8 (RGB)**	
Natural Colour	3 2 1	4 3 2	True colour visualization
False Colour (urban)	7 5 3	7 6 4	Urban structures appear blue
Colour Infrared (vegetation)	4 3 2	5 4 3	Vegetation appears red
Agriculture	4 5 1	6 5 2	Crop monitoring
Atmospheric Penetration	7 5 3	7 6 5	
Healthy Vegetation	4 5 1	5 6 2	
Land/Water	4 5 3	5 6 4	Highlights water bodies
Natural With Atmospheric Removal	7 4 2	7 5 3	
Shortwave Infrared		7 5 4	
Vegetation Analysis	5 4 3	6 5 4	

3.2.6 Field work

The main goal of conducting field work was to validate generated draft classified maps, collect accuracy assessment points for ground truthing and have a physical overview of land cover classes in the study area. Field work was conducted between 27th March and 28th April 2023. Communication and correspondence by email with two potential field assistants was made and research tools also prepared before departure from Trondheim. Research tools included, preparation of draft land cover maps, generation of accuracy assessments points for the 2023 Landsat 8 image, Maps showing the road network and access were printed. Guidance and assistance were provided both from my supervisors and the department of Geography, NTNU with the field introductory letter as shown in Appendix *7* and acquiring research equipment. A Garmin GPS MAP 64s was borrowed from the department. A field camera Nikon B500 Coolpix was hired specifically for its ability to capture clear land cover images at relatively farther distances than those captured by phone cameras.

Upon arrival for field work in Uganda, physical applications for research permits were required by the institutions with jurisdiction over the protected areas, and from the local government in Kikuube district. Uganda Wildlife Authority (UWA) and National Forestry Authority (NFA) are Ugandan state institutions mandated to supervise Kabwoya wildlife reserve and central forest reserves (Bugoma CFR, Wambabya CFR) respectively. The applications required particulars of the researcher and field assistants, an introductory letter from NTNU, a research proposal and a signed letter of indemnity. Payments for research permits were made to UWA and the NFA. The research permit approval application process took about 14 days before receiving approval from UWA as shown in *Appendix 8*. However, the NFA's final approval letter took longer than anticipated. Field work in the study area was conducted without the permit. A mini workshop was organised for field assistants to plan for field work, research tools and use of equipment were explained. On the first day, the chief administrative officer and the Natural resources officer were contacted at the Kikuube district local government offices for a general introduction and a hard copy application letter submitted to seek permission to conduct fieldwork. During interactions, land conflicts were cited to be prevalent in the district that any sight of a GPS receiver by the local community would be viewed as an attempt of land grabbing.

3.2.7 Limitations during field work

The nature of this research enabled the team to collect important data on land use, land cover and drivers of change as we drove through the study area. Pending district approval, random points within Kabwoya wildlife reserve were collected and this was used as a pilot for the remaining random points. Fieldwork within Kabwoya wildlife reserve required services of wildlife ranger from UWA to guarantee safety of the field team within the reserve. Considering the ease in accessing some points and uniformity of some land cover types; subsistence farmland, built up, plantation forest, woodland and commercial agriculture land cover types were prioritised over tropical high forest - well stocked, open water, wetland, shrubland for the remaining fieldwork period.

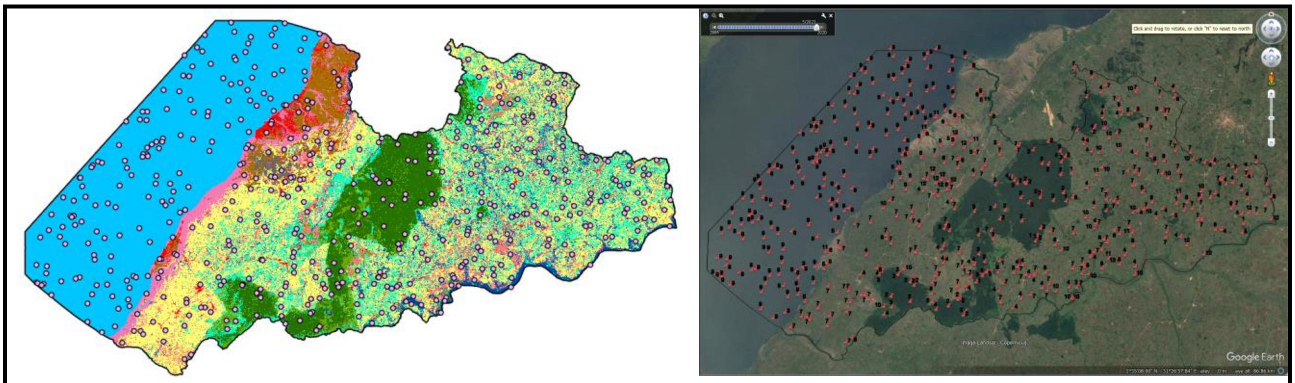
The main challenges in the field related largely to suspicion by the local community of land grabbing for random points on subsistence farmland systems and plantation forests. This was managed by wearing reflector jackets and traveling together as a field team. Data was collected by one individual as others engage with the local community to clarify the purpose of the fieldwork. Access to remote but important random points especially those in Kyangwali refugee settlement and Buhuka flats were reached using motorcycles (Boda-boda) locally used for public transport. At the end of each working day, data collected, highlights discussed and a plan for the following day made. A key contribution of fieldwork was reclassification of misclassified classes for example the shrubland pixels were previously classified as woodland.

3.2.8 Post-classification processing

Accuracy assessment

Land use/Land cover maps generated from image classification come with errors thus accuracy assessment of the maps is important so that the quality of maps is known, and map-based decisions can be made with a degree of certainty (Congalton, 1991). A reference dataset containing 500 accuracy assessment points randomly generated using the stratified random sampling technique for each classified image using the 'Create Accuracy Assessment Points' tool in Arc GIS pro was used for this study. Ground truthing (see *Figure 20*) of the accuracy assessment points was done using high resolution imagery from Google Earth pro over the study area and field survey. Opedes et al., (2022) and Islami et al., (2022) have used the same technique.

Field work was conducted in April 2023 with the help of two field assistants to ground truth random accuracy assessment points such as that shown in *Figure 21* . Accuracy assessment random points for the most recent image (2023 Landsat 8) were exported to a Global Position System receiver; GPSMAP 64s (Unit ID: 3993750669). Points in the entire study area were not covered largely due to accessibility constraints for some points, time, and budget limitations. Therefore, points from classes that were most challenging to classify were prioritized especially plantation forest and subsistence farmland. Points which were most difficult to access were from open water (Lake Albert), tropical high forest – well stocked (Bugoma central forest reserve) and wetland (Nkuse river system) land cover types. Fortunately, these classes covered large uniform areas thus minimizing large errors during ground truthing. Field observations of the land cover types guided accuracy assessment for older images (2015, 2005, 1995 and 1985) using Google Earth Pro.



a) Accuracy assessment points over the 2023 L08 classified image (Author. 2023)

b) Points ground truthed using Google Earth Pro as *kmz* files (Author, 2023)

Figure 20: 500 accuracy assessment points generated for the classified 2023 Land sat 8 image (a) and ground truthed using Google Earth Pro (b) during accuracy assessment of classified maps.

Olofsson et al., (2013, 2014) proposed the confusion matrix, a tabular computation of the user's accuracy and producer's accuracy for each class, as well as an overall kappa statistic index of agreement. The user's and producer's and overall accuracy ranges from 0 to 100% as shown in equation 2. The kappa statistic of agreement ranges from 0 to 1, where 1 represents 100 percent accuracy. The confusion matrix for this study was computed using the reference dataset and the classified maps using the 'Compute Confusion Matrix' tool in Arc GIS pro.

Figure 21: A random point (N1° 08' 25.3" E31° 00' 12.3") in a wetland part of River Nkuse in Kikuube district, Uganda (Photo taken by: Denis Lukato, 2023)

The user's accuracy or Type 1 error computes errors of commission where pixels are incorrectly classified as a known class when they should have been classified as something different. The user’s accuracy was calculated by dividing the total number of classified points that agree with the reference data (d) by the total number of classified points for that class (r). The producer's accuracy or Type 2 error computes errors of omission. The producer's accuracy indicates how accurately the classification results align with classified map. The producer’s accuracy was calculated by dividing the total number of classified points that agree with reference data (d) by the total number of reference points for that class (c). Kappa statistic of agreement, K is a measure of the accuracy of the classification as shown in equation 3. The accuracy rates ranged from 0 to 1, where 1 represented 100 percent accuracy. A kappa statistic of over 0.85 is required for validation of accuracy assessment (Anderson, 1976). *Table 5* shows the rating criteria for the different strengths of agreement.

Table 5: Rating criteria of kapa statistics

S.No	Kappa statistics	Strength of agreement
1	Less than 0.4	Poor
2	0.4 - 0.5	Fair
3	0.55 - 0.7	Good
4	0.7 - 0.85	Very good
5	More than 0.85	Excellent

Source: Tewabe & Fentahun, 2020

Equation 2

$$Wi = \frac{a}{b}$$

$$Prop = \sum^{3} Wi\frac{a}{b}$$

$$User's\ accuracy = \frac{d}{r}$$

$$Producer's\ accuracy = \frac{d}{c}$$

$$Overall\ accuracy = \sum d$$

where *a, is the number of pixels per strata and b, is the total number of pixels in the study area, d is the correctly classified pixels in the diagonal, r is the sum of row pixels, and c is the sum of column pixels.*

Equation 3

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + Xx_{+1})}{N^2 - \sum_{i=1}^{r}(x_{ii} Xx_{+1})}$$

where; *r = number of rows and columns in error matrix, N = total number of observations (pixels);* X_{ii} *= observation in row i and column i,;* X_{i+} *= marginal total of row i, and* X_{+i} *= marginal total of column i.*

3.2.9 Land use/land cover change detection

Change detection analysis is a fundamental application in remote sensing enabling the comparison of multiple temporal imagery to determine the type, magnitude, and location of change (Tempfli et al., 2009). Change detection for this study was done using the 'Change Detection Wizard' in ArcGIS pro as shown in *Figure 22*. Categorical change detection was performed to identify area that changed from one land use/land cover to another over a given period.

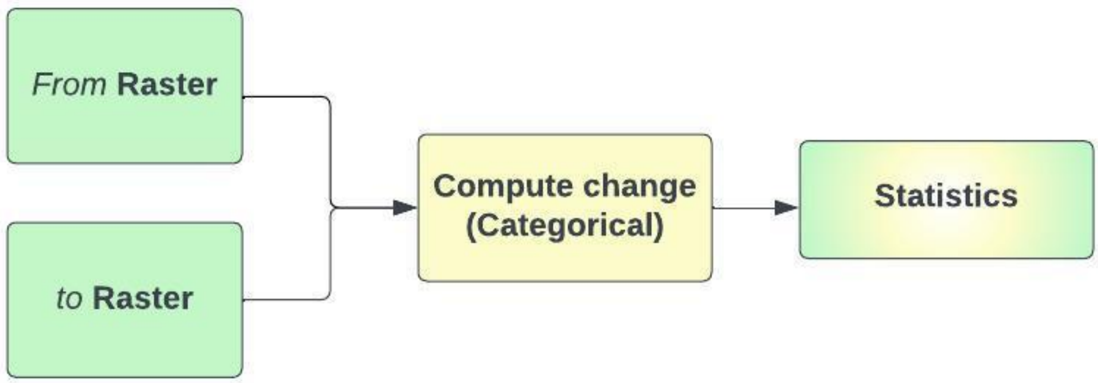


Figure 22: Generation of change detection statistics using two input rasters in the ArcGIS Pro change detection wizard (Author, 2023)

In this study, the change detection analysis was computed for all the classified images 2023, 2015, 2005, 1995, and 1985 for the periods 1985-2023, 1985-1995, 1995-2005, 1995-2023, and 2015-2023. The periods for analysis were selected to highlight land use/land cover changes when specific drivers where most pronounced in the study area. The output from change detection was used to compute statistics for Land use/land cover extent, Land use/land cover change (sq. km and percentage change), transition matrix (Equation 4) and the rate of change ; K (Equation 5) of the study area's land use/land cover classes.

Equation 4: for the transition matrix (Sij).

$$\mathrm{Sij} = \begin{bmatrix} S11 & \cdots & S1n \\ \vdots & \ddots & \vdots \\ Sm1 & \cdots & Smn \end{bmatrix}$$

Where *S is the unit area in Sq. Km, i and j are the land use type before and after the transition period, i is equal to 1, 2, 3...., m and j is equal to 1, 2, 3.... n.*

Equation 5: The rate of land use change (K)

$$\mathrm{K} = \frac{U2-U1}{U1} \times \frac{1}{T} \times 100\%$$

where *K indicates the degree of the land use dynamics; U1 and U2 are the area of a land use type at the beginning and the end of a period, respectively; and T is the time interval (years).*

3.2.10 Vegetation analysis

This accounts for seasonal changes from rainfall and temperature variations, disturbances such as urbanization, degradation, deforestation, and land use change (Hu et al., 2018; Yang et al., 2019). The Normalized Difference Vegetation Index (NDVI) is calculated as a measure of the annual vegetation growth as shown in equation 6. NDVI is higher in areas that absorb relatively higher red wavelength and reflect in the near infrared wavelengths. NDVI values range from -1 to +1 represent no vegetation to high vegetation respectively (Tempfli et al., 2009). The formula for NDVI calculation is as follows.

Equation 6

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)}$$

Where *NIR represents the Near-Infrared Band and Red represents the Red Band*

3.2.11 Reflections

Impact of the scan line error on accuracy of processed images

The failure of the ETM+ sensor since 2003 as a scan line error has had impacts on data and quality of surface reflectance of images as result of the created No data gaps. This study used the Near-Neighbour pixel method (Mean filter) based on the Geostatistical Neighbourhood Similar Pixel Interpolation for the 2005 ETM+ image to achieve a high accuracy for heterogenous areas (Yin et al., 2017). The challenge with the resultant images is that mixed pixel classes for a relatively small area in this study didn't represent single pixel classes such as built up and plantation forest. Thus, gaps were filled with pixels representing dominant classes (mostly woodland and tropical high forest-well stocked). This implied that spectral properties for small area land cover classes (such as subsistence farmland) were lost during classification.

CHAPTER FOUR

RESULTS

This chapter presents the results of the land use/land cover change analysis over the study area in line with the research objectives. The results include the accuracy assessment of the classified maps, nature, and trends of the LULC types, LULC changes, transition flows across LULC types, annual percentage rates of change and vegetation index values.

4.1 Accuracy assessment of the classification

The summary results of the accuracy assessment process for all the imagery are shown in confusion matrices in *Table 6*. The table illustrates user's, producer's, overall and kappa coefficient of agreement of the classified images as a measure of the classified error in percentage. The detailed confusion matrix tables are shown in Appendix *2-6*. The overall accuracy and respective kappa coefficients of agreement (in brackets) for the 2023, 2015, 2005, 1995 and 1985 classified images were 86% (0.836), 95% (0.942), 94% (0.931), 94% (0.934), and 94% (0.926) respectively.

Table 6: Summary results showing user's, producer's, overall accuracies, and kappa coefficients for the classification accuracy assessment of the land use/land cover maps for Kikuube district for the study periods, Author, 2023

Year	**1985**		**1995**		**2005**		**2015**		**2023**	
Land Cover Classes	**UA, %**	**PA, %**	**UA, %**	**PA, %**	**UA, %**	**PA, %**	**UA, %**	**PA, %**	**UA, %**	**PA, %**
Plantation forest	91	95	98	100	100	100	60	86	50	46
Tropical high forest-well stocked	92	100	90	100	100	95	92	100	100	86
Tropical high forest-low stocked	83	90	92	90	87	95	92	79	83	77
Woodland	96	90	95	58	95	91	95	87	73	78
Shrubland	100	78	94	100	94	80	93	93	70	100
Grassland	100	89	88	88	94	100	92	80	100	65
Subsistence farmland	96	96	93	96	88	92	97	99	86	85
Commercial agriculture	60	100	90	100	83	100	100	94	69	83
Open water	99	100	100	100	100	99	100	99	100	97
Wetland	89	73	77	94	85	85	100	89	77	95
Built up	58	87	100	100	91	100	80	100	40	80
Bare surface	100	100	91	86	80	89	80	100	100	77
Overall accuracy	**94**		**94**		**94**		**95**		**86**	
Kappa statistic	**0.926**		**0.934**		**0.931**		**0.942**		**0.836**	

UA-User's accuracy, PA-Producer's accuracy

4.2 Spatio-temporal variation in the trends of land use/land cover change

The spatial temporal changes in LULC for the 1985, 1995, 2005, 2015 and 2023 images over Kikuube district were analysed using the pixel based Maximum likelihood Classifier supervised classification. The LULC maps for each Land use Land cover class generated over Kikuube district are presented in *Figure 23.*

Table 7: Land use and Land cover extent shows the area (km^2) and the respective percentage proportions for each land use/land cover class for the 1985, 1995, 2005, 2015 and 2023 imagery for Kikuube district.

	YEAR				
LULC CLASS	**1985**	**1995**	**2005**	**2015**	**2023**
	Km^2 (%)	**Km^2 (%)**	**Km^2 (%)**	**Km^2 (%)**	**Km^2 (%)**
Plantation forest	138.6 (5)	328.8 (11)	88.1 (3)	39.5 (1)	34.8 (1)
Tropical high forest-well stocked	313.1 (10)	409.1 (14)	230.4 (8)	291.4 (10)	258.0 (9)
Tropical high forest-low stocked	206.6 (7)	231.6 (8)	267.7 (9)	141.4 (5)	70.7 (2)
Woodland	**655.0 (22)**	133.5 (4)	**621.1 (21)**	255.3 (9)	382.5 (13)
Shrubland	109.8 (4)	96.4 (3)	102.9 (3)	163.2 (5)	138.3 (5)
Grassland	94.6 (3)	99.7 (3)	98.7 (3)	79.9 (3)	88.7 (3)
Subsistence farmland	319.8 (11)	**431.8 (14)**	465.2 (16)	**871.4 (29)**	**718.5 (24)**
Commercial agriculture	20.0 (1)	53.0 (2)	73.0 (2)	88.1 (3)	176.0 (6)
Open water	888.4 (30)	895.0 (30)	887.1 (30)	873.6 (29)	878.0 (29)
Wetland	105.2 (4)	129.4 (4)	77.2 (3)	102.6 (3)	157.8 (5)
Built up	74.7 (3)	59.5 (2)	65.5 (2)	61.7 (2)	56.7 (2)
Bare surface	66.8 (2)	124.6 (4)	16.3 (1)	24.3 (1)	32.3 (1)
TOTAL	**2992.3 (100)**	**2992.3 (100)**	**2992.3 (100)**	**2992.3 (100)**	**2992.3 (100)**

Table 7 illustrates the details of land cover area (km^2 and percentage) from 1985 to 2023. Overall Open Water is the most dominant and consistent land cover type throughout the study period with more than 29% largely due to Lake Albert that covers the largest part of the land cover type. With that in mind, changes on other land cover types are given more attention. In 1985, the woodland land cover type followed by subsistence farmland were the more dominant while the least cover was commercial agriculture which was 1%. However, in 1995, subsistence farmland and tropical forest well stocked land cover types became more dominant in Kikuube district with more than 14% cover. The lowest land cover coverage in this period remained commercial agriculture and built-up with a 2% coverage. In 2005, again the woodland land cover type was the more dominant with more than 20% coverage followed by subsistence farmland. The lowest land cover was bare surface with a 1% coverage.

Additionally, in 2015 subsistence farmland was more dominant with a 29% coverage and bare surface had the lowest coverage of about 1%. Finally, in 2023, subsistence farmland was more dominant with about 24% coverage and bare surface with a coverage of about 1%.

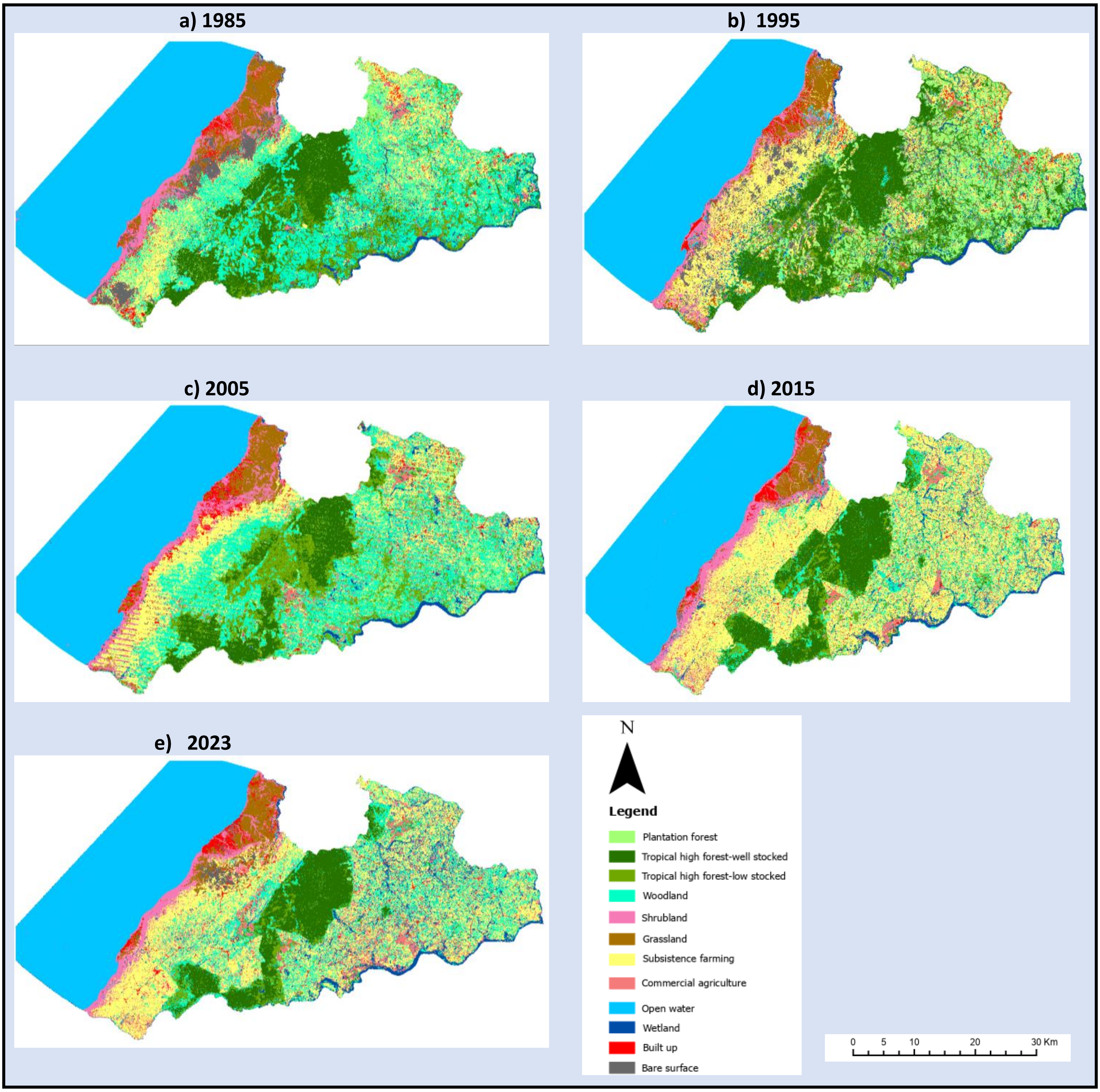


Figure 23: 1985, 1995, 2005, 2015 and 2023 land use/land cover maps of Kikuube district

Land use/land cover maps in *Figure 23* indicate that open water land cover is largely lake Albert, Tropical high forest well stocked land cover is largely Bugoma and Wambabya central forest reserves. Tropical high forest low stocked represents forms of recovery and degradation of intact forest such as land cover along the fringes of Bugoma and Wambabya central forest reserves. Grassland and shrubland land covers define the largest area of Kabwoya wildlife reserve. Grassland vegetation largely consists of *Hyparrhenia spp.* and *Themeda spp.* grassland and Shrubland vegetation are largely covered by *Grewia spp*. and *Acacia brevispica* undifferentiated dry thicket. Built up land cover was mostly represented by settlements and major town centres such as Buhuka, Bugambe, Buhimba, Hohwa, Kyangwali, Kiziramfumbi, Kabwoya etc. Commercial farmland land cover is dominantly represented by tea and sugar cane plantations mainly from Kisaru tea estate, Bugambe tea estate, Hoima sugar Ltd sugarcane estate and private planters. Plantation forest land cover was mainly from eucalyptus and pine plantations. Woodland land cover was mainly from tropical forest degradation and natural vegetation along the wetland and riverine system such as vegetation along River Nkuse and River Hohwa in Kikuube district. Subsistence farmland land cover was largely cultivated small farming plots common around homesteads.

4.3 Land use/land cover changes, 1985 to 2023

Land use and land cover changes for the period from 1985 to 2023 is shown in *Table 8*. The land cover change pattern from 1985 to 2023 indicates an overall decline in natural landcover and a general increase in human induced land cover. Natural land cover decline was largely woodland, tropical high forest-low stocked and plantation forest. The largest gain in land cover change was largely subsistence farmland and commercial agriculture minimal changes were observed in the Shrubland, Grassland, Built up and Bare surface land cover. Between 1985 and 1995, most land cover types had minimal changes with only the woodland and Plantation forest having the largest loss and gain respectively. Between 1995 and 2005, land cover declines were mainly from plantation forest, tropical high forest-well stocked and bare surface. The largest gains were from the woodland land cover. Between 2005 and 2015, land cover losses were largely from Woodland, tropical forest-low stocked and plantation forest while the largest gain was subsistence farmland. Grassland, commercial farmland, Built up, wetland, and bare surface largely stable. The least land cover changes were between 2015 and

2023 with gains from woodland, commercial agriculture and wetland and decline in subsistence farmland, tropical forest – low stocked, the largest decline was subsistence farmland.

Table 8: Trends in land use/land cover change (area statistics in Km^2) and proportional change (in percentage) for the periods 1985-1995, 1995-2005, 2005-2015, 2015-2023 and 1985-2023 in Kikuube district

LULC class	1985-2023 Area (Km^2)	1985-2023 Ratio (%)	1985-1995 Area (Km^2)	1985-1995 Ratio (%)	1995-2005 Area (Km^2)	1995-2005 Ratio (%)	2005-2015 Area (Km^2)	2005-2015 Ratio (%)	2015-2023 Area (Km^2)	2015-2023 Ratio (%)
Plantation forest	-103.79	-3.5	190.20	6.4	-240.73	-8.1	-48.61	-1.6	-4.65	-0.2
Tropical high forest-well stocked	-55.06	-1.8	95.96	3.2	-178.68	-6.0	60.99	2.0	-33.33	-1.1
Tropical high forest-low stocked	-135.84	-4.5	25.05	0.8	36.10	1.2	-126.30	-4.2	-70.68	-2.4
Woodland	-272.51	-9.1	-521.45	-17.4	487.55	16.3	-365.80	-12.2	127.19	4.3
Shrubland	28.56	1.0	-13.38	-0.5	5.52	0.2	61.24	2.1	-24.82	-0.8
Grassland	-5.91	-0.2	5.08	0.2	-0.92	0.0	-18.84	-0.6	8.77	0.3
Subsistence farmland	398.71	13.3	112.00	3.7	33.47	1.1	406.21	13.6	-152.96	-5.1
Commercial agriculture	156.03	5.2	33.06	1.1	19.97	0.7	15.12	0.5	87.88	2.9
Open water	-10.33	-0.4	6.62	0.2	-7.83	-0.3	-13.58	-0.5	4.46	0.2
Wetland	52.58	1.8	24.26	0.8	-52.21	-1.7	25.38	0.9	55.14	1.8
Built up	-17.98	-0.6	-15.20	-0.5	6.07	0.2	-3.82	-0.1	-5.02	-0.2
Bare surface	-34.47	-1.2	57.80	1.9	-108.31	-3.6	8.01	0.3	8.02	0.3

(-) Area and percentage decrease (+) Area and percentage increase

4.4 Land use/land cover transitions and rates of change

Change detection analysis in this study was determined using the transition matrices and the annual rate of change in land use/land cover from 1985 to 2023, 1985 to 1995, 1995 to 2005, 2005 to 2015 and 2015 to 2023. Diagonal values represent unchanged area for a given land cover type during the transition period. Among the largest area transitions between 1985 and 2023, about 46% of the 1985 woodland cover was converted to subsistence farmland, 10% of the woodland cover to commercial agriculture and only 20% of the 1985 subsistence farmland cover was transformed into woodland. Land cover types with the largest area that remained unchanged were tropical high forest-well stocked by 63%, subsistence farmland by 54%. Land cover transitions between 1985 and 1995 presented in Table 10 indicate that about 34% of the 1985 woodland cover transitioned to plantation forest, 26% of the 1985 woodland cover transitioned to subsistence farmland, and 39% of the 1985 tropical high forest low stocked cover transitioned to tropical high forest well stocked. Land cover types with the largest unchanged area included 87% tropical high forest-well stocked, and 45% subsistence farmland shows the transition matrix between land cover types from 1985 to 2023. Diagonal values represent unchanged area for a given land cover type during the transition period. Among the largest area transitions between 1985 and 2023, about 46% of the 1985 woodland cover was converted to subsistence farmland, 10% of the woodland cover to commercial agriculture and only 20% of the 1985 subsistence farmland cover was transformed into woodland. Land cover types with the largest area that remained unchanged were tropical high forest-well stocked by 63%, subsistence farmland by 54%. Land cover transitions between 1985 and 1995 presented in Table 10 indicate that about 34% of the 1985 woodland cover transitioned to plantation forest, 26% of the 1985 woodland cover transitioned to subsistence farmland, and 39% of the 1985 tropical high forest low stocked cover transitioned to tropical high forest well stocked. Land cover types with the largest unchanged area included 87% tropical high forest-well stocked, and 45% subsistence farmland.

Table 9: Land use/cover transition matrix for the period 1985 and 2023 (in sq. km), Kikuube district.

1985-2023 (Total Land Area: 2992.30 km^2)

Land use/cover 1985 (Initial state)	Land use/cover 2023 (Final state)											
	Cover*	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**WT**	**BU**	**BS**
	PF	**4.71**	14.57	3.38	37.39	3.40	0.56	41.30	13.50	16.58	1.14	0.52
	THF-WS	5.53	**197.44**	13.35	42.36	3.38	0.58	25.70	13.13	10.06	0.77	0.75
	THF-LS	5.46	36.70	**16.33**	44.84	3.49	0.85	51.47	25.70	19.48	1.56	0.65
	WD	10.93	6.09	28.59	**154.40**	16.23	5.60	299.97	62.81	50.40	11.70	8.19
	SH	0.10	0.00	0.03	2.46	**58.64**	6.98	22.58	2.85	2.83	8.68	2.91
	GS	0.00	0.00	0.00	0.34	12.27	**58.65**	7.97	0.40	0.08	10.79	4.08
	SF	3.39	0.44	3.12	64.81	8.58	1.90	**173.76**	30.97	20.32	8.50	3.96
	CA	0.32	0.12	1.43	3.82	0.28	0.02	2.53	**6.59**	4.74	0.08	0.02
	WT	2.29	2.61	4.06	24.20	2.33	0.27	26.91	12.14	**29.09**	0.91	0.32
	BU	0.49	0.04	0.29	5.90	7.74	3.89	32.97	5.60	3.45	**10.07**	4.17
	BS	0.05	0.00	0.13	1.91	9.90	9.36	33.24	2.27	0.70	2.45	**6.76**

*PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface. The highlighted diagonal numbers in bold represent the percentage land cover that did not change.

Table 10: Land use/cover transition matrix for the period 1985 and 1995 (in sq. km), Kikuube district.

		Land use/cover 1995 (final state)										
	Cover*	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**WT**	**BU**	**BS**
Land use/cover 1985 (Initial state)	**PF**	**11.32**	36.71	32.22	19.56	1.16	0.30	14.21	3.74	15.79	0.51	3.06
	THF-WS	0.40	**273.54**	23.46	10.21	0.06	0.00	0.05	0.53	4.66	0.02	0.14
	THF-LS	2.82	80.95	**89.58**	16.84	0.02	0.08	0.69	7.56	7.61	0.28	0.12
	WD	221.55	10.26	48.23	**51.68**	5.59	12.51	168.90	20.62	50.74	12.63	52.14
	SH	2.75	0.12	0.05	0.47	**45.96**	10.20	23.64	0.03	0.80	4.76	15.68
	GS	0.00	0.00	0.00	0.00	12.02	**50.68**	12.73	0.00	0.00	11.71	6.12
	SF	69.55	0.17	5.43	18.45	9.18	9.58	**145.57**	8.49	12.28	16.54	24.42
	CA	0.37	0.49	7.92	1.00	0.12	0.01	0.56	**4.67**	4.50	0.21	0.08
	WT	13.19	6.75	24.41	14.02	0.50	0.25	4.27	6.54	**31.91**	0.42	2.90
	BU	5.41	0.04	0.23	1.08	8.73	9.86	28.65	0.78	1.04	**10.14**	8.28
	BS	1.43	0.00	0.05	0.21	11.18	6.20	32.46	0.04	0.10	2.25	**11.62**

*PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface. The highlighted diagonal values represent unchanged area for each land cover.

Land cover transitions from 1995 to 2005 as presented in *Table 11*. The largest area transitions as proportion of the 1995 corresponding land cover types included 54% of the plantation forest cover converted to woodland, 35% of subsistence farmland converted woodland and 30% of tropical high forest-well stocked converted to Tropical high forest-low stocked. Land cover types with the largest unchanged area were 49% of tropical high forest-well stocked and 45% of subsistence farmland.

Land cover transitions between 2005 and 2015 are presented in *Table 12*. The largest transitions to other land use types as a proportion of the 2005 area were 55% of woodland converted to subsistence farmland, 31% of tropical high forest low stocked converted to tropical high forest well stocked, and 10% of subsistence farmland converted to woodland. Land cover types with the largest unchanged area were 83% tropical high forest-well stocked, and 67% subsistence farmland.

Area transitions between 2015 and 2023 presented in *Table 13* indicate that among the largest transitions, 21% of the 2015 subsistence farmland cover transitioned to woodland, 10% of the 2015 subsistence farmland cover transitioned to commercial agriculture, 31% of the 2015 woodland cover to subsistence farmland. Land cover types with the largest unchanged area were 77% tropical high forest-well stocked and 55% subsistence farmland.

Table 11: Land use/cover transition matrix for the period 1995 and 2005 (in sq. km), Kikuube district.

		Land use/cover 2005 (final state)										
	Cover*	PF	THF-WS	THF-LS	WD	SH	GS	SF	CA	WT	BU	BS
Land use/cover 1995 (Initial state)	PF	**12.29**	0.42	13.54	176.67	0.40	2.08	86.30	17.31	11.64	5.05	3.09
	THF-WS	32.60	**198.88**	122.95	34.01	0.07	0.77	9.24	3.91	3.31	1.20	2.10
	THF-LS	22.08	19.65	**85.16**	65.15	0.06	1.39	16.82	13.03	3.71	2.19	2.33
	WD	8.99	6.91	20.82	**55.14**	0.26	0.81	26.57	6.26	4.93	1.83	1.00
	SH	0.05	0.03	0.02	4.59	**42.00**	12.15	22.34	0.35	3.81	8.36	0.54
	GS	0.26	0.02	0.20	9.52	14.18	**50.10**	12.93	0.94	0.88	10.13	0.51
	SF	2.35	0.15	2.75	151.52	19.06	12.51	**194.97**	13.68	13.40	17.71	3.61
	CA	2.45	0.60	8.55	22.16	0.05	0.57	8.17	**6.90**	1.24	1.33	1.00
	WT	5.55	3.61	12.03	51.57	1.60	0.50	20.49	5.26	**26.81**	1.40	0.59
	BU	0.22	0.01	0.20	10.65	5.21	12.57	15.50	2.80	1.05	**10.89**	0.35
	BS	1.23	0.08	1.45	40.05	12.36	2.82	51.51	2.52	6.38	4.97	**1.13**

*PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface. The highlighted diagonal values represent unchanged area for each land cover.

Table 12: Land use/cover transition matrix for the period 2005 and 2015 (in sq. km), Kikuube district.

		2015 (final state)										
	Cover*	PF	THF-WS	THF-LS	WD	SH	GS	SF	CA	WT	BU	BS
2005 (Initial state)	PF	**4.96**	11.53	9.00	14.34	1.43	0.43	33.85	5.04	5.81	1.15	0.54
	THF-WS	2.54	**190.40**	11.23	13.67	0.81	0.10	8.33	1.11	1.94	0.14	0.08
	THF-LS	5.75	81.98	**56.96**	32.76	2.60	0.85	58.82	14.25	9.50	2.37	1.86
	WD	14.84	5.66	47.59	**112.62**	14.99	4.02	342.73	27.19	31.60	12.73	7.07
	SH	0.12	0.07	0.13	3.22	**60.75**	10.11	14.13	1.37	3.61	5.71	2.32
	GS	0.20	0.01	0.38	2.42	15.14	**53.20**	11.63	0.85	0.80	12.77	1.34
	SF	7.51	0.39	8.34	48.27	35.37	2.95	**311.23**	17.74	17.91	11.28	4.20
	CA	1.57	0.11	4.51	8.35	1.83	0.36	38.98	**12.68**	2.20	1.82	0.57
	WT	1.27	1.11	1.92	14.36	4.857	0.38	20.19	3.35	**27.10**	0.98	1.70
	BU	0.44	0.08	1.01	3.75	14.30	7.11	22.13	2.27	1.64	**12.26**	0.49
	BS	0.27	0.00	0.32	1.49	1.09	0.38	9.35	2.25	0.50	0.43	**0.21**

*PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface. The highlighted diagonal numbers in bold represent the percentage land cover that did not change.

Table 13: Transition matrix between 2015 and 2023 in sq. km.

	2023 (final state)											
2015 (Initial state)	**Cover***	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**WT**	**BU**	**BS**
	PF	**6.77**	1.76	0.62	14.82	0.70	0.12	7.54	3.07	3.51	0.36	0.21
	THF-WS	5.35	**225.67**	14.37	28.29	2.09	0.37	7.77	4.42	1.97	0.40	0.66
	THF-LS	4.28	20.02	**39.03**	32.24	1.82	0.83	23.20	9.97	7.98	0.56	1.46
	WD	6.96	9.55	9.51	**78.94**	7.60	2.07	78.34	21.62	35.00	2.11	3.55
	SH	0.40	0.34	0.35	5.82	**74.43**	13.07	42.55	7.26	4.82	5.77	2.98
	GS	0.24	0.01	0.03	1.42	7.34	**50.07**	6.67	1.29	0.74	10.50	1.58
	SF	8.04	0.24	2.54	179.20	24.17	12.16	**480.02**	83.48	49.74	13.86	17.93
	CA	0.76	0.05	2.77	15.83	2.39	0.56	27.26	**26.02**	10.05	1.35	1.06
	WT	1.49	0.33	1.25	18.57	5.67	0.25	22.03	11.85	**40.14**	0.63	0.41
	BU	0.37	0.02	0.13	4.72	4.66	7.86	15.82	4.14	1.38	**20.43**	2.13
	BS	0.17	0.02	0.13	2.58	4.52	1.30	7.23	2.87	2.43	0.73	**0.35**

*PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface. The highlighted diagonal values represent unchanged area for each land cover.

The percentage annual rates of change for the land cover classes for 1985-1995, 1995-2005, 2005-2015, 2015-2023, and 1985-2023 are presented in *Table 14*. For 1985-2023, woodland and tropical high forest -low stocked land cover types had the largest annual negative rate of change with -0.24% and -0.119% respectively. Land cover with largest annual gain rate of change was subsistence farmland and commercial agriculture with 0.351% and 0.137% respectively. Woodland has the largest annual loss rate of -1.74% between 1985 and 1995; moderate annual gains were noted for the plantation, subsistence farmland and tropical rain forest-well stocked at a rate of 0.64%, 0.37% and 0.32% respectively. For 1995-2005, Plantation Forest and Tropical High Forest – Well Stocked had the largest annual loss rate of -0.8% and -0.6%; largest annual gain were in the woodland land cover type at the rate of 1.63%. The largest annual loss rate between 2005 and 2015 were woodland and tropical high forest low stocked with -1.22% and -0.42% respectively; subsistence farmland has the largest annual gains of 1.36%. For 2015-2023, the largest loss rate was -0.64% and -0.3% for subsistence farmland and tropical high forest-low stocked respectively. The largest annual gains were at a rate of 0.53% and 0.37% for woodland and commercial agriculture respectively.

Table 14: Percentage annual rates of change for each land cover class for 1985-1995, 1995-2005, 2005-2015, 2015-2023, and 1985-2023 (% per annum)

	Rate of change (% per annum)				
LULC class	**1985-2023**	**1985-1995**	**1995-2005**	**2005-2015**	**2015-2023**
Plantation forest	-0.091	0.64	-0.80	-0.16	-0.02
Tropical high forest-well stocked	-0.048	0.32	-0.60	0.20	-0.14
Tropical high forest-low stocked	-0.119	0.08	0.12	-0.42	-0.30
Woodland	-0.240	-1.74	1.63	-1.22	0.53
Shrubland	0.025	-0.04	0.02	0.20	-0.10
Grassland	-0.005	0.02	0.00	-0.06	0.04
Subsistence farmland	0.351	0.37	0.11	1.36	-0.64
Commercial agriculture	0.137	0.11	0.07	0.05	0.37
Open water	-0.009	0.02	-0.03	-0.05	0.02
Wetland	0.046	0.08	-0.17	0.08	0.23
Built up	-0.016	-0.05	0.02	-0.01	-0.02
Bare surface	-0.030	0.19	-0.36	0.03	0.03

4.5 Vegetation analysis

Vegetation changes in the study area are illustrated in *Figure 24* as NDVI minimum and maximum values. For 1985, 1995, 2005, 2015 and 2023 images, there is a linear gradual increase in maximum NDVI values (0.44, 0.46, 0.51, 0.49 and 0.5 respectively) with the peak value in 2005. Minimum NDVI values have a gradual linear decline across the images in the study period (-0.0274, -0.0576, -0.0629, -0.0749 and -0.0692 respectively). Comparison of the overall minimum value is -0.0692, maximum value is 0.51 and extremes of -1,1 for minimum, maximum NDVI values, the study area has moderately health vegetation. The results show as general increase in vegetation in the study area.

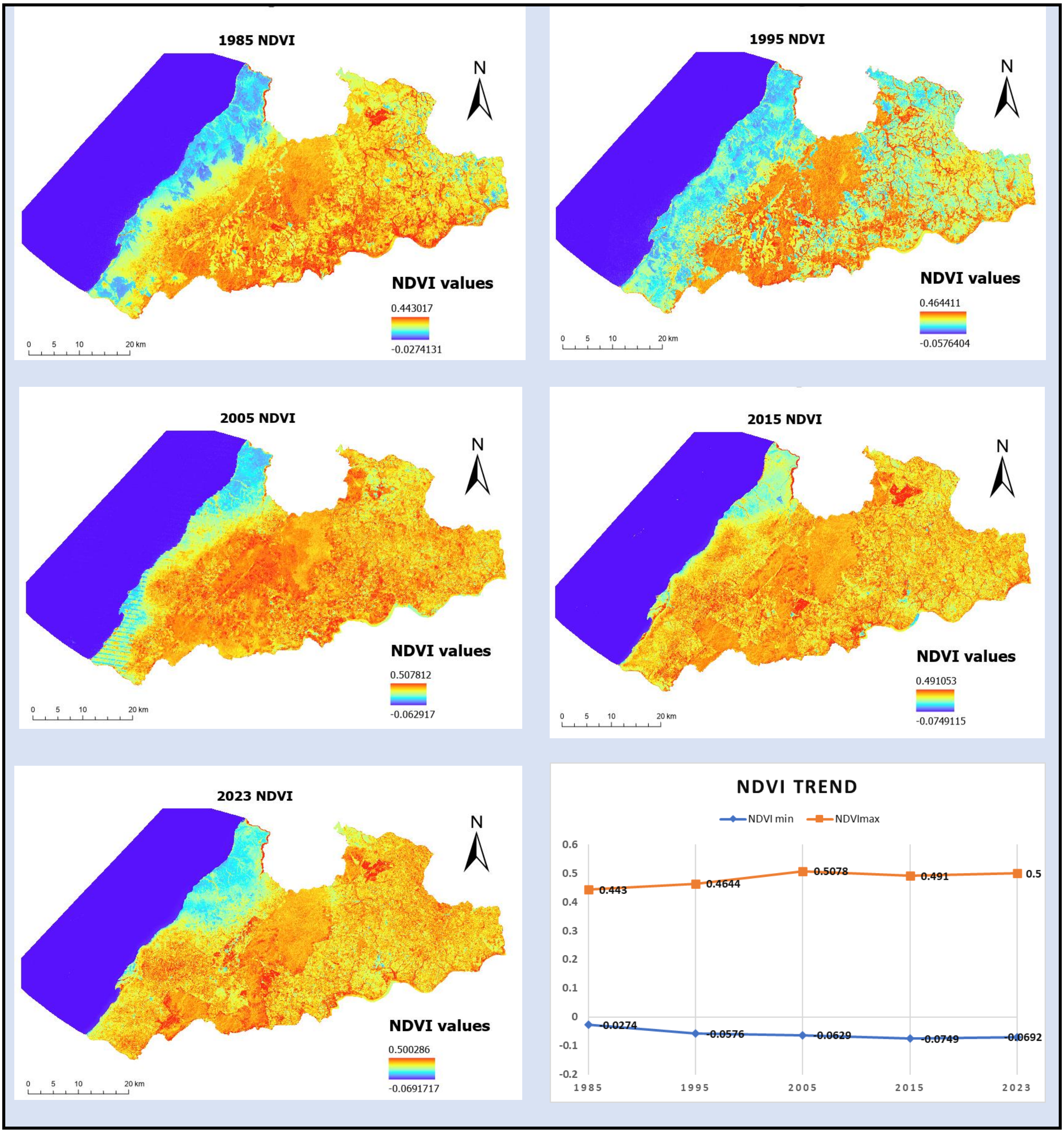


Figure 24: Vegetation analysis represented by minimum and maximum range NDVI values for 1985, 1995, 2005, 2015 and 2023. The inset shows trends across minimum and maximum values.

CHAPTER FIVE

DISCUSSION

5.1 Accuracy assessment of land use/land cover maps

Image classification during LULC analysis is only complete when the accuracy is known (Congalton, 1991). The results of the accuracy assessment for the five classified maps and the 12 (twelve) land cover classes used in this study had an overall accuracy of over 85% which is required to validate the classified maps for further quantitative analysis according to Anderson, (1976). The rating criteria for the kappa statistics used by Tewabe & Fentahun, (2020) indicates an excellent strength of agreement of classified and ground-truth data. The low user's accuracy for classes such as built up area for the 1985 map and the low producer's accuracy for the built up and plantation forest for the 2023 map may be attributed to heterogeneousness of pixels caused by the 'salt and pepper' effect where pixels from different land cover classes have very similar spectral properties and cannot be differentiated by the maximum likelihood algorithm used for this study (Mustapha et al., 2010).

5.2 Nature and extent of land use and land cover in Kikuube district

The discussion of the nature and extent relates to the types and quantities of changes in land use and land cover in the district. Throughout the study period (from 1995-2023), open water covered about 29% of Kikuube district. This is largely Lake Albert which was also included as a land cover class in this study (Briassoulis, 2020; Di Gregorio, 2005). As expected, the area covered by Lake Albert remained more or less constant over the years. Lake Albert has several landing sites such as Buhuka flats where fishing is a major economic livelihood activity (CNOOC Uganda, 2019). Other than the open water, the most dominant land cover types were woodland, which covered at least 20% in 1985 and 2005, and subsistence farmland which covered at least 24% in 2015 and 2023. Dominance of woodland and subsistence farmland at the expense of tropical high forest land cover is evidence of anthropogenic processes - such as forest degradation and deforestation which had great influence on land cover over the study period (Meyer & Turner, 1996; Turner et al., 1995).

Land cover types with the lowest areal extent throughout the study period were commercial agriculture for 1985 and 1995, and bare surface for 2005, 2015 and 2023. Commercial agriculture in Kikuube district between 1985 and 1995 was represented by mainly tea plantations in Kisaru and Bugambe tea estates established in the 1960s, covering a relatively small portion of the study area (McLeod Russel Uganda, 2020). However, the introduction and expansion of sugar cane growing in Kikuube district has increased the area under commercial agriculture (Bahati et al., 2022; Mwavu & Witkowski, 2008).

5.3 Changes, transitions, and rates of change in land use/land cover

For the entire study period (1985-2023) the largest decline was observed in woodland which on average declined by -0.24% per annum followed by tropical high forest-low stocked which declined by -0.12% per annum. As observed in the transition matrix for 1985 to 2023, most of the woodlands were converted to subsistence farmland, and commercial agriculture while tropical forest-low stock was converted to subsistence farmland and woodland. The largest increase in land cover was subsistence farmland at 0.35% per annum and commercial agriculture at 0.137% per annum. These findings indicate that through conversion and modification of land cover types; agricultural extensification, deforestation and forest degradation have been experienced in woodlands whereas agricultural intensification in subsistence farmland (Clark & Jones, 1997; Skole, 1994). Similar studies in the Albertine region on land use change have all reported a decline in woodland area (Ddamulira, 2021; Kusiima, Egeru, Namaalwa, Byakagaba, Mfitumukiza, & Mukwaya, 2022; Twongyirwe et al., 2015, 2022) and expansion of both subsistence farmland (Blerk et al., 2021) and commercial agriculture (Kusiima, Egeru, Namaalwa, Byakagaba, Mfitumukiza, & Mukwaya, 2022; Mwavu & Witkowski, 2008).

Land cover changes between 1985 and 1995 indicate that the largest decline in land cover was woodland at -1.74% per annum and the largest increase in land cover was plantation forestry at an annual rate of 0.64% and subsistence farmland at 0.37% per annum. During this period, most of the woodland was converted to plantation forest and subsistence farmland. Restoration of political stability in 1986 enabled Uganda to host more than 300,000 refugees from Sudan of which 60,000 refugees were hosted by Kikuube district in Kyangwali refugee settlement until 1994 when refugees of Rwandan origin were repatriated to Rwanda reducing the population to a few thousands (Foote et al., 1993; Lomo et al., 2001). Thus, fuelwood extraction and agricultural expansion by the high refugee population density could likely have resulted to deforestation and degradation.

Land cover changes between 1995 and 2005 indicate that the largest decline in land cover was plantation forest at -0.8% per annum; followed by tropical forest-well stocked at -0.6% per annum and the largest increase was woodland at 1.63% per annum. The transition matrix for 1995 to 2005 shows that the largest proportion of plantation forest cover was converted to woodland and subsistence farmland. The largest proportion of tropical high forest-well stocked cover was converted to tropical high forest low stocked. Transition area gains for woodland were largely from plantation forest and subsistence farmland, an indicator of massive forest degradation and deforestation. In 1997, the government of Uganda's efforts for oil prospecting and appraisal resumed through production sharing agreements with different oil companies such as Heritage oil and gas Ltd, Tullow Oil PLC in Exploration Area 2 and 3 where Kikuube district lies yielded positive results until 2005 when significant deposits were formally confirmed by the Ugandan government (Kashambuzi, 2010; PAU, 2022). Additionally, the government's adoption of the Self-Reliance Strategy; a policy for which Kyangwali refugee settlement, Kikuube district allocated plots of land for household food production to achieve integration and empowerment according to the strategy (Betts, 2021). Furthermore, the National Forest policy 2002, and the National forestry and tree planting Act, 2003 strengthened conservation and sustainable extraction of forest resources from central forest reserves such as Bugoma CFR and Wambabya CFR found in Kikuube district which likely minimized destruction of natural land cover in the study area (Turyahabwe & Banana, 2008). Therefore, population growth from in-migration following successful oil exploration findings, land fragmentation from agricultural expansion for refugee land allocation, and fuel wood extraction by refugees are likely to have driven forest degradation of tropical forest cover and deforestation of plantation forest.

Land cover changes between 2005 and 2015 indicate that the largest decline was woodland (-365.80 km^2) at -1.2% per annum, and tropical forest-low stocked (-126.3 km^2) at -0.4% per annum and the largest increase was subsistence farmland (406.21 km^2) at 1.36% per annum. The transition matrix for 2005 to 2015 shows that the largest proportion of woodland forest cover was converted to subsistence farmland. This was a period of policy and legal framework development of sugar, refugees, and oil development in Uganda. The 2010 Sugar Policy paved way for regulation to the rapidly growing sugar cane sector that saw a rise in out growers to supplement production quantities of major sugar companies. Enacting the 2006 Refugee Act and the Refugees Regulation Act 2010 aimed at reducing refugee populations in settlements by allowing refugees the right to work and freedom of movement. Thus, the population growth of Kyangwali refugee settlement remained low with a population increase from 20,000 to 26,000 refugees between 2006 and 2015 (Gianvenuti et al., 2020; The Refugees Regulations, 2010; The Refugee Act 2006, (Uganda), 2006; Omata & Kaplan, 2013). Additionally, legislation governing oil resources included the National Oil and Gas Policy, 2008; the Petroleum (Exploration, Development, Production) Act, 2012 and the Petroleum (Refining, Conversion, Transmission and Midstream Storage) Act, 2013 regulated all the upstream and midstream oil activities which mainly involved continued oil exploration, construction of oil roads, and land acquisition and resettlement of project affected persons and continued in-migration which may be attributed to deforestation and degradation in woodland tropical forest cover and the increase in agricultural cover.

Land cover changes between 2015 and 2023 indicate that the largest decline in land cover was subsistence farmland (-152.95 km^2) at -1.64% per annum and the largest increase was woodland (127.19 km^2) at 0.53% followed by commercial agriculture at 0.37% per annum. The transition matrix for land cover flows from 2015 to 2023 indicate that woodland cover transition gains in area were mostly from subsistence farmland, tropical high forest-well stocked, and tropical high forest-low stocked. During this period, Kikuube district registered the highest peak of the refugee population with over 130,000 refugees in 2023. This growth was due to the influx from the DRC in 2017 that doubled the refugee population from 35,000 to 85,000 by 2018 (Gianvenuti et al., 2020). The ReHoPE, and CRRF policy strategies designed to manage the refugee population were proposed by the government of Uganda. However, mismanagement of allocated funds through corruption was a policy failure that may have resulted to unplanned LULC changes (Betts, 2021). Additionally, rapid growth of commercial agriculture is attributed to growth and expansion of sugar cane farming by Hoima sugar Ltd in Kikuube district. The 2020 Sugar Act was passed to promote sugar cane farming by large companies and control sugar prices. However, the weakness of the 2020 Sugar Act due to inadequate regulation of out-grower schemes may contribute to unplanned immigrant labour. The transition of tropical forest to woodland may be attributed to forest degradation from encroachment and increased demand for fuelwood by refugees (Blerk et al., 2021) and out-grower schemes involved in sugarcane growing (Bahati et al., 2022). Conversion of subsistence farmland to woodland may be attributed to expansion of sugar cane plantations by Hoima sugar works on formally agricultural woodland through acquisition of 22 square miles leased from Bunyoro Kitara Kingdom (Jjingo, 2020; Kivabulaya, 2016). Therefore, agricultural expansion, fuelwood extraction from population growth, policy factors are more pronounced for refugees and commercial agriculture than oil development.

The land cover with the least change is grassland. This may be attributed to the fact that the land cover type dominantly lies within Kabwoya wildlife reserve which is a protected area (Uganda Wildlife Authority, 2023). The maximum index for vegetation increased from 0.44 to 0.5 whereas the minimum index decreased from -0.0274 to -0.692 between 1985 and 2023. These results show that the vegetation increased in Kikuube district over the study period. The lower vegetation index values for the area along the escarpment and the rift valley floor in comparison with the top of the escarpment show that the pattern of vegetation distribution is influenced by the average annual rainfall and temperature variations within Kikuube district (CNOOC Uganda, 2019).

5.4 Oil exploration, refugee population dynamics and commercial agriculture as primary drivers of LULC change.

Land use/land cover changes observed in Kikuube district emanate from historical events which have influenced decisions on land use both directly and indirectly by landowners (Briassoulis, 2020). Major historical events that have shaped land use in Kikuube district revolve around oil exploration and development, refugee population dynamics and commercial agriculture. A review of research literature and available historical records have highlighted different drivers of change in land use and land cover in Kikuube district. Geist & Lambin, (2002) noted that these factors can include, demographic changes, government policies, institutional factors, economic factors, socio-cultural factors, technological factors interacting at different spatial and temporal scales to cause land use changes. *Figure 25* show how oil exploration, refugee population dynamics and commercial agriculture are linked to the land use/land cover change framework.

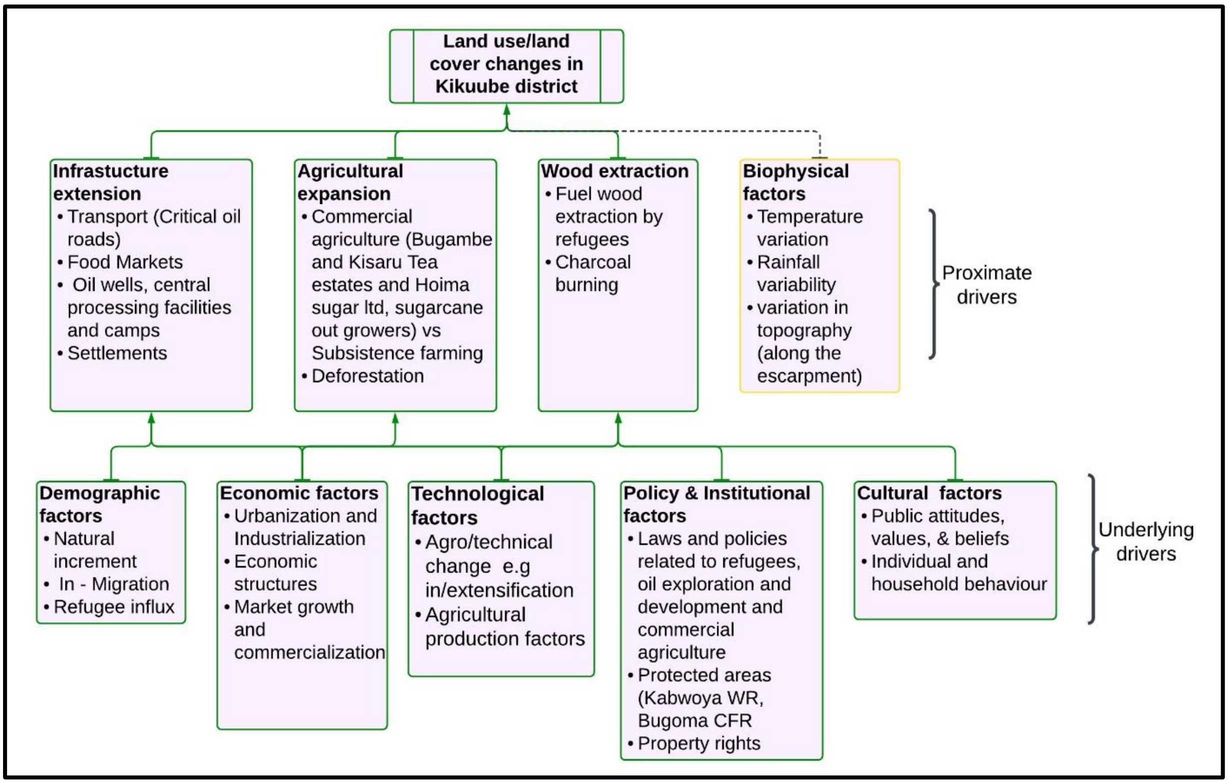


Figure 25: Linking oil exploration, refugee population dynamics and commercial agriculture to the land use/land cover change framework used for this study.

Population growth in Kikuube district increased at an annual rate of 5% (Uganda Bureau of Statistics, 2017) while the proportion of refugees increased from 12% to 25% between 2014 and 2020 (UNHCR, 2021, 2022a). Studies in the Albertine region by have highlighted human population growth due to the refugee influx in Kyangwali refugee settlement (Blerk et al., 2021), in-migration for oil opportunities especially since 2006 when the Ugandan government commercialized oil resources (Ddamulira, 2021; Dowhaniuk et al., 2018) and resettlement of displaced communities to less populated areas for oil infrastructure development (Ssekandi et al., 2017). Commercial sugar cane growing contributes to population growth by attracting less skilled labour to work in sugar cane plantations (Mwavu & Witkowski, 2008). High population density of 171 people per km^2 in Kikuube district increases pressure of natural resources causing land fragmentation, agricultural expansion, demand for wood and an increase in human settlement (Bahati et al., 2022).

Globalization and market demand for sugar and petroleum products has shaped land use change in Kikuube district. Existing market demand for sugar in East Africa and the world has led to increased investments in sugar production by expansion of Hoima sugar Ltd in Kikuube district in 2015 for sugar cane growing and growth of out-grower schemes (Bahati et al., 2022; Kivabulaya, 2016; The Independent, 2023).

Several policies and laws may have impacted land use decisions especially those directly related to oil exploration, forestry, land use, commercial agriculture, and refugees. The discovery of commercially viable oil deposits in Uganda led to development of legislation starting with the National Oil and Gas policy, 2008; the subsequent petroleum laws followed such as the Petroleum (Exploration, Development and Production) Act, 2013 to regulate petroleum activities and establishment of the regulatory institution- The Petroleum Authority of Uganda. The Petroleum (Refining, Conversion, Transmission and Midstream Storage) Act, 2013 to sustainably manage midstream activities in the oil and gas sector. Refugee legislation in Uganda has evolved throughout the study period, with Uganda already party to the UN Convention for Refugees ratified in 1978, the Self Reliance Strategy policy, 2000; the National Refugee act, 2006; and the Refugees Regulations act, 2010. The integration approach of these policies and laws makes land use/land cover changes based not only on refugee settlements alone but the entire host population. The 1938 Sugar Control Act has long been used to regulation sugar exports outside East Africa. However, increasing sugar demand led to growth of out-growers thus requiring a new policy-The 2010 National sugar policy and later in the 2020 Sugar Act that created market zones, sugar cane prices and a regulatory body-The National Sugar Board. It is also evident that land cover types within protected areas; Bugoma central forest reserve and Kabwoya wildlife reserve have the least land use/land cover changes save for policy failures that may be attributed to illegal logging and encroachment for fuelwood collection and agricultural expansion.

Topography and climate are observed to be significant factors influencing the distribution of land cover types. The rift valley floodplain generally received less than mean annual rainfall and high mean temperatures. This is further supported by the low vegetation distribution from NDVI maps from mainly grassland and shrubland along the escarpment and the floodplain compared to the top of the escarpment (CNOOC Uganda, 2019).

In summary, this study has evidently highlighted the influence of oil development activities, refugee population changes and commercial sugarcane growth on LULC change. However, the complex nature of the causes of LULC changes and the feedback mechanisms for land use decisions makes it challenging to identify the most significant driver of change accurately. With oil development at the midstream stage, several activities are yet to be implemented, such as the construction of the feeder and the East African crude oil pipelines, construction of some oil roads, oil production in the Mputa and Nzizi wells, and subsequently the decommissioning stage. Thus, LULC changes from oil development are yet to be more pronounced and cumulative. LULC changes from refugee population dynamics seem to be unpredictable as this depends on influxes from other countries but since refugee policies support integration, direct refugee impacts on land use change could be minimized. Even though sugarcane growing is relatively new in Kikuube district, the 2020, sugar act governing sugar having been cited to be silent on out-grower schemes, makes it a challenge to manage LULC changes outside largescale commercial plantations (Mbowa et al., 2022).

Reflections

The increasing demand of critical resources, growth of global market demand for sugar and exploitation of oil resources require increased presents challenges associated with sustainable management of associated LULC changes while meeting human needs. This study has revealed that while forest degradation and deforestation from agricultural expansion, wood extraction and infrastructure extension have caused LULC changes, there was an increase in the vegetation the increasing NDVI values across the study period.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

This study quantified LULC changes in Kikuube district between 1985 and 2023 with a focus on LULC changes from oil development, Refugee population dynamics and commercial sugarcane growing all interacting across space and time. This study had three main research questions as summarized as follows.

What is the nature and extent of land use/land cover in 1985, 1995, 2005 and 2023 Kikuube district?

Findings indicated that Kikuube district has up to twelve different land use/land cover types which include plantation forest, tropical high forest well stocked, tropical high forest low stocked, woodland, shrubland, grassland, wetland, open water, subsistence farmland, commercial agriculture, built up, and bare surface on an area of 2992 km^2 based on the NFA land classification system (NBS, 2003). Most (about 30%) of the district is covered by open water – part of Lake Albert. This is followed by woodland at 22% and 21% in 1985 and 2005 respectively; and subsistence farmland which has increased over the years from 14% to 29% and 24% in 1995, 2015 and 2023 respectively. Land cover types with the lowest percentage coverage are commercial agriculture, mainly, sugar cane growing at 0.6% and 1.7% in 1985 and 1995 respectively and bare surface at 0.5%, 0.8% and 1% in 2005, 2015 and 2023 respectively. Land use change has been through both conversion and modification in a form of deforestation, forest degradation, (re)afforestation, agricultural extensification.

What spatial/temporal changes have occurred in land use and land cover between 1985-1995, 1995-2005, 2005-2015 and 2015-2023 in Kikuube district?

LULC changes throughout the study period revealed a decline in natural land cover types and an increase in human/induced land cover types. The largest overall decline in land use was observed to be in woodlands, tropical forest cover. Subsistence farmland and commercial farmland were observed to increase throughout the study period. More stable land uses were mainly open-water, grasslands, Shrubland and bare surface. Additionally, the magnitude of land use and land cover changes generally decreased across the study time periods; 1985-1995>1995-2005>2005-2015>2015-2023. However, Kikuube district's greenness increased across the study period.

What are the primary drivers of land use/land cover change between 1985 and 2023 in Kikuube district?

LULC changes between 1985 and 2023 have been shaped by oil exploration and development activities, refugee population changes and growth of sugarcane growing. Much as oil development has largely transitioned from the upstream to the mid-stream phase in Kikuube district, oil development has driven land cover changes through policy change, population growth through in migration, and displacement, infrastructural extension through construction of camps, construction of critical oil roads. Much as refugee policies, laws and strategies has been generally more proactive to manage refugee populations through integration and self-reliance, the refugee population growth rate has been shaped mainly by refugee influxes from DRC and South Sudan (The Refugees Regulations, 2010; The Refugee Act, 2006). Population driven land use change has resulted to agricultural expansion and fuelwood extraction (Lambin et al., 2003). Thus, accounting for the decline in natural land cover and increase in subsistence farmland in Kikuube district. The growth and expansion of sugarcane growing by Hoima sugar ltd and out growers between 2010 and 2015 in Kikuube district has mainly been influenced by external market structures in which the high regional demand for sugar drives growth (Kivabulaya, 2016; The Independent, 2023). Unplanned land use changes from policy failure with the 2020 sugar act not adequately regulating out grower schemes can lead to poverty driven deforestation where immigrant workers paid low wages turn to natural resources for their livelihoods (Mbowa et al., 2022).

A key contribution of this study is twofold; Firstly, is to document LULC changes with a focus on multiple drivers and how their historical development influences how they interact across space and time. These were oil development, refugee population changes and sugarcane growing; and finally, to document LULC changes in Kikuube district before 2006, when commercial oil reserves were declared. It is recommended that further research should focus on two aspects; household perceived drivers of change and implications of land use/land cover changes in Kikuube district and using object-based classification that might produce reduced errors in classification since it not does not produce the salt and pepper effect from the maximum likelihood classifier algorithm used in this study.

References

Aboda, C., Vedeld, P. O., Byakagaba, P., Lein, H., & Nakakaawa, C. A. (2022). Household capacity to adapt to resettlement due to land acquisition for the oil refinery development project in Uganda. *Environment, Development and Sustainability*, 1–23. https://doi.org/10.1007/S10668-022-02607-W/TABLES/7

Ampim, P. A. Y., Ogbe, M., Obeng, E., Akley, E. K., & MacCarthy, D. S. (2021). Land cover changes in Ghana over the past 24 years. *Sustainability*, *13*(9), 4951.

Anderson, D. M., & Browne, A. J. (2011). The politics of oil in eastern Africa. *Journal of Eastern African Studies*, *5*(2), 369–410.

Anderson, J. R. (1976). *A land use and land cover classification system for use with remote sensor data* (Vol. 964). US Government Printing Office.

Bahati, I., Martiniello, G., & Abebe, G. K. (2022). The implications of sugarcane contract farming on land rights, labor, and food security in the Bunyoro sub-region, Uganda. *Land Use Policy*, *122*, 106326. https://doi.org/10.1016/J.LANDUSEPOL.2022.106326

Betts, A. (2021). Refugees and patronage: A political history of uganda's "progressive" refugee policies. In *African Affairs* (Vol. 120, Issue 479). https://doi.org/10.1093/afraf/adab012

Black, R., & Sessay, M. (1997). Forced migration, land-use change and political economy in the forest region of Guinea. *African Affairs*, *96*(385). https://doi.org/10.1093/oxfordjournals.afraf.a007885

Blerk, L. van, Cutler, M., Hewitson, L., Hunter, J., Bamutaze, Y., Kintu, I. M., Bukenya, B., & Nakaiza, J. K. (2021). *Displaced Communities, Environmental Change and Sustainable Livelihoods in Uganda*. https://doi.org/10.20933/100001221

Briassoulis, H. (2020). *Analysis of Land Use Change: Theoretical and Modeling Approaches* (L. Scott & J. Randall (eds.)). WVU Research Repository. https://researchrepository.wvu.edu/rri-web-book

Chen, J., Zhu, X., Vogelmann, J. E., Gao, F., & Jin, S. (2011). A simple and effective method for filling gaps in Landsat ETM+ SLC-off images. *Remote Sensing of Environment*, *115*(4), 1053–1064.

Clark, J., & Jones, A. (1997). Driving forces behind European land use change: an overview. *The User Needs for More Harmonized Land Use Information at the National and EU Level. Report on the CLAUDE (Coordinating Land Use and Cover Data Analyses in Europe) Workshop*, 24–31.

CNOOC Uganda. (2019). *Kingfisher Field Development Area, Uganda: Socio-Economic Assessment*. https://www.eia.nl/projectdocumenten/00006430.pdf

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, *37*(1), 35–46.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Review ArticleDigital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing*, *25*(9), 1565–1596.

CSCO, W. W. F. and. (2017). *Safeguarding People & Nature in the East African Crude Oil*

(EACOP) Pipeline Project: A Preliminary Environmental and Socio-Economic Threat Analysis. WWF and CSCO Kampala, Uganda.

Ddamulira, R. (2021). *THE CO-EXISTENCE OF SUSTAINABLE FOREST MANAGEMENT AMIDST OIL DEVELOPMENT ANALYZING RESOURCE POLICY OPTIONS FOR UGANDA-EAST AFRICA*.

Di Gregorio, A. (2005). *Land cover classification system: classification concepts and user manual: LCCS* (Vol. 2). Food & Agriculture Org.

Dowhaniuk, N., Hartter, J., Ryan, S. J., Palace, M. W., & Congalton, R. G. (2018). The impact of industrial oil development on a protected area landscape: demographic and social change at Murchison Falls Conservation Area, Uganda. *Population and Environment*, *39*(3), 197–218. https://doi.org/10.1007/S11111-017-0287-X/FIGURES/6

Dubb, A., Scoones, I., & Woodhouse, P. (2017). The political economy of sugar in Southern Africa–introduction. In *Journal of Southern African Studies* (Vol. 43, Issue 3, pp. 447–470). Taylor & Francis.

Emery, W., & Camps, A. (2017). The History of Satellite Remote Sensing. *Introduction to Satellite Remote Sensing*, 1–42. https://doi.org/10.1016/B978-0-12-809254-5.00001-4

Feng, Q., Liu, J., & Gong, J. (2015). UAV remote sensing for urban vegetation mapping using random forest and texture analysis. *Remote Sensing*, *7*(1), 1074–1094.

Foote, K. A., Hill, K., & Martin, L. G. (1993). *Demographic change in sub-Saharan Africa*. National Academy Press Washington, DC.

Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation. *BioScience*, *52*(2). https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2

Gianvenuti, A., Jalal, R., & Kirule, J. (2020). *Assessment of Forest Resource Degradation and Intervention Options in Refugee-Hosting Areas of Western and Southwestern Uganda*. https://www.fao.org/documents/card/en/c/CA7832EN/

The Refugees Regulations, Pub. L. No. S.I. 2010 No. 9 (2010). https://www.refworld.org/docid/544e4f154.html

Group, W. B. (2016). *An Assessment of Uganda's Progressive Approach to Refugee Management*. World Bank.

Guweddeko F. (2000). Uganda's Search for Oil and Bush War Delayed Obote Drilling Oil. *Series of Two Articles in The Monitor, Kampala, November 1 and 2, 2000*.

Hoyos, L. E., Cabido, M. R., & Cingolani, A. M. (2018). A multivariate approach to study drivers of land-cover changes through remote sensing in the dry Chaco of Argentina. *ISPRS International Journal of Geo-Information*, *7*(5). https://doi.org/10.3390/ijgi7050170

Hu, Y., Dong, Y., & Batunacun. (2018). An automatic approach for land-change detection and land updates based on integrated NDVI timing analysis and the CVAPS method with GEE support. *ISPRS Journal of Photogrammetry and Remote Sensing*, *146*, 347–359. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2018.10.008

Hunt, D. (2004). Unintended consequences of land rights reform: the case of the 1998

Uganda Land Act. *Development Policy Review*, *22*(2), 173–191.

Ibem-Ezera, V. (2010). *Environmental Control in Oil & Gas Exploration & Production: A Case Study of the Niger Delta Region of Nigeria, West Africa*.

Islami, F. A., Tarigan, S. D., Wahjunie, E. D., & Dasanto, B. D. (2022). Accuracy Assessment of Land Use Change Analysis Using Google Earth in Sadar Watershed Mojokerto Regency. *IOP Conference Series: Earth and Environmental Science*, *950*(1). https://doi.org/10.1088/1755-1315/950/1/012091

Jjingo, E. (2020, October 4). *Kikuube residents tap into Hoima Sugar Ltd for improved livelihood*. The Observer. https://observer.ug/businessnews/66754-kikuube-residents-tap-into-hoima-sugar-ltd-for-improved-livelihood

Johnson, L. (2007). Assessing the impacts of energy developments and developing appropriate mitigation in the Uganda portion of the Albertine Rift. *Wildlife Conservation Society and Uganda Wildlife Authority, Kampala, Uganda*.

Kashambuzi, R. J. (2010). *The story of petroleum exploration in Uganda : 1984-2008 : a matter of faith*.

Kasozi, A. B. K. (1994). *Inequality and Violence in Uganda*. McGills-Queen’s University Press.

Kevin Butler. (2013, July 24). *Band Combinations for Landsat 8*. Imagery & Remote Sensing. https://www.esri.com/arcgis-blog/products/product/imagery/band-combinations-for-landsat-8/

Kikuube district Local government. (2023). *Population – KIKUUBE DISTRICT LOCAL GOVERNMENT*. https://kikuube.go.ug/population/

Kirimi, F., Thiong’o, K., Gabiri, G., Diekkrüger, B., & Thonfeld, F. (2018). Assessing seasonal land cover dynamics in the tropical Kilombero floodplain of East Africa. *Journal of Applied Remote Sensing*, *12*(2), 26027.

Kivabulaya, F. (2016, May 2). *President Museveni Launches New Hoima Sugar Factory :: Uganda Radio Network*. URN. https://ugandaradionetwork.com/story/president-museveni-launches-new-hoima-sugar-factory

Kusiima, S. K., Egeru, A., Namaalwa, J., Byakagaba, P., Mfitumukiza, D., & Mukwaya, P. (2022). Anthropogenic induced land use/cover change dynamics of Budongo-Bugoma landscape in the Albertine region, Uganda. *The Egyptian Journal of Remote Sensing and Space Science*, *25*(3), 639–649. https://doi.org/10.1016/J.EJRS.2022.05.001

Kusiima, S. K., Egeru, A., Namaalwa, J., Byakagaba, P., Mfitumukiza, D., Mukwaya, P., Mensah, S., & Asiimwe, R. (2022). Interconnectedness of Ecosystem Services Potential with Land Use/Land Cover Change Dynamics in Western Uganda. In *Land* (Vol. 11, Issue 11). https://doi.org/10.3390/land11112056

Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources*, *28*. https://doi.org/10.1146/annurev.energy.28.050302.105459

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., Folke, C., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F.,

… Xu, J. (2001). The causes of land-use and land-cover change: moving beyond the myths. In *Global Environmental Change* (Vol. 11, Issue 4). Pergamon. https://doi.org/10.1016/S0959-3780(01)00007-3

Liu, M. ;, Wei, H. ;, Dong, X. ;, Wang, X.-C. ;, Zhao, B. ;, Zhang, Y., Liu, M., Wei, H., Dong, X., Wang, X.-C., Zhao, B., & Zhang, Y. (2022). Integrating Land Use, Ecosystem Service, and Human Well-Being: A Systematic Review. *Sustainability 2022, Vol. 14, Page 6926*, *14*(11), 6926. https://doi.org/10.3390/SU14116926

Lomo, Z., Naggaga, A., & Hovil, L. (2001). The phenomenon of forced migration in Uganda: An overview of policy and practice in an historical context. *Refugee Law Project, Working Paper*, *1*.

Lulla, K., Nellis, M. D., Rundquist, B., Srivastava, P. K., & Szabo, S. (2021). Mission to earth: LANDSAT 9 will continue to view the world. *Https://Doi.Org/10.1080/10106049.2021.1991634*, *36*(20), 2261–2263. https://doi.org/10.1080/10106049.2021.1991634

Maciej Serda, Becker, F. G., Cleary, M., Team, R. M., Holtermann, H., The, D., Agenda, N., Science, P., Sk, S. K., Hinnebusch, R., Hinnebusch A, R., Rabinovich, I., Olmert, Y., Uld, D. Q. G. L. Q., Ri, W. K. H. U., Lq, V., Frxqwu, W. K. H., Zklfk, E., Edvhg, L. V, …)2009. (فاطمی, ح. Principles of remote sensing : an introductory textbook. *Uniwersytet Śląski*, *7*(1), 343–354. https://doi.org/10.2/JQUERY.MIN.JS

Mamdani, M. (1987). Extreme but not exceptional: towards an analysis of the agrarian question in Uganda. *The Journal of Peasant Studies*, *14*(2), 191–225.

Martiniello, G. (2021). Bitter sugarification: sugar frontier and contract farming in Uganda. *Globalizations*, *18*(3), 355–371.

Martiniello, G., & Azambuja, R. (2019). Contracting sugarcane farming in global agricultural value chains in eastern Africa: Debates, dynamics, and struggles. *Agrarian South: Journal of Political Economy*, *8*(1–2), 208–231.

Masek, J., Gao, F., Schwaller, M., & Hall, F. (2006). On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. *IEEE Transactions on Geoscience and Remote Sensing*, *44*(8), 2207–2218.

Mbowa, S., Guloba, M., Mwesigye, F., Nakazi, F., Mather, D., Bryan, E., Ogwang, A., & Atwine, B. (2022). *Revisiting Policy And Institutional Arrangements Affecting Sugarcane Outgrowers And Millers In Uganda*.

McLeod Russel Uganda. (2020). *Kisaru Tea Estate*. http://mcleodrusseluganda.com/gardens/kisaru.html

National Oil and Gas Policy for Uganda, 1 (2008). http://www.energyandminerals.go.ug/downloads/NATIONALOILANDGASPOLICYFORUGANDA.pdf

MEMD. (2017). *Progress of implementation of the National Oil and Gas Policy for Uganda*. https://bowmanslaw.com/wp-content/uploads/2017/03/NOGP-Progress-Report-Feb-2017.pdf

Meyer, W. B., & Turner, B. L. (1994). Changes in land use and land cover: a global perspective. In *Changes in land use and land cover: a global perspective*. Cambridge University Press. https://doi.org/10.2307/3060264

Meyer, W. B., & Turner, B. L. (1996). Land-use/land-cover change: challenges for geographers. *GeoJournal*, *39*(3), 237–240.

MohanRajan, S. N., Loganathan, A., & Manoharan, P. (2020). Survey on Land Use/Land Cover (LU/LC) change analysis in remote sensing and GIS environment: Techniques and Challenges. *Environmental Science and Pollution Research*, *27*, 29900–29926.

Moser, S. C. (1996). A partial instructional module on global and regional land use/cover change: Assessing the data and searching for general relationships. *GeoJournal*, *39*(3), 241–283. https://doi.org/10.1007/BF00188374/METRICS

Msoffe, F. U. (2010). *Land use change in Maasailand drivers, dynamics and impacts on largeherbivores and agro-pastoralism*.

Mulumba, D. (2014). *Humanitarian assistance and its implication on the integration of refugees in Uganda: Some observations.*

Mustapha, M. R., Lim, H. S., & Mat Jafri, M. Z. (2010). Comparison of neural network and maximum likelihood approaches in image classification. *Journal of Applied Sciences*, *10*(22), 2847–2854. https://doi.org/10.3923/JAS.2010.2847.2854

Mwavu, E. N., & Witkowski, E. T. F. (2008). Land-use and cover changes (1988–2002) around budongo forest reserve, NW Uganda: implications for forest and woodland sustainability. *Land Degradation & Development*, *19*(6), 606–622. https://doi.org/10.1002/LDR.869

Nakakaawa, C. A., Vedeld, P. O., & Aune, J. B. (2011). Spatial and temporal land use and carbon stock changes in Uganda: Implications for a future REDD strategy. *Mitigation and Adaptation Strategies for Global Change*, *16*(1), 25–62. https://doi.org/10.1007/S11027-010-9251-0/FIGURES/5

NBS. (2003). National biomass study. In *National Biomass Study Technical Report of 1996-2002.* National Biomass Study, Forest Department.

Nedd, R., Light, K., Owens, M., James, N., Johnson, E., & Anandhi, A. (2021). A synthesis of land use/land cover studies: Definitions, classification systems, meta-studies, challenges and knowledge gaps on a global landscape. *Land*, *10*(9), 994.

Ogwang, T., & Vanclay, F. (2019). Social Impacts of Land Acquisition for Oil and Gas Development in Uganda. *Land 2019, Vol. 8, Page 109*, *8*(7), 109. https://doi.org/10.3390/LAND8070109

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V, Woodcock, C. E., & Wulder, M. A. (2014). Good practices for assessing accuracy and estimating area of land change. *Remote Sensing of Environment*, *148*, 42–57.

Olofsson, P., Foody, G. M., Stehman, S. V, & Woodcock, C. E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, *129*, 122–131.

Omata, N., & Kaplan, J. (2013). Refugee livelihoods in Kampala, Nakivale and Kyangwali refugee settlements: patterns of engagement with the private sector. In *RSC Working Paper Series* (Vol. 95). https://www.rsc.ox.ac.uk/publications/refugee-livelihoods-in-kampala-nakivale-and-kyangwali-refugee-settlements-patterns-of-engagement-with-the-private-sector

Opedes, H., Mücher, S., Baartman, J. E. M., Nedala, S., & Mugagga, F. (2022). Land Cover Change Detection and Subsistence Farming Dynamics in the Fringes of Mount Elgon National Park, Uganda from 1978–2020. *Remote Sensing*, *14*(10). https://doi.org/10.3390/rs14102423

Osapiri, J. (2021). Legal incentives to diversify agricultural production in Uganda (suggesting lessons for the EAC). *KAS African Law Study Library, 7*(4), 621–630.

The Refugee Act 2006, (Uganda), (2006). https://www.refworld.org/%0Apdfid/4b7baba52.pdf

Patey, L. A. (2015). *Oil in Uganda: Hard bargaining and complex politics in East Africa* (Issue 60). OIES Paper: WPM.

PAU. (2022). *History of Petroleum Exploration in Uganda*. Petroleum Authority of Uganda. https://petroleum.go.ug/index.php/who-we-are/who-weare/petroleum-exploration-history

PEPD. (2015). *Status of licensing in the Albertine graben of Uganda*. http://www.petroleum.go.ug/uploads/resources/Status_of_Licensing_Map_2014.pdf

Plumptre, A. J., Davenport, T. R. B., Behangana, M., Kityo, R., Eilu, G., Ssegawa, P., Ewango, C., Meirte, D., Kahindo, C., & Herremans, M. (2007). The biodiversity of the Albertine Rift. *Biological Conservation*, *134*(2), 178–194.

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

Rudel, T., & Roper, J. (1997). The Paths to Rain Forest Destruction: Crossnational Patterns of Tropical Deforestation, 1975-90. *World Development*, *25*(1). https://doi.org/10.1016/S0305-750X(96)00086-1

Salemi, C. (2021). Refugee camps and deforestation in Sub-Saharan Africa. *Journal of Development Economics*, *152*. https://doi.org/10.1016/j.jdeveco.2021.102682

Schmidt, G., Jenkerson, C. B., Masek, J., Vermote, E., & Gao, F. (2013). Landsat ecosystem disturbance adaptive processing system (LEDAPS) algorithm description. In *Open-File Report*. https://doi.org/10.3133/ofr20131057

Skole, D. L. (1994). Data on global land-cover change: acquisition, assessment and analysis. *Changes in Land Use and Land Cover: A Global Perspective*, 437–471.

Song, X. P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature*, *560*(7720). https://doi.org/10.1038/s41586-018-0411-9

Ssekandi, J., Mburu, J., Wasonga, O., Macopiyo, L., Charles, F., Ssekandi, J., Mburu, J., Wasonga, O., Macopiyo, L., & Charles, F. (2017). Effects of Post Eviction Resettlement on Land-Use and Cover Change in Uganda’s Oil Exploration Areas. *Journal of Environmental Protection*, *8*(10), 1144–1157. https://doi.org/10.4236/JEP.2017.810072

Tempfli, K., Kerle, N., Huurneman, G. C., Janssen, L. L. F., Bakker, W. H., Van Der Meer, F. D., Feringa, W., Parodi, G. N., Gieske, A. S. M., Pohl, C., Gorte, B. G. H., Reeves, C. V, Grabmaier, K. A., Van Ruitenbeek, F. J., Hecker, C. A., Schetselaar, E. M., Horn, J.

A., Weir, M. J. C., Westinga, E., & Woldai, T. (2009). *Principles of Remote Sensing An introductory textbook Editors* (Klaus Tempfli, Norman Kerle, Gerrit C. Huurneman, & Lucas L. F. Janssen (eds.); 4th ed., Vol. 2). The International Institute for Geo-Information Science and Earth Observation (ITC). https://webapps.itc.utwente.nl/librarywww/papers_2009/general/principlesremotesensing.pdf

Tewabe, D., & Fentahun, T. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *Cogent Environmental Science*, *6*(1). https://doi.org/10.1080/23311843.2020.1778998

The Independent. (2023, February 10). *Hoima Sugar Limited plants cane on 6 square miles of leased land*. The Independent. https://www.independent.co.ug/hoima-sugar-limited-plants-cane-on-6-square-miles-of-leased-land/

Townshend, J., Justice, C., Li, W., Gurney, C., & McManus, J. (1991). Global land cover classification by remote sensing: present capabilities and future possibilities. *Remote Sensing of Environment*, *35*(2–3), 243–255.

Turner, B. L., Skole, D., Sanderson, S., Fischer, G., Fresco, L., & Leemans, R. (1995). *Land-Use and Land-Cover Change: science/research plan*. International Geosphere-Biosphere Programme, Stockholm; Report, 35.

Turyahabwe, N., & Banana, A. Y. (2008). An overview of history and development of forest policy and legislation in Uganda. *International Forestry Review*, *10*(4), 641–656.

Twongyirwe, R. (2015). . Forests under threat? Changes in land use and forest cover in rural western Uganda. *Cambridge University*. https://doi.org/10.17863/CAM.16446

Twongyirwe, R., Bithell, M., Richards, K. S., & Rees, W. G. (2015). Three decades of forest cover change in Uganda's Northern Albertine Rift Landscape. *Land Use Policy*, *49*, 236–251. https://doi.org/10.1016/J.LANDUSEPOL.2015.07.013

Twongyirwe, R., Fisher, E., Karungi, C., & Ndugu, N. (2022). Projected land use change in an oil-rich landscape in Uganda: A participatory modelling approach. *The Extractive Industries and Society*, *10*, 101071. https://doi.org/10.1016/J.EXIS.2022.101071

Uganda Bureau of Statistics. (2017). *The National Population and Housing Census 2014—Area Specific Profile Series: Hoima*. Uganda Bureau of Statistics Kampala, Uganda.

Uganda Investment Authority. (2019). *KIKUUBE DISTRICT Investment Profile BRIEF DISTRICT PROFILE*.

Uganda Wildlife Authority. (2023). *Kabwoya*. https://ugandawildlife.org/wildlifereserves/kabwoya/

UNHCR. (1951). *The refugee convention*. United Nations High Commissioner for Refugees. https://www.unhcr.org/sites/default/files/legacy-pdf/4ca34be29.pdf

UNHCR. (1992). *UNHCR - Persons covered by the OAU Convention Governing the Specific Aspects of Refugee Problems in Africa and by the Cartagena Declaration on Refugees (Submitted by the African Group and the Latin American Group)*. UNHCR. https://www.unhcr.org/excom/scip/3ae68cd214/persons-covered-oau-convention-governing-specific-aspects-refugee-problems.html

UNHCR. (2021, February 4). *Uganda - Refugee Statistics January 2021 - Kyangwali -*

Uganda | ReliefWeb. Reliefweb. https://reliefweb.int/report/uganda/uganda-refugee-statistics-january-2021-kyangwali

UNHCR. (2022a, July). *Country - Uganda Refugee population*. UNHCR-Uganda. https://data.unhcr.org/en/country/uga

UNHCR. (2022b, September 14). *Document - Uganda - Refugee Statistics August 2022 - Kyangwali*. UNHCR. https://data.unhcr.org/en/documents/details/95609

UNHCR. (2023, April). *Uganda Refugee Statistics April 2023 - Active Population by Settlement*. https://data.unhcr.org/en/documents/details/100476

Williams, D. L., Goward, S., & Arvidson, T. (2006). Landsat: Yesterday, today, and tomorrow. *Photogrammetric Engineering and Remote Sensing*, *72*(10), 1171–1178. https://doi.org/10.14358/PERS.72.10.1171

World bank. (2023). *Uganda Refugee Statistics 1961-2023 | MacroTrends*. https://www.macrotrends.net/countries/UGA/uganda/refugee-statistics

Wulder, M. A., Roy, D. P., Radeloff, V. C., Loveland, T. R., Anderson, M. C., Johnson, D. M., Healey, S., Zhu, Z., Scambos, T. A., & Pahlevan, N. (2022). Fifty years of Landsat science and impacts. *Remote Sensing of Environment*, *280*, 113195.

Yang, Q., Zhang, H., Peng, W., Lan, Y., Luo, S., Shao, J., Chen, D., & Wang, G. (2019). Assessing climate impact on forest cover in areas undergoing substantial land cover change using Landsat imagery. *Science of The Total Environment*, *659*, 732–745. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.12.290

Yin, G., Mariethoz, G., Sun, Y., & McCabe, M. F. (2017). A comparison of gap-filling approaches for Landsat-7 satellite data. *International Journal of Remote Sensing*, *38*(23), 6653–6679. https://doi.org/10.1080/01431161.2017.1363432

Zhu, X., Liu, D., & Chen, J. (2012). A new geostatistical approach for filling gaps in Landsat ETM+ SLC-off images. *Remote Sensing of Environment*, *124*, 49–60.

Appendices

Appendix **1**: Band characteristics for the Landsat 4-5 TM, Landsat 7 ETM+ and Landsat 8 OLI & TIRS used for this study; Source: (Kevin Butler, 2013).

Landsat 5			**Landsat 7**			**Landsat 8**		
Band Name	Wavelength (µm)	Resolution (m)	Band Name	Wavelength (µm)	Resolution (m)	Band Name	Wavelength (µm)	Resolution (m)
						Band 1 Coastal	0.43 – 0.45	30
Band 1 Blue	0.45 – 0.52	30	Band 1 Blue	0.45 – 0.52	30	Band 2 Blue	0.45 – 0.51	30
Band 2 Green	0.52 – 0.60	30	Band 2 Green	0.52 – 0.60	30	Band 3 Green	0.53 – 0.59	30
Band 3 Red	0.63 – 0.69	30	Band 3 Red	0.63 – 0.69	30	Band 4 Red	0.64 – 0.67	30
Band 4 NIR	0.76 – 0.90	30	Band 4 NIR	0.77 – 0.90	30	Band 5 NIR	0.85 – 0.88	30
Band 5 SWIR 1	1.55 – 1.75	30	Band 5 SWIR 1	1.55 – 1.75	30	Band 6 SWIR 1	1.57 – 1.65	30
Band 7 SWIR 2	2.08 – 2.35	30	Band 7 SWIR 2	2.09 – 2.35	30	Band 7 SWIR 2	2.11 – 2.29	30
			Band 8 Pan	0.52 – 0.90	15	Band 8 Pan	0.50 – 0.68	15
						Band 9 Cirrus	1.36 – 1.38	30
Band 6 TIR	10.40 – 12.50	120/30	Band 6 TIR	10.40 – 12.50	30/60	Band 10 TIRS 1	10.6 – 11.19	100
						Band 11 TIRS 2	11.5 – 12.51	100

Appendix 2: Confusion matrix generated using 509 accuracy assessment points ground truthed for 2023 classified image (Author, 2023)

LULC class	PF	THF-WS	THF-LS	WD	SH	GS	SF	CA	OW	WT	BU	BS	Total	U_Accuracy	Kappa
PF	5	4	0	1	0	0	0	0	0	0	0	0	10	0.5	0
THF-WS	0	43	0	0	0	0	0	0	0	0	0	0	43	1	0
THF-LS	1	0	10	1	0	0	0	0	0	0	0	0	12	0.833333	0
WD	2	1	3	47	0	0	10	0	0	0	0	1	64	0.734375	0
SH	0	0	0	1	16	0	0	0	5	0	0	1	23	0.695652	0
GS	0	0	0	0	0	15	0	0	0	0	0	0	15	1	0
SF	2	1	0	6	0	3	103	3	0	0	1	1	120	0.858333	0
CA	0	1	0	1	0	0	6	20	0	1	0	0	29	0.689655	0
OW	0	0	0	0	0	0	0	0	147	0	0	0	147	1	0
WT	1	0	0	2	0	0	2	1	0	20	0	0	26	0.769231	0
BU	0	0	0	1	0	5	0	0	0	0	4	0	10	0.4	0
BS	0	0	0	0	0	0	0	0	0	0	0	10	10	1	0
Total	11	50	13	60	16	23	121	24	152	21	5	13	509	0	0
P_Accuracy	0.454545	0.86	0.769231	0.783333	1	0.652174	0.85124	0.833333	0.967105	0.952381	0.8	0.769231	0	0.86444	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.83575

U_Accuracy- User's accuracy, P_Accuracy- Producer's accuracy, PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface

Appendix 3: Confusion matrix generated using 510 accuracy assessment points ground truthed for 2015 classified image (Author, 2023)

LULC class	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**OW**	**WT**	**BU**	**BS**	**Total**	**U_Accuracy**	**Kappa**
PF	6	0	0	2	0	0	2	0	0	0	0	0	10	0.6	0
THF-WS	0	45	4	0	0	0	0	0	0	0	0	0	49	0.918367	0
THF-LS	0	0	22	1	0	0	0	0	0	1	0	0	24	0.916667	0
WD	0	0	2	41	0	0	0	0	0	0	0	0	43	0.953488	0
SH	0	0	0	0	25	1	0	0	1	0	0	0	27	0.925926	0
GS	0	0	0	0	1	12	0	0	0	0	0	0	13	0.923077	0
SF	0	0	0	3	1	0	141	0	0	1	0	0	146	0.965753	0
CA	0	0	0	0	0	0	0	15	0	0	0	0	15	1	0
OW	0	0	0	0	0	0	0	0	146	0	0	0	146	1	0
WT	0	0	0	0	0	0	0	0	0	17	0	0	17	1	0
BU	0	0	0	0	0	1	0	1	0	0	8	0	10	0.8	0
BS	1	0	0	0	0	1	0	0	0	0	0	8	10	0.8	0
Total	7	45	28	47	27	15	143	16	147	19	8	8	510	0	0
P_Accuracy	0.857143	1	0.785714	0.87234	0.925926	0.8	0.986014	0.9375	0.993197	0.894737	1	1	0	0.952941	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.94203

U_Accuracy- User's accuracy, P_Accuracy- Producer's accuracy, PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface

Appendix 4: Confusion matrix generated using 508 accuracy assessment points ground truthed for 2005 classified image (Author, 2023)

LULC class	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**OW**	**WT**	**BU**	**BS**	**Total**	**U_Accuracy**	**Kappa**	
PF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
THF-WS	0	15	0	0	0	0	0	0	0	0	0	0	0	15	1	0
THF-LS	0	0	38	0	0	0	0	0	0	0	0	0	0	38	1	0
WD	0	0	2	39	1	0	0	1	0	0	2	0	0	45	0.866667	0
SH	0	0	0	1	99	0	0	4	0	0	0	0	0	104	0.951923	0
GS	0	0	0	0	0	16	0	0	0	1	0	0	0	17	0.941176	0
SF	0	0	0	0	0	1	16	0	0	0	0	0	0	17	0.941176	0
CA	1	0	0	1	4	3	0	69	0	0	0	0	0	78	0.884615	0
OW	0	0	0	0	2	0	0	0	10	0	0	0	0	12	0.833333	0
WT	0	0	0	0	0	0	0	0	0	148	0	0	0	148	1	0
BU	0	0	0	0	1	0	0	1	0	0	11	0	0	13	0.846154	0
BS	0	0	0	0	0	0	0	0	0	0	0	10	1	11	0.909091	0
Total	0	0	0	0	2	0	0	0	0	0	0	0	8	10	0.8	0
P_Accuracy	1	15	40	41	109	20	16	75	10	149	13	10	9	508	0	0
Kappa	0	1	0.95	0.95122	0.908257	0.8	1	0.92	1	0.993289	0.846154	1	0.888889	0	0.942913	0
LULC class	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.931202

U_Accuracy- User's accuracy, P_Accuracy- Producer's accuracy, PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface

Appendix 5: Confusion matrix generated using 502 accuracy assessment points ground truthed for 1995 classified image (Author, 2023)

LULC class	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**OW**	**WT**	**BU**	**BS**	**Total**	**U_Accuracy**	**Kappa**
PF	54	0	0	0	0	1	0	0	0	0	0	0	55	0.981818	0
THF-WS	0	61	4	3	0	0	0	0	0	0	0	0	68	0.897059	0
THF-LS	0	0	36	2	0	0	0	0	0	1	0	0	39	0.923077	0
WD	0	0	0	21	0	0	1	0	0	0	0	0	22	0.954545	0
SH	0	0	0	0	15	0	0	0	0	0	0	1	16	0.9375	0
GS	0	0	0	2	0	15	0	0	0	0	0	0	17	0.882353	0
SF	0	0	0	2	0	1	67	0	0	0	0	2	72	0.930556	0
CA	0	0	0	1	0	0	0	9	0	0	0	0	10	0.9	0
OW	0	0	0	0	0	0	0	0	150	0	0	0	150	1	0
WT	0	0	0	5	0	0	0	0	0	17	0	0	22	0.772727	0
BU	0	0	0	0	0	0	0	0	0	0	10	0	10	1	0
BS	0	0	0	0	0	0	2	0	0	0	0	19	21	0.904762	0
Total	54	61	40	36	15	17	70	9	150	18	10	22	502	0	0
P_Accuracy	1	1	0.9	0.583333	1	0.882353	0.957143	1	1	0.944444	1	0.863636	0	0.944223	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.934138

U_Accuracy- User's accuracy, P_Accuracy- Producer's accuracy, PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface

Appendix 6: Confusion matrix generated using 505 accuracy assessment points ground truthed for 1985 classified image (Author, 2023)

LULC class	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**OW**	**WT**	**BU**	**BS**	**Total**	**U_Accuracy**	**Kappa**
PF	**PF**	**THF-WS**	**THF-LS**	**WD**	**SH**	**GS**	**SF**	**CA**	**OW**	**WT**	**BU**	**BS**	23	0.913043	0
THF-WS	0	48	1	2	0	0	0	0	0	1	0	0	52	0.923077	0
THF-LS	0	0	29	5	0	0	0	0	0	1	0	0	35	0.828571	0
WD	1	0	0	105	2	0	1	0	0	0	0	0	109	0.963303	0
SH	0	0	0	0	18	0	0	0	0	0	0	0	18	1	0
GS	0	0	0	0	0	16	0	0	0	0	0	0	16	1	0
SF	0	0	0	1	0	0	51	0	0	0	1	0	53	0.962264	0
CA	0	0	0	0	0	0	0	6	0	4	0	0	10	0.6	0
OW	0	0	0	1	0	1	0	0	146	0	0	0	148	0.986486	0
WT	0	0	0	1	0	0	1	0	0	16	0	0	18	0.888889	0
BU	0	0	0	1	3	1	0	0	0	0	7	0	12	0.583333	0
BS	0	0	0	0	0	0	0	0	0	0	0	11	11	1	0
Total	22	48	32	116	23	18	53	6	146	22	8	11	505	0	0
P_Accuracy	0.954545	1	0.90625	0.905172	0.782609	0.888889	0.962264	1	1	0.727273	0.875	1	0	0.938614	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.926318

U_Accuracy- User's accuracy, P_Accuracy- Producer's accuracy, PF- Plantation Forest, THF-WS - Tropical high forest well stocked, THF-LS - Tropical high forest low-stocked, WD - Woodland, SH - Shrubland, GS-Grassland, Subsistence farmland, CA - Commercial Agriculture, OW – Open Water, WT – Wetland, BU - Built-up, BS- Bare surface.

Appendix 7: Letter of Introduction used to seek permits during field work.

NTNU

Faculty of Social and Educational Sciences
Department of Geography

Date 13.03.2023 Our reference

Your date Your ref

To whom it may concern

Letter of introduction

We hereby confirm that Isaac Fred Nandala (born 2nd July 1994) is a student on the 2-year master's degree in *Natural Resources Management specializing in Geography* at the Department of Geography, Norwegian University of Science and Technology.

He will conduct his fieldwork and data collection during 27 th March – 26th April of 2023 in Uganda.

We would be grateful for any assistance given to him during this process. This includes granting interviews, assisting him in making appointments, handing out materials and making information accessible to him.

Regards

Per Ivar Chutko

Per Ivar Chutko
Advisor

NTNU
Norwegian University of Science and Technology
Department of Geography
Trondheim, Norway

Address	Org. no. 974 767 880	Location	Phone	Executive officer
7491 Trondheim Norway	postmottak@su.ntnu.no www.ntnu.no/geografi	Dragvoll Bygg 7, nivå 4	+47 73558907	

Please address all correspondence to the organizational unit and include your reference.

Appendix 8: The Uganda Wildlife authority research permit letter of approval to collect land use/land cover data for Kabwoya wildlife reserve; protected area, Kikuube district-Uganda.

UWA
Conserving for Generations

UGANDA WILDLIFE AUTHORITY

OFFICE OF THE EXECUTIVE DIRECTOR
PLOT 7 KIRA ROAD KAMWOKYA
P. O. Box 3530, Kampala, Uganda

Our Ref: COD/96/05 — 3rd April 2023

Isaac Fred Nandala
Norwegian University of Science and Technology
Trondheim
NORWAY

RESEARCH APPLICATION APPROVAL

I am in receipt of your application dated 28th March 2023 seeking to undertake research in Kabwoya Wildlife Reserve titled; ***"Landuse and Landcover changes in Kikuube district"***.

This is to inform you that permission has been granted with effect from 4th April 2023 to 15th May 2023. Permission is further granted to **Ms. Florence Nansumbi** to work with you. You are expected to submit to Uganda Wildlife Authority (UWA) a progress report by September 2023 and a final report of your findings by end of November 2023. In case you are unable to work within these dates, please notify the Authority in writing.

You will be required to pay to UWA a research application fee of **UGX 20,000 (twenty thousand shillings only)**.

Please report to the Warden in Charge, Kabwoya Wildlife Reserve (KWR) on arrival for registration, payment of fees and further guidance.

Conserving for Generations
Yours sincerely,

EXECUTIVE DIRECTOR
UGANDA WILDLIFE AUTHORITY

John Makombo
FOR: EXECUTIVE DIRECTOR

Copy: Warden in Charge, Kabwoya Wildlife Reserve
Chief Warden, Murchison Falls Conservation Area

Tel: +256-41-4355000, +256-31-2355000 Fax: +256-41-4346291, E-Mail: info@wildlife.go.ug, Website: www.ugandawildlife.org

NTNU

Norwegian University of
Science and Technology