IMPACT OF SPATIOTEMPORAL LAND USE AND LAND COVER CHANGE ON LAND UNDER MAIZE CULTIVATION IN LIKUYANI SUB-COUNTY, KAKAMEGA COUNTY, KENYA

Henry Kangwana Shilibwa

A thesis submitted in partial fulfilment of the requirements for the award of the degree of Masters of Science in Geospatial Information Science and Remote Sensing of Masinde Muliro University of Science and Technology

December, 2023

DECLARATION

This thesis is my own original work prepared with no other than the indicated sources and has not been presented for a degree or any other award in any other University or any other institution.

Signature.. Date………………………….

Henry Kangwana Shilibwa

SGI/G/01-56870/2017

CERTIFICATION

We the undersigned certify that we have read and hereby recommend for acceptance by Masinde Muliro University of Science and Technology, a thesis entitled "**Impact of Spatiotemporal Land Use and Land Cover Change on Land Under Maize Cultivation in Likuyani Sub-County, Kakamega County Kenya".**

Signature.. Date………………………….

Dr. Edward N. Masibayi

Department of Disaster Preparedness and Engineering Management

Masinde Muliro University of Science and Technology

Signature.. Date………………………….

Prof. Edward M. Neyole (Ph.D.)

Department of Disaster Preparedness and Engineering Management

Masinde Muliro University of Science and Technology

PLAGIARISM STATEMENT

STUDENT DECLARATION

1. I hereby declare that I know that the incorporation of material from other works or a paraphrase of such material without acknowledgement will be treated as plagiarism according to the Rules and Regulations of Masinde Muliro University of Science and Technology.
2. I understand that this thesis must be my own work.
3. I know that plagiarism is academic dishonesty and wrong, and that if I commit any act of plagiarism, my thesis can be assigned a fail grade (F).
4. I further understand I may be suspended or expelled from the university for academic dishonesty.

Name: Henry Kangwana Shilibwa Signature………………………

Reg. No: SGI/G/01-56870/2017 Date…………………………………

SUPERVISOR(S) DECLARATION

We hereby approve the examination of this thesis. The thesis has been subjected to plagiarism test and its similarity index is not above 20%.

1.Name………………………………….Signature…………………Date…………….

2.Name………………………………….Signature……………..…..Date……………

COPYRIGHT

DEDICATION

This work is dedicated to my late father, Major Shilibwa, and my mother, Achayo, whose inspiration and steadfast support helped to mold my path. A particular thank you to my wife Beatrice, whose support cheered me on when I was feeling down. Throughout this quest, my daughters Easter, Barbra, Lucinda, and Marylyn have provided important inspiration, understanding, and support.

ACKNOWLEDGEMENT

I wish to acknowledge those whose assistance and support made this study possible. My most sincere appreciation goes to my supervisor Dr. Masibayi, a faculty member in the Department of Disaster Preparedness and Engineering Management at Masinde Muliro University of Science and Technology, for the great counsel you gave me at the beginning of my research quest and for the support you continued to provide me with during this study. Professor Neyole, who works in the same department, has my sincere gratitude for his kind contributions and careful oversight, which allowed my research to advance and align.

Furthermore, I express my gratitude to Mr. Okuku, a lecturer at Masinde Muliro University of Science and Technology within the aforementioned department, for his unwavering support and insightful advice in the field of remote sensing. My appreciation also goes to RCRMD staff in Nairobi for their assistance in acquiring remote sensing satellite data. Kakamega office agricultural production officer, west Kenya Sugar Agricultural manager Mr. Kodhek, the Turbo Forest staff for their assistance and support in acquiring data.

ABSTRACT

Likuyani Sub -County is ideal climate and high-quality soil for farming, especially maize cultivation—a major crop in Kenya—Likuyani Sub-County has established itself as the nation's main hub for the production of maize and seeds. Though Kenya has a reputation for producing maize, recent reports have shown a worrying reduction in the country's output, forcing the government to import the crop to make up for the gap. This decrease is associated with rapid population increase, which leads to significant changes in land usage and the division of agricultural land into smaller, less profitable units. A major problem, particularly in arid and semi-arid areas, is the potential negative impact of these changes on rural livelihoods. The goal of the study was to understand the complex dynamics and driving forces behind changes in land use and land cover, with a particular emphasis on land used on production of maize in Likuyani Sub-County between 1997 and 2017. Sentinel 2A, Landsat 7 ETM+, and Landsat 8 OLI/TIRS satellite imagery for the corresponding years were carefully examined utilizing pixel-oriented supervised image classification methods. For verification and analysis, questionnaires, GPS data collecting, ground observations, and additional data were used. ArcGIS, Microsoft Office software, and ERDASS IMAGINE are examples of analytical tools that made data interpretation and statistical analysis easier. Between 1997 and 2017, the analysis showed a notable yearly decrease of 8.92% in area used for maize production, in contrast to an annual growth of 10.87% in land occupied by structures. Coverage of grasses and shrubs decreased by 0.31% every year, whereas sections of woodland and swamps stayed mostly unchanged. Regression analysis among other statistical techniques revealed the detrimental impact of land alterations on maize producing land. The study urges the quick identification and use of the best land management techniques in Likuyani Sub-County in light of these findings. The identification, development, and implementation of sustainable land management methods necessitates the active participation of all pertinent stakeholders, especially local populations.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDECIES

LIST OF ACRONYMS AND ABBREVIATIONS

AAS	Australian Academia of Science
AFA	Agriculture and Food Authority
AGSR	African agricultural status report
AOI	Area of Interest
CA	Consumer Accuracy
DVI	Differencing Vegetation Index
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organization
FCC	False color composite
GIS	Geographic Information Systems
GOK	Government of Kenya
ISODATA	Iterative Self-Organizing Data Analysis Technique
KALRO	Kenya Agricultural Research Organization
LULCC	Land use land cover change
MSS	Multi Spectral Scanner
NCPB	National Cereals and Produce Board
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red
OLI/ TIRS	Operational Land Imager and Thermal Infrared Sensor

PA	Producer Accuracy
PCA	Principal Component Analysis
RGB	Red Green Blue
RIMs	Registry Index Maps
SLUC	Spatiotemporal Land Use Change
SLUCC	Spatiotemporal Land Use Change Coverage
SPCA	Selective Principal Components Analysis
SPSS	**S**tatistical Package for Social Sciences
SWIR	Short Wave Infra-Red
TM	Thematic Mapper
UTM	Universal Transverse Mercator
VNVIR	Visible and Near Visible Infrared

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Foundation lays groundwork by highlighting spatiotemporal usage of land and changing coverage as worldwide has a variety of effects on various land cover types. These changes have a huge impact on maize, the primary staple food crop in Kenya. This key assertion serves as the foundation for the issue description, objectives, and hypotheses that are discussed in this work. The chapter explains why it is crucial to investigate this issue by highlighting the substantial effects that land use changes have on maize farming and productivity. The study's rationale and basis are finally provided by this introductory chapter, which highlights the critical necessity to comprehend and address the effects of changing land use on Kenya's maize crop.

Olang (2019) highlights a substantial influence on global environmental changes and related concerns. Anthropogenic changes in LULC have had negative effects on the environment, including deforestation, biodiversity loss, more frequent flooding, changes in global climate patterns brought on by global warming, and land degradation that upsets the natural equilibrium and ecological balance. According to Aboud (2017), this change in land cover has become an urgent worldwide concern. Remote sensing technology, particularly satellite-based techniques, has been used for a long time to monitor and evaluate LULC changes globally. Spatial and temporal remotely sensed data are used to track and comprehend these significant changes. Low productivity and environmental degradation are correlated with rising population growth rates in emerging nations, primarily in Sub-Saharan Africa (Lambin and Geist, 2018).

Land alterations affect ecology, hydrology, agriculture, forestry, and the environment, according to FAO (2017). In the instance of Kenya, fragmentation brought on by urbanization and population increase has resulted in a continuous decline of arable agricultural land. Large state-owned farms that were once utilized to produce seeds have been divided up and their ownership has shifted from state to private. These private lands were sold to other property owners who used them for different purposes after being further partitioned (GoK, 2019).

A multitude of studies have aimed to comprehend the dynamic alterations arising from observed shifts in land cover, prompting significant concerns. Technological advancements, have played a pivotal role in investigating these changes by providing precise and timely data. Poongothai's 2016 research, utilizing GIS and remote sensing, specifically focused on detecting alterations in usage and coverage of land. The study highlighted notable decrease with respect to agricultural property within the watershed, primarily attributed to human activities. They too concluded that these tools are effective in recognizing alterations, noting a considerable expansion in the built-up area compared to agricultural spaces in urban regions.

In Kenya, more than 85% of people use maize as their main food source, with an estimated 98–100 kg of maize consumed per person year, according to research by Onono *et al.* (2018). Furthermore, Rosegrant's research (2018) projects that maize will be the most widely grown crop worldwide by 2025, particularly in poorer countries.

Understanding the importance of maize, the nation has set up settlement plans to help locals return while also increasing agricultural output, which continues to be a vital component of the nation's economy and food security.

1.2 Statement of the problem

More than 50% of Kenya's GDP comes from the country's agricultural industry, either directly or indirectly through other connections. This industry employs more than half of Kenya's labor force and 70% of people who live in the country's uplands (FAO, 2021). When compared to the first two decades following independence, the growth of this industry has spiraled downward in recent years. FAO (2021) reports that among other things, usage of land and coverage have contributed to the sector's spiral decline by reducing the amount of area under cultivation, which has decreased agricultural productivity.

The transformation usage of land and coverage Likuyani commenced following transition in land ownership to the Kenyan government after independence. Initially, these lands were utilized by white settlers for extensive maize and wheat cultivation. However, following independence, these settlers vacated the land, as highlighted in the County Integrated Development Plan (CIDP) of 2018. Subsequently, the Kenyan government repurposed a significant portion of this land for large-scale seed production, the promotion of agricultural schemes, and the manufacturing of crucial agricultural inputs.

However, recent trends show that these lands have undergone subdivision, transitioning from state ownership to private ownership due to increased demand for settlement areas, according to the Government of Kenya (GoK) report in 2019. As observed by Lewis (2018), this shift coincided with a consistent reduction in the land area dedicated to maize production, including in regions like Likuyani sub-county, as documented by ongoing land use changes. Despite efforts, the declining trend in land allocated for maize cultivation continues, prompting Kenya to expend substantial foreign exchange on maize imports annually, despite diminishing areas earmarked for maize production. Population growth is among the main contributing factors on LULCC in Likuyani Sub County. Improvement and development of infrastructure (opening up of roads and rural electrification), fertile lands and favorable land market prices, has contributed to influx of immigrants from far and neighboring counties into the area.

Evidently, an increase in population has a detrimental effect on the development on the area's natural resources and land. The amount of land in the Sub-County that is used for maize cultivation has drastically decreased due to the subdivision of property into ever smaller sections. Food insecurity will ultimately result from the same situation occurring in areas that produce maize (Chumo, 2018). The primary economic activity of Likuyani Sub-County is maize cultivation, which is reliant on a single rainy season (Wanyonyi, 2016). Spatiotemporal land use changes for example deforestation and conversion of wetlands to farms may increase food production for a period of time. Spatiotemporal land use changes may increase production of some crop while at the same time decrease production of other crops in an area.

Introduction of none maize and none food commercial crops considered to have a higher commercial value than food crops for example eucalyptus tree farming are on the increase with negative consequences under food security and maize production. In his thesis titled "The Economic Impact of Climate Change on Maize Production in Kenya," Lewis (2018) examined how climate change affected Kenya's maize crop. Analyzing this is crucial to have a better understanding of how Kenya's primary stable food source, maize output, is impacted by spatiotemporal land use change. To bridge this informational void, usage of land and coverage dedicated to maize cultivation, using Likuyani Sub County as a representative sample. The study aimed to generate insights applicable to other regions engaged in maize production across Kenya.

1.3 Research Objectives

The overall objective of this study was to investigate the impact of spatiotemporal land use and land cover for maize cultivation land in *Likuyani* sub-county, within Kakamega county Kenya with specific years between 1997 to 2017 particularly focusing on areas dedicated to land under maize cultivation.

1.4 Specific objectives

The specific objectives of the study were, To;

i. Ascertain LULCC that occurred in Likuyani Sub County between 1997 and 2017,

ii. Evaluate spatiotemporal LULCC affecting different land cover classes in respect to land under maize cultivation in the Likuyani sub-county between 1997 and 2017,

iii. Explore the determinants influencing LULCC in the maize-producing areas of Likuyani Sub County during the period spanning from 1997 to 2017

1.5 Hypotheses

The study was guided by the following hypothesis;

i) There were no significant LULCC that occurred in *Likuyani* Sub County between the years 1997 and 2017.

ii) Spatiotemporal LULCC had no significant impact on land cover classes between the years 1997 and 2017.

iii) There were no significant determinants influencing LULCC on maize producing areas between the years 1997 to 2017 in *Likuyani* sub-county

1.6 Justification of the study

The study's findings offer valuable guidance for both county and national governments in crafting policies to protect essential maize cultivation regions. For instance, utilizing the data to set minimum land sizes can deter uneconomical land subdivision and control the growth of non-food crop farming in these pivotal maize-producing zones. Ultimately, the study outcomes serve as a comprehensive resource, empowering stakeholders to make informed decisions and institute measures that prioritize the preservation and sustainable productivity of these crucial maize-producing areas. Based on newly obtained data, this study will help formulate appropriate strategies to address the concerns expressed and serve as a foundation for enhancing the current regulatory frameworks. The academic community will find this study interesting as it adds to the body of knowledge and identifies areas that warrant additional investigation.Farmers can learn from this study the value of growing maize and the effects of changing land use on areas used for growing maize.

1.7 Scope of the study

The area lies between latitude 00 37’ 40” E and 00 54’ 17” E, longitude 35 00’ 43” N and 35 09’ 19” N. Likuyani sub county consists of five wards. These are Sinoko, Sango, *Likuyani*, *Nzoia* and *Kongoni*. According to 2009 census, the region’s population was 215,137 in an area 301.9 square km giving an average of 712 people per square km then. Within the same time frame, results from the research area's sizable population might be extrapolated to other areas that grow maize.

Focus was with regards to dynamics and causes spatiotemporal coverage and usage of land on maize-producing land in Likuyani sub-county in Kakamega County Kenya between 1997 and 2017. Due to availability of clear and consistent Landsat and sentinel 2A satellite images were readily available during this period The majority of Kenyans rely mostly on maize as a staple meal, and the climate in Likuyani Sub-county is ideal for growing it for both personal use and income. The sub county has witnessed transformation particularly in land use change, with considerable impact on land under maize production.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section explores complex dynamics in spatiotemporal changes usage in land and coverage, examining the key players and their effects on the areas used for maize production. Using image classification techniques, the methodology creates maps of land use and cover within a given region throughout several temporal periods. The focus is on data extraction from these categorization maps and comparison analysis over different time periods, made easier by ArcMap-generated error matrices that measure the coverage of different geographic categories. Through an examination of the fundamental drivers of usage of land and coverage shifts and their implications for the landscape of land under maize farming, this section seeks to consolidate the key conclusions drawn from the comprehensive studies.

2.2 Changes in coverage of land and use

LULCC, is a variety changes brought about by humans that take place on Earth's surface. According to "The Encyclopedia of the Earth" (2016), land cover refers to everything that is present on the surface of the land, including vegetation, ice formations, water bodies, topographical features, open spaces, and man-made structures such as towns, mines, and dams. These activities include farming, logging, building roads, creating industrial zones, and a host of other human-driven interventions (Hussein, 2019). For numerous years, human activities have involved modifying land to fulfill basic needs like food production.

However, the current pace and scale of these alterations far exceed historical rates, resulting in unprecedented impacts on local, regional, and global ecosystems and environmental processes (Kabubo,2020). Alterations in usage of land and coverage are intricately connected the competition between various land utilization purposes, predominantly agriculture and human settlement. In Kenya and East Africa, shifts in land use have led to the replacement of natural vegetation with agricultural lands, grazing zones, urban developments, and human settlements (Kabubo *et al.*, 2017). It is widely acknowledged that variations in land use significantly impact the extent of cultivated land and food production, as highlighted in Renny's work (2016). Changes in land use often result in alterations to land cover. These alterations manifest in various forms such as the conversion of forests into mining areas, transformation of farmlands into urban centers, conversion of pasture into cropland, or changing woods into irrigated areas. Land management practices contribute to these changes, encompassing modifications in how the land is utilized. This process often involves subdividing the land and adopting different crop cultivation techniques. It's crucial to note that alterations in usage of land and coverage have profound implications, they can significantly impact the functioning of the Earth's system.

2.3 Usage and coverage of Land Change trends

The sophisticated process of "land-use changes" involves the transformation of land cover, a process referred to as land conversion (Noe, 2018). Despite its complexity, there's limited understanding of the interactions between natural and human factors that influence both hydrological processes and land-use patterns (LUCID, 2017).

The expansion of agriculture into steppes, savannas, and woodlands has been vital in meeting the global food demand. However, the pace and nature of agricultural expansion have varied across regions as economies, populations, and civilizations developed over time (UN-FAO, 2019). Despite these global perspectives on usage of land and coverage, the focus of these studies did not aim to contribute to an understanding of land-use trends.

Likuyani Sub-county is made up of settlement schemes that were created from the "Million Acre" settlement scheme initiative which was initiated between 1962 and 1966 through a program to purchase one million acres of land from the European settlers, by the Kenyan government (Chune, 2017). The large parcels of land were grouped into settlement schemes then subdivided and allocated to the indigenous Africans at a low interest loan payable in thirty years. The establishment of settlement schemes in Kenya served a dual purpose: to mitigate rural-urban migration in pursuit of employment and sustenance, while simultaneously recognizing agriculture as a major employer for a substantial segment of the Kenyan populace. These initiatives were specifically designated for the cultivation of maize, beans, and sunflowers, as well as dairy farming, as noted by Chune (2017). The focus on these agricultural activities within the settlement schemes aimed to offer sustainable livelihood options and employment opportunities to rural communities, thereby reducing the pressure of migration to urban areas in search of work. This strategic approach sought to harness the agricultural potential of these regions while concurrently addressing socioeconomic factors influencing migration trends in Kenya. Likuyani Sub County was curved out of the former Lugari district as Likuyani constituency and with formation of counties, it became Likuyani Sub County.

Land in Likuyani sub-county was subdivided according to schemes ranging from 15 acres to 100 acres.The term land use primarily denotes the various purposes to which land is allocated, encompassing residential and commercial zones, conservation areas, construction of infrastructures like dams, mining operations, or agricultural activities. Renny (2018) emphasizes the profound impact of LULCC, a significant human-driven activity, in substantially reshaping the ecology within specific geographical areas.

In many developing nations, the LULCC phenomenon has sharply increased since the era of industrialization and high population expansion (Lambin, 2019). The majority of developing nations, like Kenya, rely heavily on the exploitation and utilization of their land resources, particularly for agricultural purposes (Wanjala, 2018). Global food production is commonly acknowledged to be threatened by changes in the spatiotemporal LULCC. The main factors contributing to spatiotemporal land use change: population growth, poverty, land subdivision, settlement, land tenure, industrialization, fluctuating market prices of farm produce and land, climate change among others. Studies conducted by (Siddhartho, 2017) have shown that LULCC is responsible for extensive depletion of wetland area. It can be argued that LULCC can be responsible for lose in other land cover classes in this case land under maize production. Other cash crops and none food crops like sugar cane and eucalyptus tree that attract more ready income are slowly, but gradually replacing maize in the sub-county whose outcome may eventually lead to food insecurity. Large tracts of agriculture have gradually given way to settlement due to continued migration and internal population expansion (Renny, 2018).

The study therefore, investigate spatiotemporal changes in usage of land and coverage on the extent of land utilized for maize cultivation within the Likuyani sub-county. Effective planning of land use and sustainable management practices for ensuring food security necessitates a comprehensive understanding of spatiotemporal impacts maize production (Renny, 2018). Land use change holds substantial influence over agricultural practices.

2.4 Factors influencing spatiotemporal changes in usage of land and coverage

Quite a number individuals from nearby counties have moved into Likuyani Sub County, drawn by the area's high maize yield and metropolitan population makeup. Likuyani, main farming activity in the range has been and still is maize farming. The fertile soils and high rain fall provided high maize yields enough for local consumption and the surplus for export to other counties. Over the years, factors, among them, population increase have put the land under pressure as settlement encroaches on farm land ever reducing the land area under maize farming (KALRO, 2021). The area of land that was under maize production has been reducing. Due to market acquisition, this population growth has made land subdivision worse. Eldoret-Malaba Road and Eldoret-Kitabale Road, which are both major thoroughfares, border Likuyani. Due to this, the area becomes more appealing and easily accessible to land speculators, who in turn encourage the subdivision of land for habitation at the expense of agricultural and food production. Mather and Needle (2018) pointed out that poverty and population increase are typically linked to high rates of deforestation in many developing nations.

According to Allen and Barnes (2019), pressure from population increase and the need for greater food supplies is mostly to blame for the majority of tropical deforestation. The findings from comprehensive studies on tropical deforestation indicate that the increase in population was not consistently the primary factor contributing to changes in forest cover. Authors such as Angelsen and Kaimowitz (2019) and Geist *et al.* (2019) have underscored this perspective. However, over extended periods, fluctuations in population numbers also exert significant influence on alterations in usage of land and coverage. The clearance of forests results from various factors, each with unique impacts. Different agricultural practices contribute to forest clearing: recent in-migrants often resort to slash-and-burn agriculture, while subsequent generations practice fallow agriculture.

Families settled for long periods tend to employ diverse production methods, whereas smaller families opt for crop-livestock combinations, leading to higher forest loss rates. In contrast, larger families tend to adopt perennial production methods, associated with lower forest loss rates. Moreover, changes in land use occur due to displacements, like small ranchers displaced by larger ones or upland croppers displaced by lowland ranchers, as evidenced in studies by Humphries (2018) and Walker *et al.* (2016). As highlighted Indian *et al.* (2017) and Fearnside (2017), have been observed to either incite or be closely intertwined with increased migration patterns. Throughout history, humans have augmented agricultural output by expanding land under cultivation. Contrary to certain claims, the availability of suitable land is severely restricted in most developing nations, with a significant surplus of cultivable land often lying within rainforest areas or marginal zones, as evidenced in studies by Young (2019) and D¨o¨os (2016).

Many agricultural techniques in various basins were developed during periods of much smaller populations and more accessible resources. However, despite the insights gained from these studies, none of them have sufficiently provided a clear understanding of how the growing population in a sub-catchment affects its resources in both present times and future scenarios. The urban population has exhibited a more rapid growth trajectory than its rural counterpart worldwide, especially noticeable in developing nations. This surge in urban population has coincided with significant alterations in urban structure and functionality.

Lambin *et al.* (2019) emphasize the significance of considering the complex interactions between socio-economic factors, environmental drivers, and the intricate human-environmental conditions influencing land-use policies and future dynamics of usage of land and coverage. Their approach aims not to discard the development of a conceptually-grounded framework but rather advocates for advancements that integrate broad socio-economic and biophysical drivers with specific localized human-environmental conditions shaping land-use. Developing nations, decision-making process regarding usage of land and coverage change is heavily influenced diverse array cultural aspects. These cultural elements intertwine with political and economic disparities, as noted by Leemans *et al.* (2018), thereby shaping resource access and land-use dynamics.

2.4.1 Changing Climate

Changes in land cover are naturally triggered by climate change. Although the risks associated with climate change are widespread, Wanyama (2017) points out that their effects appear to be most noticeable in emerging nations. Their strong reliance on natural resources, pervasive poverty, poor ability to adapt, lack of technological capacities, and existence of environmental stress are the main causes of this (Mwendwa & Giliba, 2012; Norrington & Thornton, 2011). Furthermore, the situation in underdeveloped countries is made worse by the lack of awareness about these changes and the appropriate mitigation and adaptation efforts. Over 75% of Kenya's population is employed in agriculture, which continues to be the country's main source of income (FEW NET, 2013). As per African Agricultural Status Report (AGRA, 2016), global temperatures are experiencing an upward trend, with a 0.58 degree Celsius increase by 2012.

A few plant species have disappeared leading to climate change, and ecology has changed and pattern of precipitation has changed. The protracted droughts and flooding that certain portions of Kenya have experienced are consequences of environmental changes. These statistical characteristics can be caused by human activity like pollution and land use or by natural processes like variations in solar radiation and volcanoes (AAS, 2019). Variability in rainfall patterns due to climate change is exacerbated by droughts and floods, which affect changes in land cover. Crop fields damaged and livestock lost, with dire consequences including starvation. Rosegrant (2019) claims that the nation experiences droughts every two to three years. Climate change, both local and global, is intricately and interactively correlated with land use.

The main ways that land use influences climate are through variations in land surface area and changes in greenhouse gas emissions. Variability in the climate so influences land use, including deciding what is best and most appropriate for a particular location. Persistent water stress results in waterways overflowing their banks during floods or rivers drying up during protracted droughts, drastically altering the amount and quality of water available (Ojwang, *et al.*, 2016). Maize is heavily dependent on significant rainfall in its early stages. Crop failure is eventually caused by prolonged drought. Farmers are choosing to plant other crops that can withstand extended dry spells as a result of the ongoing loss of crops brought on by fluctuations in rainfall.

2.4.2 Increase in Population

The primary areas directly impacted by population growth are food production and land use changes. That is to say, the supply of land is set and does not grow as the population does. Other sectors often lose out on necessary land due to demand from this growing population (Njiru, 2016). Population growth and decreased agricultural land utilization will have a significant impact on maize production, which will increase food security.

The rise in population within a region often leads to a decrease in land allocated for maize and crop cultivation, as segments of agricultural land are transformed into residential areas. Human societies have historically engaged in migration and settlement across different regions for various reasons, as highlighted by Ambwere (2018). In Likuyani Sub County, some of the factors contributing to population growth have been linked to political conflicts and instability in neighboring counties.

These circumstances have prompted people to relocate to Likuyani Sub County in response to the turmoil in their original areas. Political unrest in 1992 caused a large-scale migration out of nearby counties like Wareng, Bungoma, and Nandi. Many immigrants who were escaping these areas took sanctuary in Likuyani and Lugari Sub Counties, which were regarded as urban centers and safe havens free of intertribal strife and violence. The need for protection and security in the midst of the unrest in their own places was a major motivator for this movement. An international problem is the growing population. The population of the planet has been increasing throughout time. The population of the world rose from 7.35 billion in 2015 to 7.5 billion in 2017, and estimates indicate that it may reach 11.2 billion by the year 2100, according to Mike (2017).

As population increases, the available land area remains the same but there is more demand to shelter the ever-increasing population resulting in more land use change. In Kenya, the majority of family members think that land is theirs. Large property holdings in Likuyani Sub-County, spanning from 15 to 100 acres, have drawn immigrants from neighboring highly populated counties such as Vihiga County, resulting in a population growth in Likuyani Sub-County. Some of the new landowners believe that growing other crops would be a better investment than growing maize when they develop and settle on the property.

2.4.3 Land Subdivision

The practice of breaking up a large land lot into smaller pieces for the purpose of selling, inheritance, better managing the smaller component, or using the separate portions for different purposes is known as land subdivision. The majority of Kenyan societies follow a succession and inheritance culture in which assets, including land, are divided among heirs one after the other or among a family's sons solely. According to inheritance regulations, the heirs must divide the land into equal portions. The land eventually becomes divided into ever-smaller portions, making it unusable for any kind of profitable agricultural activity, if this pattern is maintained by the succeeding generations on the same plot of land (Mise, 2017). The area used for maize production is significantly impacted by this change in land use.

The land holdings are subdivided to produce multiple parcels with various characteristics. In the event that the divided portion or parcel is sold, the new owner is not required to carry on with the existing uses of the land. In their studies on land subdivision in Malaysia and the Philippines, some academics, including Niroula. (2016), discovered land subdivision was not thought to be a barrier to paddy farming in these countries, it actually increased farm productivity by fostering efficiency. The two situations, however, are not comparable because paddy is farmed on marshy terrain and farmers only live on a portion of the land, leaving the overall area under cultivation unchanged.

Land subdivision is also influenced by land markets. Landowners are easily convinced to sell up a portion of their property for investment in other businesses or for personal use as land values rise. The prices of land are mostly determined by development and policies of the government. Kongoni town has grown as a new sub county headquarters since Likuyani Sub County was established, and this has increased demand for housing sub county employees and company owners. Prospectors are drawn to the newly constructed, bituminous, all-weather roads. The farms that are close to these growing municipalities are quickly transitioning from agricultural to populated areas. The majority of people living in Likuyani Sub County are poor because maize is their primary source of income. Land subdivision is mostly caused by unchecked land titling and growing population pressure.

In order to examine the size and amount of land subdivided within the study area, the RIMs of four settlement plans were specifically chosen, scanned, and digitalized using ArcGIS. Through a comparison between digitized and the original allocation, the extent of land subdivision in the area was determined, as well as the lowest subdivision that is incapable of supporting sustainable maize production. It was feasible to calculate the number of divided land pieces that are unable to produce a sustainable amount of maize for any sustainable economic purpose by using SQL on the digital schemes.

2.4.4 Market values and business opportunities

A variety of social-economic factors influence several dynamic land use patterns, which alter biodiversity (Maina, 2016). Which crops a farmer grows each year depends on market prices.

Since maize is farmed in Likuyani Sub County both as a cash crop and a subsistence crop, this directly relates to the farming of maize there. Farmers are deterred from producing the same crop and instead choose to cultivate crops that command higher prices in the market by the declining market prices of maize. A major factor in the change in land use is economic opportunity. Crops with high potential earnings will be grown by farmers. According to conversations with agricultural officers, the establishment of sugar plants in Kakamega County (West Kenya Sugar Factory and Butali Sugar Factory) could potentially endanger the area's maize-growing land. Compared to maize, sugar cane is a more profitable cash crop for farmers per acre. Compared to maize, which swings more frequently and is impacted by imports and a large harvest, the sugarcane market is far more consistent and predictable. Given the circumstances, more farmers would probably choose to plant sugar cane because the crop yields more sugar than maize does.

2.5 Effects of changes in land cover and land use throughout time on areas used for maize production

significantly influences maize productivity due to spatiotemporal land-use changes. This shift reflects a global trend where human history is marked by intensive exploitation leading to substantial alterations in usage of land and coverage. Likuyani sub-county's transition from maize agriculture to alternative non-maize cultivation profoundly affects maize output, attributing to the shrinking land availability amidst increase in populace. Assessing the impact of land use land cover change on land cover classes. The onset of the agrarian revolution saw significant changes in land use and land cover, primarily driven by the expansion of agricultural land at the expense of forested areas.

This shift was a response to the growing population's food demands, resulting in increased food production (Pellikka *et al.*, 2013). As reported by FAO (2016), there was a notable trend of forest loss at a rate of 7 million hectares annually and a gain of 6 million hectares per year in agricultural land between 2000 and 2010. Most of this expansion occurred in low-income countries experiencing population growth. Despite initial gains in food production, recent years have seen a decline due to the persistent population increase. The land previously allocated for agriculture is now sought after for population settlement, leading to land subdivision into smaller units. This fragmentation has led to the conversion of agricultural land for housing and non-food activities, subsequently reducing food supply (FAO, 2016).

In Kenya, the consequences of land use and cover change are evident, particularly in Likuyani Sub-County, where arable land has diminished due to urbanization, population growth, and migration. State-owned farms initially designated for agricultural purposes have been subdivided and repurposed for settlement, leading to a decline in agricultural production (GoK, 2009). Reports by Kang'ethe (2011) and Limo (2016) highlight the correlation between declining maize production, unpredictable rainfall, urbanization, land subdivision, and reduced land size allocated for agricultural activities. This decline has forced the government to resort to importing maize from neighboring countries to cover the production shortfall.

The indirect impacts of land use and cover change on agriculture are visible in the Nkuku dam region in Malawi. Mzuza *et al.* (2019) observed that increased population growth, driven by displaced persons from Mozambique's civil war, led to escalated demand for cultivation land. Consequently, encroachment into marginal and protected forests ensued, causing land degradation and siltation in the dam used for irrigation and domestic purposes. Continued siltation could potentially reduce the dam's water storage capacity, indirectly affecting agricultural activities. Similarly, in Kenyan rangelands, fragmentation of large land parcels into smaller units has limited available land for livestock farming and nomadic pastoralism. Kebaso's (2017) study in Kaputiei, Kajiado North, indicates a significant shift from agricultural to residential land use.

This transition has drastically reduced rangelands available for grazing due to increasing settlements, directly impacting livestock rearing and subsequently leading to a decline in beef production. Overall, land use and cover change have reduced the land area available for agriculture, resulting in diminished agricultural productivity, leading to food insecurity. This situation, exacerbated by population growth and urbanization, has prompted local and international interventions emphasizing the pivotal role of agriculture in addressing societal challenges. Kenya's Vision 2030, a strategic roadmap for sustainable economic development, proposes interventions aimed at increasing agricultural land size by utilizing uncultivated lands and opening up new cultivation areas.

2.6 Detection in usage and coverage of land

Technique in detecting variations status of land cover by monitoring same area of land at various spatial moments is known as "change detection of land use land cover change" (Biswajit, 2017). Depending on the needed outcomes, the pace or time gap of the observation can be hours, days, or years. Finding differences between two or more multi-date photographs is the goal of change detection (Marien, 2018). There are several methods for detecting changes, but each one is appropriate for a certain task based on the goals and the features of the research field. Using a sensor to record the electromagnetic radiation that an object or event emits or transmits, learning details about an object at a distance without physically touching it. This is accomplished by detecting, logging, and processing electromagnetic energy that is reflected or transmitted, then using the data for analysis and application (Fors, 2016).

Numerous remote sensing data sets have been stored in libraries, making it simple and possible to access these data sets for the purpose of assessing or researching spatiotemporal land use changes that impact a wide range of research topics, including urban sprawl, changes in agricultural practices, mining areas, forest changes, snowmelt, and many more. Land use can be deduced from the features of land cover, which are assessed using remote sensing techniques. These days, LULC change analysis and detection heavily rely on the use of remote sensing technology. This can be attributed to the abundance of easily accessible, dependable, accurate, and reasonably priced data that can be extracted quickly and affordably to evaluate and track these changes. Numerous change detection algorithms have been developed in recent decades since remote sensing data has been the primary means of detecting changes.

As an illustration, consider the following: post-classification change differencing, vegetative index differencing (DVI). The foundation of G.I.S primarily provides data on the quantity, type, location, and evolution of land cover that has taken place throughout time (Maina, 2016). G.I.S improves combination of data of various sorts and from many sources.

The following four stages combine to generate the picture categorization procedure:

i) Establishing the land cover dynamics occurring over a period of time

ii) Identification of the type of the changes (whether modifications or conversions).

iii) Quantifying the spatial area of the modifications and/ or conversions and computation of statistics

iv) Assessment of the direction and pattern followed by the changes (UCAR, 2010).

This study employs remote sensing as a crucial tool due to its capacity for comprehensive multi-temporal analysis, offering valuable insights into the evolution of land cover changes. Remote sensing, especially through satellites like Landsat and Sentinel 2A, furnishes accurate details regarding the extent of alterations in land use, primarily determined by the image's spatial resolution (Joseph, 2016). Satellites employed in remote sensing follow a sun-synchronous orbit, ensuring consistent illumination when capturing images in successive years or over a series of days, facilitating long-term monitoring and historical research. In this study, a combination of multi-date medium-resolution imagery, supplemented by high-resolution ground data from Google Earth and ground truth GPS points, was utilized to detect and assess usage of land and coverage over a 20-year period at 5-year intervals. Geographic Information Systems (GIS) were employed to integrate and analyze this diverse dataset.

Table 2.1: Landsat 4, 5 and 7 bands, wavelength and areas used for mapping

Landsat 4-5 Thematic Mapper (TM) &LS 7 Enhanced Thematic Mapper Plus (ETM+)		
Band	Wavelength Micro m	Where Useful for Mapping
Band 1-Blue	0.45-052	Distinguishing soil from vegetation Bathymetric map
Band 2-Green	0.52-0.60	Emphasizing peak vegetation Assessing plant vigor
Band 3-Red	0.63-0.69	Discriminating vegetation slopes
Band 4-NIR	0.77-0.90	Emphasizing biomass content
Band 5-SWIR	1.55-1.75	Discriminating moisture content of soil & vegetation
Band 6- TIR	10.40-12.50	Thermal mapping & estimated soil moisture content
Band 7- SWIR	2.09-2.35	Mineral deposits & Hydro-thermally altered rocks
Band 8-PAN	0.52-0.90 LS-7 only	15m Sharper image definition

Source USGS, 2017(Mapping, Remote sensing and Geospatial data)

Table 2.2: Landsat 8 sensors showing bands, wavelength and areas used for mapping

Landsat 8 Operational Land Imager (OLI) & Thermal infrared sensor (TIRS)		
Band	Wavelength Micro m	Where Useful for Mapping
Band 1 coastal aerosol	0.43-0.45	Coastal and aerosol studies
Band 2 Blue	0.45-0.51	Distinguishing soil from vegetation Bathymetric mapping
Band 3-Green	0.53-0.59	Emphasizing peak vegetation Assessing plant vigor
Band 4-Red	0.64-0.67	Discriminating vegetation slopes
Band 5-NIR	0.85-0.88	Emphasizing biomass content
Band 6-(SWIR) 1	1.57-1.65	Discriminating moisture content of soil & vegetation
Band 7-(SWIR) 2	2.11-2.29	Improved soil and vegetable moisture contend
Band 8-PAN	0.50-0.68	15m Sharper image definition
Band 9-Cirrus	1.36-1.38	Improved detection of cirrus clouds
Band 10-TIRS 1	10.60-11.19	Thermal mapping & soil moisture estimation (100m)
Band 11-TIRS 2	11.50-12.51	Improved thermal mapping & soil moisture estimation

Source USGS, 2017 (Mapping, Remote sensing and Geospatial data)

Table 2.3: Sentinel 2 A bands central wavelength and their spatial resolution

Band No	Central Wavelength (nm)	Spatial Resolution (m)	Colour Description
1	443	60	AEROSOL
2	490	10	BLUE
3	560	10	GREEN
4	665	10	RED
5	705	20	VNVIR
6	740	20	VNVIR
7	783	20	VNVIR
8	842	10	VNVIR
8a	865	20	VNVIR
9	945	60	SWIR
10	1375	60	SWIR
11	1610	20	SWIR
12	2190	20	SWIR

Source: USGS, 2017 (Mapping, Remote sensing and Geospatial data)

In order to conduct a thorough assessment on spatiotemporal usage of land and coverage in Likuyani Sub County, Landsat images for the years 1997, 2002, 2007, 2012, and 2017 were obtained at ten-year intervals using the Enhanced Thematic Mapper Plus (ETM+) on Landsat 7, Operational Land Imager (OLI), Thermal infrared sensor TIR on Landsat 8, and sentinel 2A. Things taken into account when obtaining the pictures were;

i) Images need to be collected at about the same time of day to reduce differences in sun angle.

ii) ideally, images from different years should be within the same month to avoid seasonal and phonological differences.

iii) Differences in vegetation greenness.

2.7 Image Classification

The goal of change detection techniques is to pinpoint changes in usage of land and coverage in land use in a given area over a certain limit. In order to detect changes in objects or phenomena, this entails comparing several photos taken in the same research region at various dates (Marien, 2018). There are many ways to carry out change detection; picture classification is the strategy used in this study. Assigning individual pixels in an image to distinct classes or categories is the process of image categorization. Six essential components of visual interpretation are necessary for this process to be carried out by a human analyst: tone/hue, texture, pattern, shape, size, and association (Lillesand *et al.*, 2017).

Analyst finds homogeneous representative samples of different surface cover categories within the images, referred to as training areas, in supervised classification. The choice of these training locations is based on the analyst's knowledge of the real surface cover types depicted in the image as well as their familiarity with the surrounding area (Fors, 2017). Conversely, unsupervised classification entails the analyst first classifying spectral classes according to numerical information in the data, then connecting these classes to information categories. Typically, the analyst specifies the number of groups or clusters to be detected. This method uses clustering algorithms to identify natural groupings or patterns in the data (Fors, 2017). The classification process in remote sensing often utilizes statistical algorithms, with some of the most commonly employed ones being the minimum distance to means, parallelepiped, and maximum likelihood classifiers (Stacy, 2019).

These classifiers, referred to as hard classifiers, offer distinct methods for categorizing pixels within an image based on their spectral characteristics. Pixels not assigned initially are categorized based on their minimum distance to the mean vector of the closest category of interest (Stacy *et al.*, 2019). This method is effective when dealing with fewer intended category classes but may encounter reduced accuracy in imagery with higher spectral variance among classes (Lillesand *et al.*, 2017). The parallelepiped classification technique establishes spectral ranges within each training site to represent the intended category. These spectral ranges from parallelepiped groupings in multiple bands of the image dataset, outlining the lower and upper pixel values. However, issues arise concerning covariance, affecting the interdependency of bands, which may impact classification outcomes (Lillesand *et al.*, 2017).

Classification algorithm chosen due its widespread use and suitability for land use mapping, as supported by various research studies (Ayku *et al.*, 2019). By quantifying the area occupied by various features in sequential images taken over different years. The chosen images, captured during months with minimal phrenological change, particularly between December and March, allowed easy identification of bare land, dry vegetation, and maize-growing areas within the study region.

2.8 Accuracy Assessment

Either a qualitative or quantitative assessment can be made. When evaluating a map qualitatively, you compare what you see on the ground with what you see on the map or image to see if it "looks right."

On the other hand, quantitative evaluations make an effort to pinpoint and quantify map flaws derived from remote sensing. In these evaluations, map data is compared to ground truth data, which is taken to be 100% accurate (Anupam, 2017). The classification of images into distinct land cover categories introduces the possibility of errors, making accuracy assessment a crucial step to evaluate the precision. Assessing of the accuracies is fundamental for ensuring the reliability of information derived from the data and making informed decisions. Classification errors occur when pixels or features are mis-assigned to different categories. Omission errors happen when a feature is excluded from the evaluated category, while commission errors occur when an incorrect feature is included in the category (Anupam, 2017).

2.9 Conceptual Framework

The following section outlines the methodology used to conduct this study, aligning with the objectives outlined in chapter one. The framework illustrated in figure 2.1 presents the interconnected components of this study. Within this framework, there exist key drivers that significantly influence land use change, encompassing population increase, climate change, land subdivision, and alterations in land use patterns. Population growth is closely associated with an augmented demand for land, primarily for construction purposes. However, the availability of land remains fixed. Consequently, with a surge in population, the escalating demand for land for construction purposes inevitably leads to trade-offs, necessitating the sacrifice of other land uses. This dynamic interaction among independent variables—such as population increase and land demand represents the dependent variable under scrutiny (Peter, 2015).

These components form the core structure of the study's framework, outlining the interdependence and influence of various factors on land use transformations.

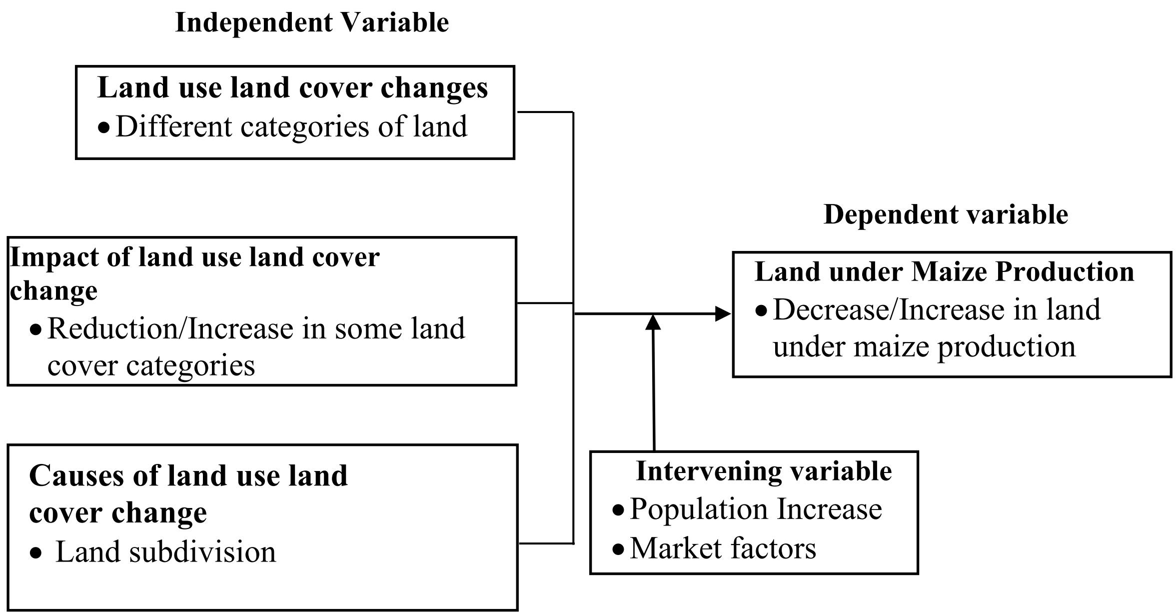


Figure 2.1: Conceptual Framework

Source: Researcher (2021)

CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

This chapter describes the study area in terms of its location, physical and topographical characteristics, climatic conditions, sources of subsistence, demographic characteristics, and administrative units. In addition, it describes the research's design, methodology, sampling strategy, data acquisition, and analysis methods. Other aspects of the study, including the dependability and validity of the research instruments, limitations and restrictions, and ethical considerations, are also discussed.

3.2 Study Area

The research domain The Likuyani sub-county spans around 309 square kilometers. Situated between 1300 and 1800 meters above sea level is the Sub-County. 2013 saw the creation of the sub county from the former Lugari constituency. It is divided into five wards: Likuyani, Kongoni, Sango, Nzoia, and Siniko. It is located in the far north of Kakamega County, bordering Tongaren sub County of Trans Nzoia County to the south, Kiminini Sub County of Trans Nzoia County to the north, Soy and Turbo sub counties of Uasin Gishu County to the east, and Lugari Sub County to the south. Eastward is Bungoma County. The Northern and Western sub counties are separated from one another by the River Nzoia, whereas Eldoret Kitale and Eldoret Turbo highway form almost form the boundary with the Eastern and southern sub counties.

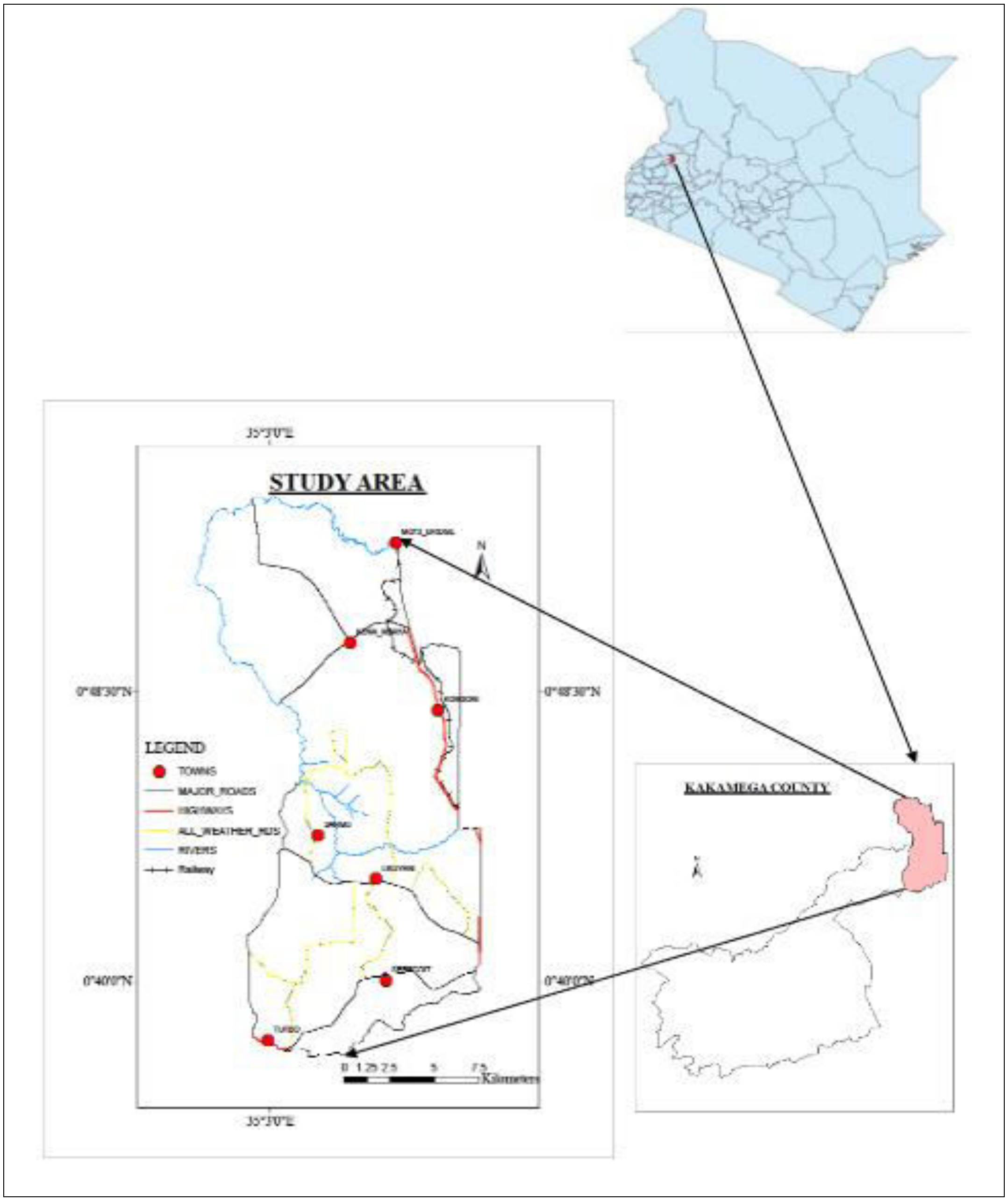


Figure 3.1: Map of the study area

Source: Researcher (2021)

The sub-county consists of seven distinct settlement schemes: Soy, Sango, Kongoni, Sergoit, Moi’s Bridge, Mabusi, and Nzoia. A significant portion of the southern and central areas is covered by planted forests, notably the Turbo Forest.

This region experiences a seasonal pattern of rainfall, with long rains occurring from March to July and short rains falling between September and November. The primary economic activities revolve around dairy farming, alongside the cultivation of beans and maize. Forest management within the area is overseen by the Kenya Forest Service. Maize cultivation, serving as both a staple food and a cash crop, is a prominent agricultural practice in this region. Planting typically commences in March during the onset of the long rains, with harvesting occurring from the end of November, marking the commencement of the dry season. Maize farming serves both commercial and subsistence purposes and is entirely reliant on rainfall. It's worth noting that this sub-county boasts the highest potential for agricultural land compared to all other sub-counties in Kakamega County, as depicted in Table 3.1.

Table 3.1: Potential agricultural land area per Sub County within Kakamega County

Sub County	HIGH	MEDIUM	LOW	ALL OTHER LAND
	AREA IN SQ KM			
MALAVA	70	291	30	36.4
LURAMBI	50	50	-	62
BUTERE	-	146	-	52
IKOLOMANI	-	118.9	-	32
LIKUYANI	296.5	-	-	5.3
SHINYALU	200	155.6	30.7	25
LUGARI	215	-	40.8	
MATETE	80	10	-	10.9
MATUNGU	-	240	-	36
NAVAKHOLO	160	-	-	13.3
MUMIAS WEST	-	24.16	-	34.8
MUMIAS EAST	-	-	-	
KHWISERO	-	114	10	21.6

Source: Ministry of land (2021)

3.2.1 Climate

The Sub-County has an equatorial climate and rainfall pattern due to its close proximity to the equator. The region experiences a bimodal rainfall pattern, with lengthy rains often falling between March and August and short rains in October and November. Temperatures range from 18 to 24 degrees Celsius. Typically, the entire region experiences a dry spell from December to February. With an average of roughly 1300 mm, the yearly rainfall received ranges from 1000 to 1600 mm. The land sizes at inception of the schemes in 1963 were allocated as in Table 3.2.

Table 3.2: Land sizes and acreage per settlement scheme at inception

Scheme name	Acreage (acres)	No. of land parcels
Sango Scheme	15	540
Kongoni Scheme	35	334
Moi's Bridge	25	356
Nzoia Scheme	25 to 35	237
Mabusi Scheme	25 to 35	129
Soy Scheme	40 to 100	156
Sergoit Scheme	40 to 100	190

Source: Lands Adjudication and settlement schemes office Kakamega 2021

3.2 Research design

This research used a descriptive methodology to conduct its investigation. Primary and secondary sources provided both quantitative and qualitative data. Primary data was obtained by field observations to ascertain the true type of ground cover, GPS field verification survey to gather coordinates at specific sites to confirm the correctness of the picture categorization, and questionnaires given to respondents. Secondary data came from the Agriculture and Food Authority Year Book of Sugar Statistics 2020, Land Adjudications Office Records, Topographic Maps, Registry Index Maps, Satellite Images, and Kakamega County Bureau of Statistics offices.

3.3 Sampling Strategy

Purposive sampling methods were utilized to select specific Registry Index Maps (RIMs) associated with settlement schemes as the primary sources of data for this study. The RIMs chosen for digitization and analysis pertained to four specific settlement schemes: Nzoia, Sango, Soy, and Sergoit. These selections were made based on their spatial positioning in relation to significant geographical features such as forests, rivers, and major roads within the study area.

The Nzoia settlement scheme, situated in the northern region, is adjacent to the Nzoia River. The Sango settlement scheme covers the central area and shares boundaries with the Turbo forest. Soy settlement scheme spans the eastern part of the study area and shares boundaries with the Eldoret-Kitale Highway (The Great North Road) as well as the Turbo forest. Lastly, the Sergoit settlement scheme occupies the southern part and is contiguous with both the Turbo-forest and the Eldoret-Malaba Highway.

3.4 Data Collection tools and sources

Table 3.3 Provides details of data type and source under which they were obtained and was used in this research

Table 3.3: Summary of the data type and source

Data Type	Source
Landsat 7 and Landsat 8 imagery	Downloaded from USGS Portal USGS Glo-Vis (https://glovis.usgs.gov/) websites
Sentinel 2A imagery	Obtained from Regional Center for Mapping and Resource Management
Topographic maps	Survey of Kenya Kakamega office
Registry Index Maps	Survey of Kenya Kakamega office
Number and acreage of Land Parcels allocated	Settlement Scheme land Records Office
Land under Sugarcane cultivation	AFA
Maize Production	Ministry of Agriculture Records
Google Earth Images	Google Earth
Ground points and questionnaire	GPS Handheld Receiver. (Trimble Geo-Explorer) and Structured Questionnaire
Population Data	KNBS

Source: Field Data (2021)

3.5 Data preprocessing

The process involved converting the hard copies of Topographic maps and RIMs into suitable data formats through scanning. Afterward, these datasets underwent georeferencing using ArcGIS 10.2, specifically within the Universal Transverse Mercator (UTM) coordinate system (UTM zone 36 N, WGS-84). This standardization was crucial to ensure consistency and compatibility with the coordinate system of the satellite imagery intended for use in the study. Additionally, Landsat and Sentinel-2A images were enhanced for visualization in ERDAS IMAGINE 2013 through linear equalizing stretch techniques. However, the Landsat and Sentinel 2A image classification techniques employed in this study allowed for the quantification of spatiotemporal land use change, which in turn allowed for the inference of land change related to land under maize production as indicated on figure 3.2.

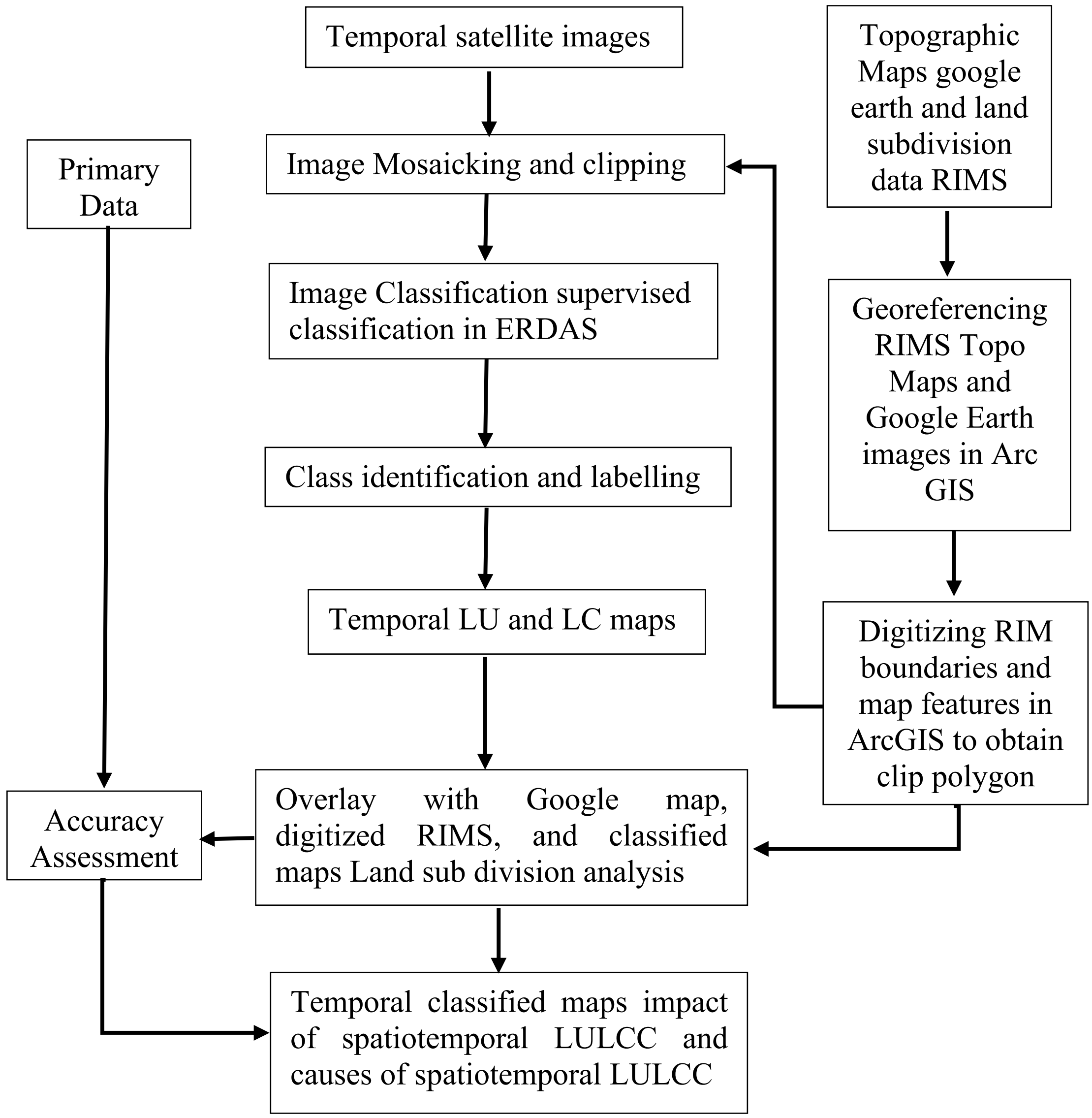


Figure 3.2: Flow diagram used in developing the Classified maps generated from temporal satellite images

Source: Researcher, 2021

3.6 Research Design

De Vaus (2001) defines research design as the overarching strategy a researcher adopts to systematically integrate various study components, ensuring an effective resolution of the research problem. It acts as a roadmap, guiding the collection, measurement, and interpretation of information (Kothari, 1990; Kothari & Garg, 2014). In essence, it is the systematic execution of a research technique within a study, facilitating assessment by readers and encouraging replication (Sovacool et al., 2018). Research methods can vary based on the study's nature, and a research design encompasses any predetermined system, culture, or plan to address a research topic. Its primary goal is to ensure that collected data adequately addresses the research question (De Vaus, 2001). The plan employed to carry out this research is described in this section, and it is based on the particular goals and research designs chosen, as indicated in Table 3.4.

Table 3.4: Summary details of the approach adopted, measurable indicator, research design and expected output as per each objectives

Objective	Approach	Measurable indicator	Research Design	Output
i)To Ascertain LULCC that occurred in Likuyani Sub County between 1997 and 2017	Acquire and classify Landsat and Sentinel images between the years 1997 and 2017 at five year interval	Land use land cover Change per category.	Longitudinal survey	Land use land cover maps
ii) Evaluate spatiotemporal LULCC affecting different land cover classes in respect to land under maize cultivation in the Likuyani sub-county between 1997 and 2017	Generate individual land cover land use percentage cover Per year	Land use land cover Individual category Percentage cover Change	Longitudinal and Correlation survey	Individual Land use land cover Class areas. Tables, Graphs and pie Charts
iii) To Explore the determinants influencing LULCC in the maize-producing areas of Likuyani Sub County during the period spanning from 1997 to 2017	Ground observations, GPS points, RIMS and Questionnaires Reports	Land Parcel acreages, Observed changes on the ground	Descriptive survey	Quantitative statistics from questionnaires & No of parcels, Individual land parcel acreages From RIMs.

3.7 Target population

The research was done in Kenya's Kakamega County, specifically in the Likuyani sub-county. We specifically targeted 1,123 respondents since they have direct control over land ownership. All land parcel owners in the chosen settlement projects in Likuyani Sub County were included in the target population. Among these were the Sango, Sergoit, Soy, and Nzoia colonization plans. The target population for the study is provided in Table 3.5

Table 3.5: Study target population

Settlement scheme	Number of Land parcels
Sango	540
Sergoit	190
Soy	156
Nzoia	237
Total	1123

Source: Field Data (2021)

3.8 Sample size and sampling Techniques

The selection of settlement schemes within Likuyani Sub County for the sample frame was based on their geographical positioning and proximity to surrounding land cover types and infrastructure. Specifically, settlement schemes adjacent to forests, towns, and major highways were included in the sample frame.

3.8.1 Sampling techniques

The selection of respondents for the causes of land use and land cover change data was carried out using a purposive sampling technique. The study sample population was determined subsequent to ground trothing and an analysis of land use, land cover, and the extent of land subdivision. This approach aimed to target areas exhibiting substantial instances of land subdivision, ensuring that the sampling focused on locations with notable occurrences of land division.

3.8.2 Sample size

The number of land parcels allotted to farmers at the start of the settlement schemes, as reported in the Survey of Kenya land settlement scheme data, was used to compute the sample size. A sample size needs to be sufficiently enough to be representative of the entire population, according to Mugenda & Mugenda (2015). The sample size was determined by the researcher using the Krecjie and Morgan (2015) formula, as indicated below;

$$S = \frac{X^2 NP(1-P)}{d^2(N-1) + X^2 P(1-P)}$$

Where

S is the desired sample size

$\mathbf{X}^2$ is the table value of chi-square for one degree of freedom at desired confidence level which is 1.96 x 1.96= 3.8416

N is the population size

P is the population proposition assumed to be 0.05 since this will provide maximum sample size and is the degree of accuracy expressed as a portion 0.05.

$$\mathbf{S} = \frac{3.8416 \text{ X } 1123\text{X } 0.5 \ (1-0.5)}{0.05^2 \ (1123-1) + 3.8416 \text{ X } 0.5(1-0.5)} = \mathbf{286} \text{ Respondents}$$

According to Kothari (2015), a representative sample size is one which is at least 10% of the targeted population. The researcher drew a sample size of 286 respondents (n=286).

Table 3.6: Sample size distribution per each settlement scheme and area occupied in hectares

Settlement scheme	Sample Population %	Area (Hect)
Sango	225	4353.9
Sergoit	13	3705.2
Soy	7	3036.5
Nzoia	41	3448.5
Total	286	11095.6

Source: Field data (2021)

3.9 Data collection Methods, instruments and processes

The investigation relied on a blend of primary and secondary data sources. Secondary data encompassed Topographic and Registry index maps (RIMs) sourced from the Survey of Kenya offices. Remotely sensed satellite images, including Landsat 5 Thematic Mapper for 1997, Landsat 7 Enhanced Thematic Mapper Plus for 2007, Landsat 8 Operational Land Imager (OLI) & Thermal Infrared Sensor (TIRS) for 2017, and the Sentinel image from RCMD for 2017 at a spatial resolution of 10 meters, were obtained from the EROS data center. Primary data were collected through structured questionnaires administered to landowners (Appendix I) and ground observations supported by GPS points for validation. Ancillary data were gathered from the Agriculture and Food Authority's 2020 records, providing information on the average acreage of sugar cane harvested in the sub-county, while population data were sourced from KBS. The study utilized software tools such as ERDAS IMAGINE 2013, SPSS, and ArcGIS 10.3.

3.9.1 Document Analysis

An examination of the respondent's records was conducted, with a focus on the Ministry of Lands' records and performance from 2007 to 2017. This entails the examination of printed documentary items (Kothari, 2018). The researcher examined the land ownership papers to ascertain the effects of property subdivision on the area in Likuyani Sub County, Kenya, that is used for maize production.

3.9.2 Clipping Study Area Boundaries

The base map and the study area's borders were to be provided by the topographic maps. All of the data was first saved in an ArcMap geodatabase. The two hard copies of the Topographic maps were scanned, and the soft copies were placed in the geodatabase to produce the boundary map of the study area. After being imported into ArcMap, the soft copies underwent georeferencing. After that, the topographic maps were mosaicked to provide a full perspective of the research area, from which Likuyani Sub County's map boundary layer could be recovered via on-screen digitizing.

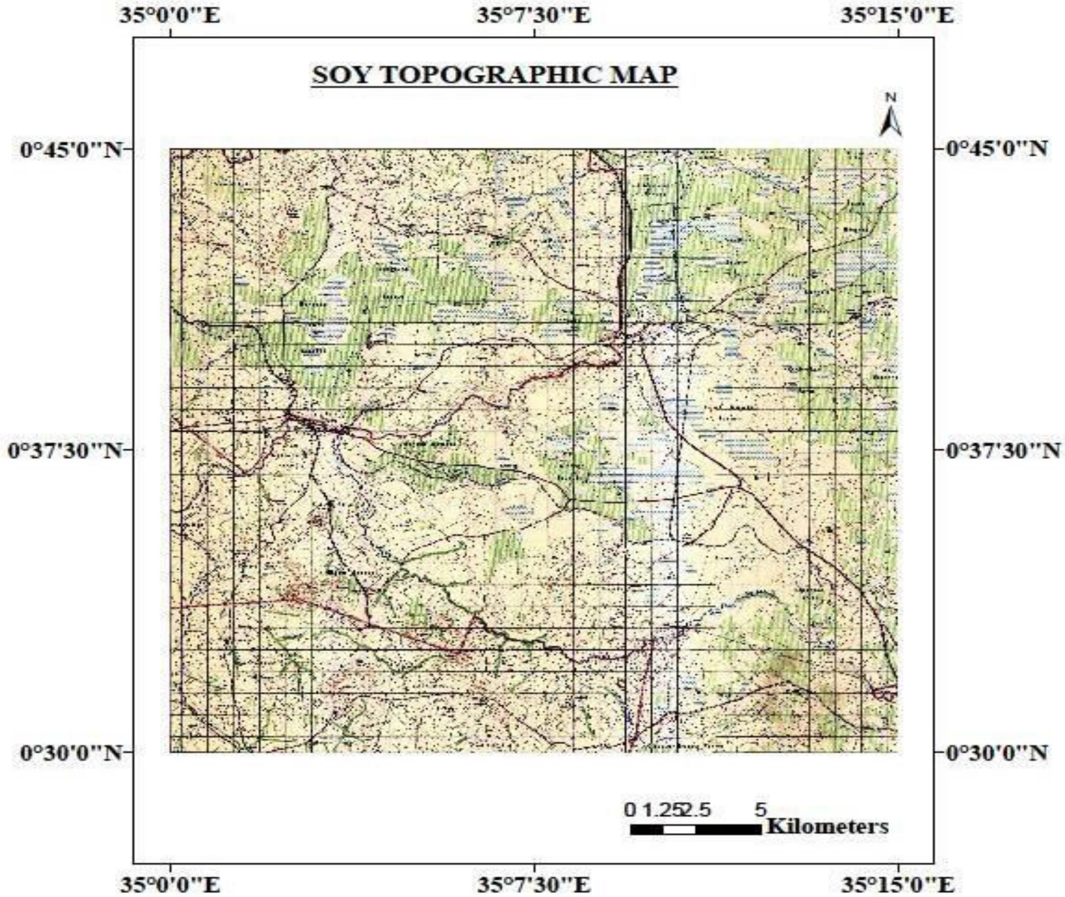


Figure 3.3: Clipping of the study area boundary

Source:

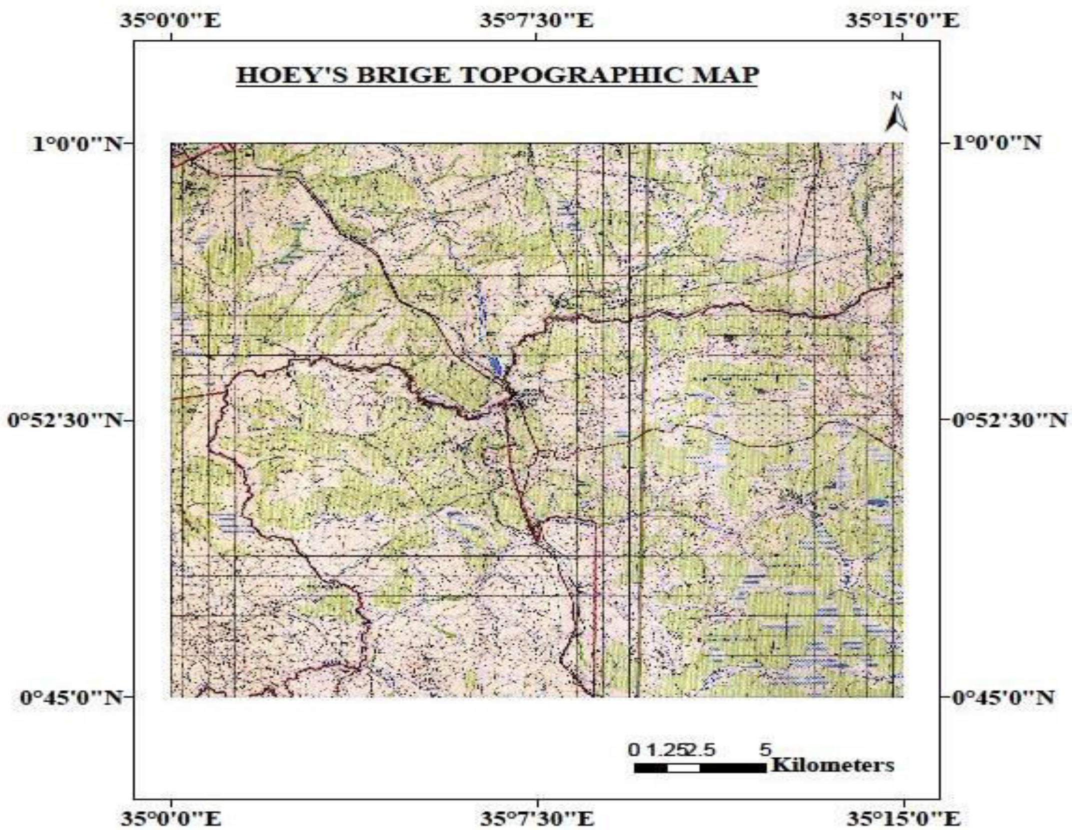


Figure 3.4: HOI'S BRIDGE 89-1 Topographic map before geo-referencing and mosaicking

Source:

The Topographic maps four corner coordinates were used to accomplish georeferencing. The illustration below in Figure 2 shows this. The digital version of the Likuyani Sub County shape file feature class was created using georeferenced topographic maps. The extended study area boundary is represented by the shape file. The shape file was extracted with the intention of using it to trim the large photos, leaving only the study region to deal with.

3.9.3 Interview Schedule

The researcher conducted interviews with local area chiefs, forest officials, and Ministry of Land officials. Interviews serve as a means to explore a group's attitudes and opinions comprehensively. The interview guides were structured to encompass all the objectives outlined in the study. According to Kothari (2018), interviews often yield more reliable, valid, and theoretically satisfactory results compared to questionnaires, particularly in societies where personal interaction holds significant value. Kothari further suggests that interviews tend to elicit better cooperation and more informative responses compared to questionnaires. The interview schedules comprised open-ended questions designed to prompt respondents to provide insightful and detailed information. The various datasets employed in this study were;

i) RIMs of selected settlement schemes within Likuyani sub county.
ii) Two topographic maps (Hoey's Bridge index 89/1 and Soy index 89/3) at a scale of 1:50,000 covering the boundaries of the study area.
iii) Landsat 7, Landsat 8 and Sentinel 2A satellite images for the years 1997 2002, 2007, 2012 and 2017.
iv) Google Earth images of the study area.
v) Population statistics of Likuyani
vi) Land subdivision data
vii) Maize production data
viii) Structured Questionnaire
ix) Sugar cane production data

3.9.4 Software

The data processing involved the use of several software tools, including ArcGIS 10.2, a scanner, and ERDAS 2016. The scanner was utilized to convert hard copy analogue maps, such as the topographic and RIMs maps, into digital format. ArcGIS 10.2 played a key role in various tasks, including geo-referencing the topographic and RIM maps of selected settlement schemes, digitizing the study area boundary and land parcels, overlaying and clipping the area of interest from the images, generating the error matrix for accuracy assessment, and quantifying the number of land parcels within each selected settlement scheme along with their respective areas.

Furthermore, ERDAS IMAGINE software was used for layer stacking the bands of the images, which involved combining selected bands of multispectral images to create a single composite image. The acquired images were already georeferenced in UTM zone 36 North datum WGS 84, ensuring compatibility and consistent projection among the maps. Field data collection for ground trothing involved the use of a GPS receiver to capture point coordinates of features. Table 3.7 outlines the specific data obtained and utilized for this research.

Table 3.7: Data set scale date and sensor considered during data collection

DATA SET	SCALE	Date	Sensor
Landsat 7	30m	1997	TM
Landsat 8	30m	2002	ETM+
Landsat 8	30m	2007	OIL
Landsat 8	30	2012	OIL
Sentinel-2A	10m	2017	MSS
Topographic maps	1;50,000		
RIMs	1;10,000		
Land subdivision data	No of Parcels		
Google Earth Maps	Sub Meter		
Questionnaire Data			
Maize production Data	Tonnage		
Sugar Cane Production Data	Acreage		

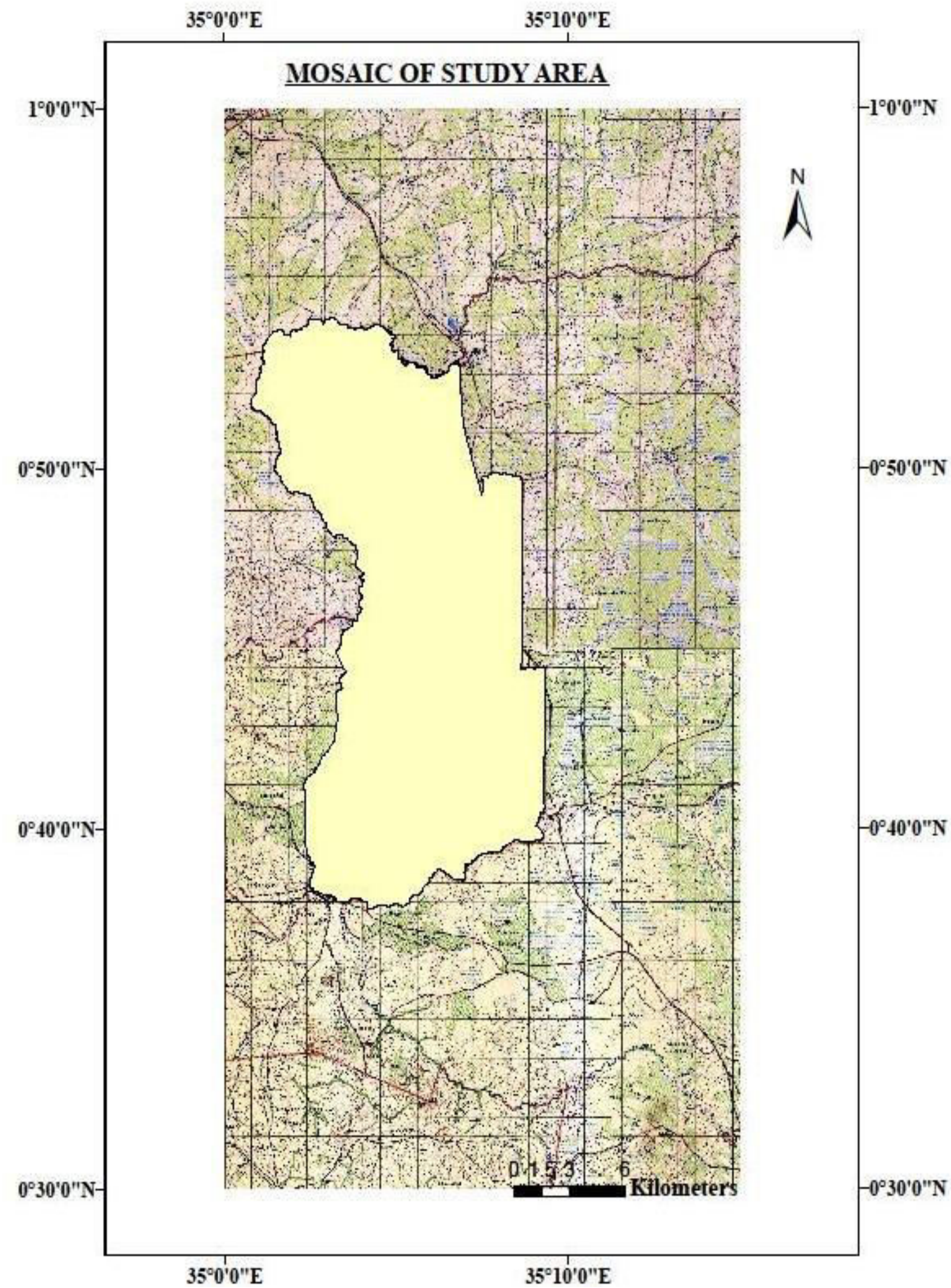


Figure 3.5: Mosaicked geo-referenced Topographic maps with Likuyani Sub County shapefile

3.9.5 Assessing impact of land use land cover change

Mapping land use land cover changes in the study region between 1997 and 2017 using Landsat and Sentinel 2A images of the respective years served as the basis for assessing the impact of land use land cover changes in the study area. After careful consideration, Landsat and Sentinel 2A sensors were chosen.

i) For long term change detection, Landsat has robust and continuous data inventory stores for every part of the world from 1972 till today. Since this study aims to detect the LULC changes in Likuyani from 1997 to 2017, Landsat data was the best available option.

ii) Landsat satellite has a repeat imaging interval of 16 days.

iii) Sensor increases the flexibility of data selection, especially when cloud cover is a major limitation in satellite data selection (Siddhartho, 2019).

iv) Both sensors acquire images in multispectral bands, a fact that is very important in image classification.

v) Sentinel 2A also has continuous data inventory since June 2015 to date. It has higher spatial resolution than Landsat. (Sentinel 2A has a 10m spatial resolution while Landsat has 30m spatial resolution). Both Landsat and Sentinel 2A image data are free.

After selecting the satellite sensor, the images were selected by considering the factors below.

a. The images were to be free from cloud cover. Cloud cover obscures features to be mapped thus affecting the quality of image classification.

b. Season of the year when the image was acquired. Images had to be acquired within the same season of the year so as to avoid changes in phenology because variation in plant phenology changes appearance of land use feature and can impact the classification accuracy. After considering the above facts, Landsat 7 (1997 Landsat ETM+ imagery), Landsat 8, (Operational Land Imager OLI, TIRS) and Sentinel 2A (2017) images were selected for this study. These images were between the months of December and March the same dry season in the study area.

Table 3.8: Satellite image bands used in LULC detection

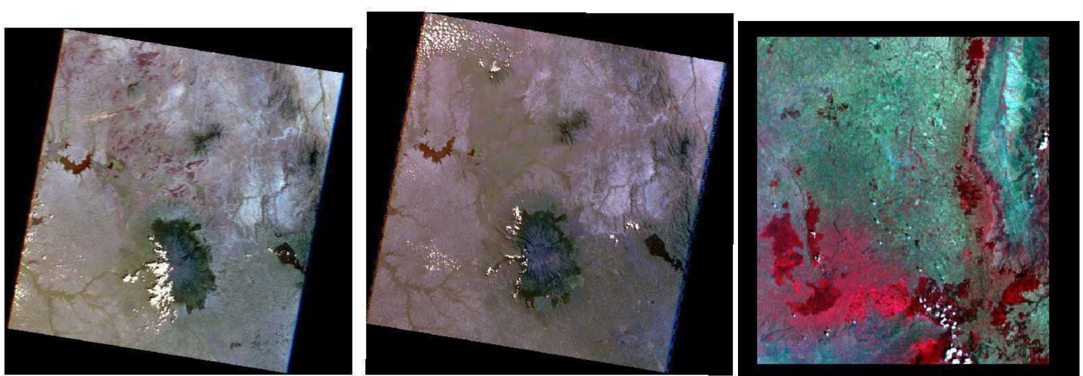
Year	Month	Satellite image	Bands	Spatial Resolution
1977	December	Landsat 7 ETM+	1 to 5	30m
2002	December	Landsat 8 OIL	2 to 5	30m
2007	February	Landsat 8 OIL	2 to 5	30m
2012	January	Landsat 8 OIL	2 to 5	30m
2017	March	Sentinel 2A	2 3 4 & 8	10m

3.9.6 Image processing

The images obtained required preprocessing before meaningful analysis could take place. Image processing involves a series of operations performed on an image to extract useful information. This included several essential steps such as layer stacking, compositing, clipping, and image classification to derive valuable insights and information from the imagery.

3.9.7 Layer Stacking and Compositing

The acquired photos had already undergone georeferencing and radiometric and other error correction. The downloaded Landsat pictures came as multispectral TIFF format bands that were compressed and stored in a folder that was chosen every five years. The software EARDASS IMAGINE was used to composite the bands. A composite image was created by layer stacking Landsat 7 Enhanced Thematic Mapper plus (ETM+) bands 1, 2, 3, 4, and 5 for the year 1997. The same method was used using Landsat 8, Landsat Operational Land Imager (OLI), and Thematic Infrared Sensor (TIRS), except in this instance, bands 2, 3, 4, and 5 were chosen for the years 2002, 2007, and 2012 at a spatial resolution of 30 meters. Sentinel 2A bands 2, 3, 4, and 8 with a spatial resolution of 10 meters for the year 2017.



A b c

Figure 3.6: Composite 1997 Landsat 7 Image. Composite 2007 Landsat 8 Image. Composite 2017 Sentinel 2A

Source; Landsat 8 and Sentinel 2A

3.9.8 Clipping the composite images

A large region was covered by the composited photos. The swath width of the Landsat sensor is 180 km, but that of Sentinel 2A is 290 Km.

The area of interest, "Likuyani Sub County," was obtained by cropping these pictures to obtain a section of the photographs covering the research area. Using ArcGIS clip raster tools from raster processing tools, the digitized Likuyani shapefile was used to clip the area of interest from all the composited pictures. The cropped photos that depict the research region can be obtained on figure 3.7.

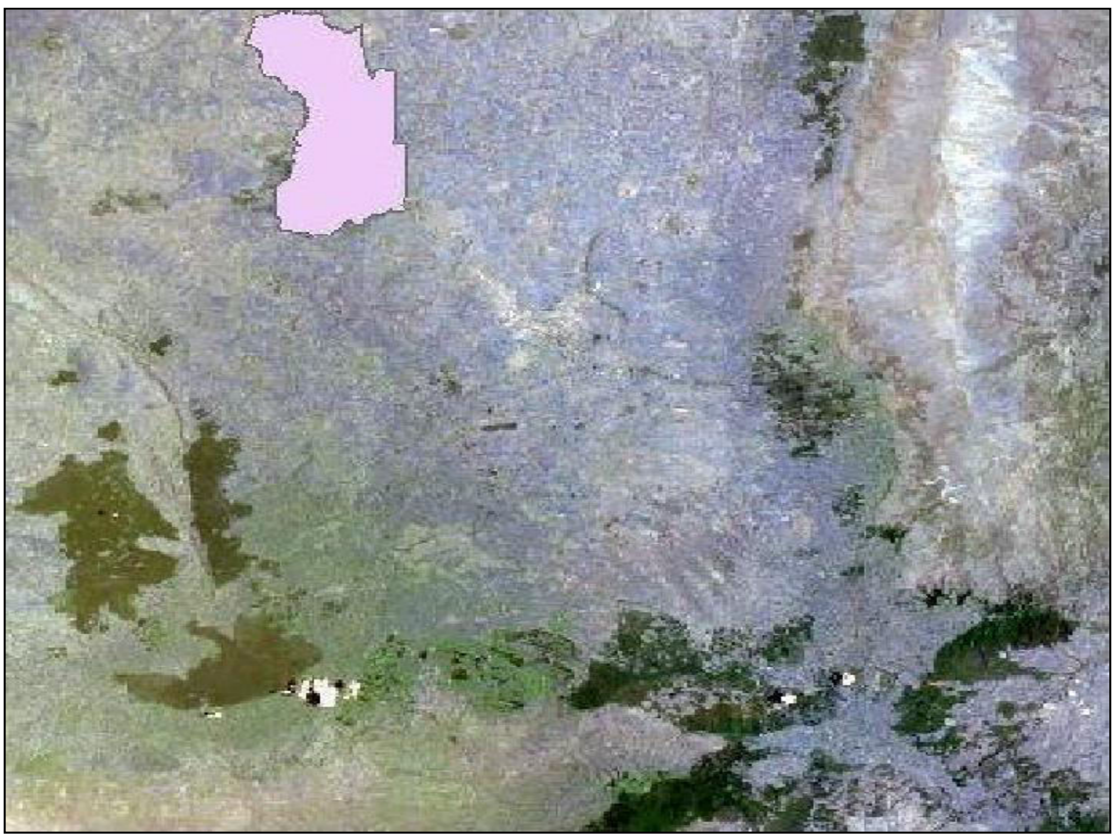


Figure 3.7: Study area overlaid on 2017 Sentinel 2A Image before clipping

Source: Sentinel 2A Image

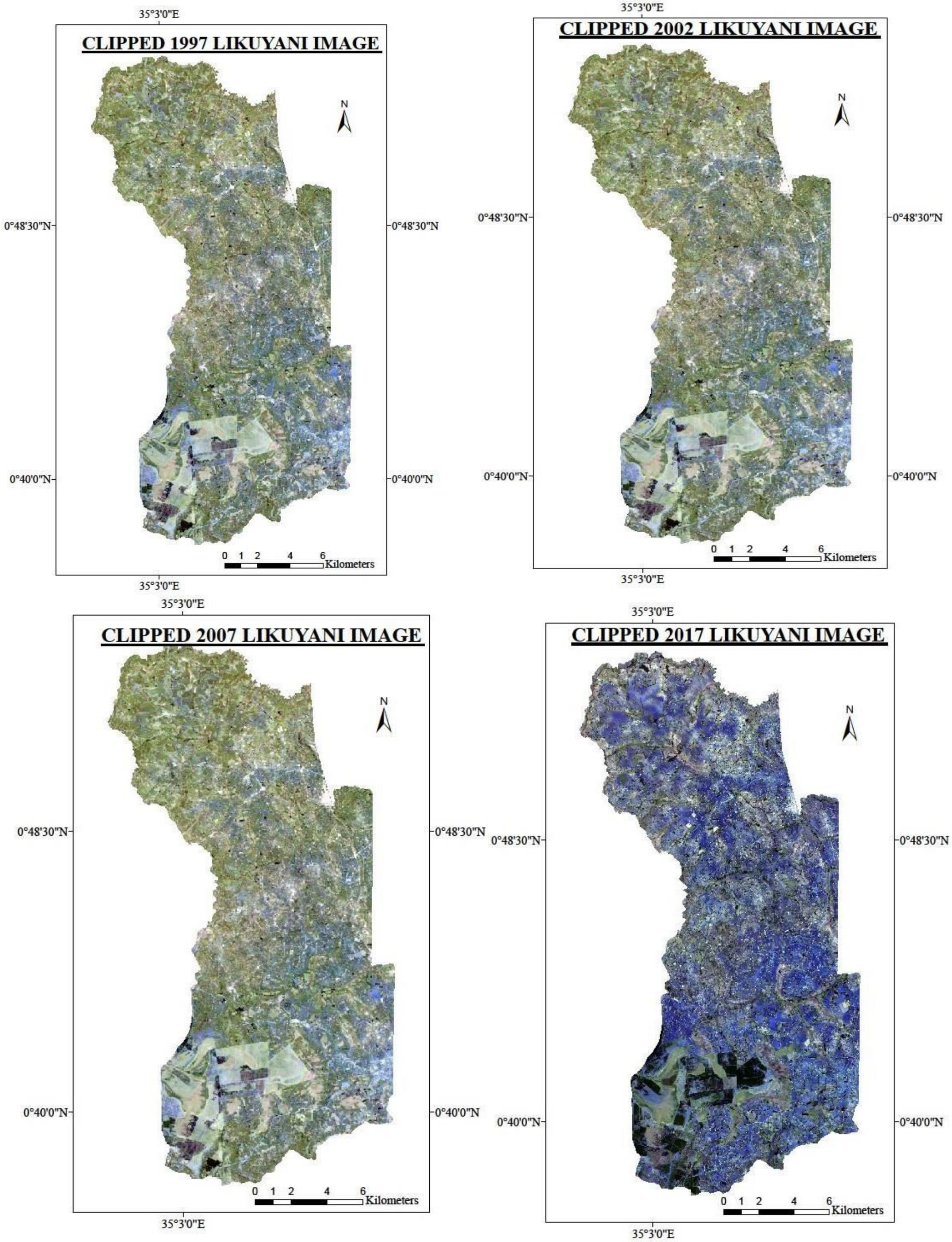


Figure 3.8: Clipped 2007 Landsat 7 Image, Clipped, 2017 Landsat 8 Image. Clipped Sentinel 2A Image

3.9.9 Image Classification

After the images were composited and cropped, the next step was to classify the photographs. The literature review provides an explanation of the image classification procedure. Depending on the needs and specifications of the researcher as well as the desired results, a variety of image categorization techniques are employed. As stated in the literature review, there are two primary techniques for classifying images: supervised and unsupervised. Supervised categorization was employed in this investigation. The following methods were employed in this study's supervised picture classification: sites training were defined, Extraction of Signatures, and Classification of the Image.

3.9.10 Delineating training polygons

The process of defining training polygons involved selecting areas as training sites for specific land cover classes using the on-screen digitizing method. This method utilized a color composite image with strong contrast for digitizing, capturing spectrally similar pixels as polygons representing training sites. The Landsat 7 bands 1, 2, 3, 4, 5, and 7 were layered, stacked, and composited to form the 1997 image. Landsat 8 bands 2, 3, 4, 5, and 7 were similarly composited and layered to generate the 2002, 2007, and 2012 images. For Sentinel 2A, bands 2, 3, 4, and 8 were layered and composited to create the 2017 image. Each band of the Landsat and Sentinel 2A images has distinct reflectance and absorption characteristics, capturing unique signatures for various Land Use and Land Cover (LULC) features. After studying band combinations, specific bands were chosen to enhance image features for improved visual interpretation.

For Landsat images, the band combination 4 3 2 (band 4 in red, band 3 in green, and band 2 in blue) provided enhanced contrast for visual identification and interpretation of features in RGB color composite. Given Sentinel 2A's varied band resolutions (10 meters, 20 meters, and 60 meters), only the four bands with 10-meter resolution were selected (bands 9, 4, 3, and 2). The band combination chosen for Sentinel 2A was band 4 in red, band 3 in green, and band 2 in blue, which constitutes a true color (RGB) composite band 9 infrared. This composite allows features to appear in their natural colors, facilitating easier identification at the higher 10-meter resolution provided by the Sentinel 2A sensor. Combining band 9, 4, and 2 yielded a false color image that was utilized to differentiate buildings from other categories. In band combination vegetation appears red while build up areas appear grey in color.

The creation of training sites involved using ERDAS IMAGINE's Area of Interests (AOI) tools to delineate homogeneous areas representing specific land cover classes. Approximately thirty training polygons were generated for each land cover class, utilizing high-resolution images from Google Earth for ground trothing purposes due to its sub-meter resolution enabling clear feature identification. Additionally, GPS points collected during field visits were used in conjunction with Google Earth maps to validate and refine the training sites.

3.9.11 Extracting Signatures

The signature file contains essential information about the distinct spectral responses of each category of interest (Stacy 2019). Upon importing the clipped image of the study area into the ERDAS IMAGINE software, it was displayed on the screen to initiate the classification process. An Area of Interest file (AOI) was created, facilitating the delineation of homogeneous features. Within this module, the information from each selected pixel was categorized, leading to the creation of a file containing detailed information about each class. The signature editor tool within the software was utilized to register the description of class types and colors for each delineated feature into the signature file.

In the final stage of this process, the image underwent classification. This step involved employing statistical algorithms to analyze the spectral bands of the imagery and evaluate how closely each pixel related to the identified training samples representing the categories of interest across the entire image dataset. The classification algorithm selected for this research was the maximum likelihood classifier, chosen based on explanations provided in the literature review. Six classes were identified for classification in the Landsat and Sentinel 2A images, following guidelines outlined by Anderson (2006). The classes designated for classification in both the Landsat and Sentinel 2A images were categorized as indicated in table 3.9

Table 3.9: Land cover Classes and classification

Land Cover Classification	Description
Bare Land	Contained areas or fields with little or no vegetation at the time of image acquisition. Characteristics of this class include fallow agricultural fields, bare sediment or soil Areas, areas cleared of vegetation and plowed fields.
Forest	Contained large homogeneous vegetative land covers of Trees or thick shrubs.
Buildings	Contained commercial, private and, isolated residential Structures or buildings.
Swamp	Contained land cover with papyrus grass filled or bush with water. Generally, these are areas where the groundwater table is at, near or above the surface for Significant part of the year.
Grass/Shrub	Contained a mixture of grassland, areas covered by different species of bushes and isolated trees with Varying density from one location to another.
Farm Land	This contained planted agricultural fields with vegetation and unplowed harvested area at the time of image Acquisition.

Using the maximum likelihood technique, supervised classification was carried out on Landsat 7, Landsat 8, and Sentinel 2A pictures for the years 1997, 2002, 2007, 2012, and 2017, respectively. Training sites for this process were taken from the previously described processes. Figures 8, 9, and 10 show the results of the picture classification. After that, these outputs were entered into ArcGIS and Choropleth maps were created for every year; refer to figures 1, 13, and 14. Every year, an accuracy assessment was conducted for the image.

3.9.12 Accuracy Assessment

The accuracy assessment process involved the utilization of high-resolution Google Earth maps with sub-meter resolution and GPS points collected from accessible regions in the study area adjacent to roads as ground truth data. These datasets were input into ArcGIS, and employing the analysis tools within ArcGIS, an error matrix was created for each classified image. Through these matrices, the overall accuracy, user's accuracy, and producer's accuracy for the images were computed. In the Error Matrix, each row represents an output class, while each column represents a ground truth class. The value within each matrix cell signifies the number of pixels (raster cells) corresponding to the output class and ground truth class combination. Cells along the diagonal indicate where the output class matches the input class, indicating the number of accurately classified pixels for each class. Values outside the diagonal represent incorrectly classified pixels. The Overall Accuracy is calculated by dividing the total number of correctly classified raster cells (sum of the diagonal values) by the total number of cells in the ground truth raster and expressing the result as a percentage (Randall, 2011). The Error Matrix provides two accuracy measures for individual classes. The accuracy values for each column indicate the percentage of cells in that ground truth class that were correctly classified. Values below 100% suggest errors of omission, indicating ground truth cells that were omitted from the output class. This metric is referred to as the producer's accuracy.

Producer's accuracy = Total number of samples that were correctly classified in a given category divided by Total number of samples that are classified to that particular category.

Conversely, the accuracy values for each row show the percentage of sample cells in each output class that were correctly classified. Values less than 100% indicate errors of commission (cells incorrectly included in the output class). This value is sometimes termed the user's accuracy (Randall, 2011).

User's accuracy = Total number of samples that are correctly classified in a given category divided by Total number of samples in that category

Overall accuracy is defined as the ratio between the total number of samples which are correctly classified and the total number of samples considered for the accuracy assessment. From the error matrix, overall is calculated as below;

Overall accuracy = Total number of samples that are correctly classified in all categories divided by Total number of samples.

Overall accuracy can be summed as total number of samples in the diagonals divided by the total number of samples in the error matrix.

3.9.13 Land Subdivision

The issue of land subdivision emerged as a significant factor contributing to land use and land cover change in sub-Saharan Africa. Discussions with the agricultural officer stationed in Kongoni, Likuyani Sub-District, revealed that land parcels smaller than half an acre did not support sustainable maize production in Likuyani Sub County. Farmers occupying such parcels used part of the land for settlement purposes, leaving a fraction for maize cultivation.

To assess the extent of land subdivision in the study area, a purposive sampling method was employed to select specific settlement schemes based on their geographic attributes, such as proximity to towns, forests, and major roads. Registry Index Maps (RIMs), acquired as hard copies from the Kakamega Land Survey office, were scanned and processed using ArcGIS. These maps were georeferenced in ArcMap, utilizing four-corner coordinates and aligned with the same datum as the Topographic maps and RIMs (WGS 1984 UTM). Subsequently, a feature class was created within the ArcMap geodatabase to digitize the boundaries of land parcels within the selected settlement schemes, forming a comprehensive map (as depicted in figure 3.12). This digitized data allowed for queries on land parcel acreage to be computed and analyzed.

Additionally, records obtained from the Survey of Kenya Kakamega office detailing the historical records of land subdivision in the area since the inception of the schemes were utilized. This data was instrumental in analyzing the trends of land subdivision within the region over time.

3.10 Validity of the Research Instruments

The researcher determined whether the questionnaire's content was measuring what it was designed to assess in order to guarantee the validity of the research tool. To evaluate the study equipment, the researcher asked the lecturers and supervisors for their professional opinions. The questionnaires were designed with the study's research goals in mind. According to Kothari (2018).

3.11 Reliability of the Research Instruments

A research instrument's ability to yield consistent results after testing and retesting is referred to as its reliability (Kothari, 2014). It represents the level of consistency found in the instrument's scores. In order to guarantee uniformity among interviewers, predetermined sets of interview questions that complemented the goals of the study were applied consistently. By aligning the questionnaire with the essential competences needed for the research, this uniformity served to improve the questionnaire's validity and reliability. Cronbach's alpha was used in this study to assess the validity of the questionnaires that participants filled out. A coefficient called Cronbach's alpha (α), which ranges from 0 to 1, is utilized to assess the internal consistency or coherence of test items. It also assesses the degree to which a subset of test items correlates with a specific behavior or characteristic. Table 3.10; presents the results of the reliability test

Table 3.10: Reliability test as per each parameter

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha
Spatiotemporal land use	4.8591549	.323	.076	.349[a]
Land under maize production	4.6619718	.370	.027	.066[a]
Implications on land under maize production	4.9295775	.695	.389	.151[a]

a. The value is positive due to a positive average covariance among items

Source: (Field Data 2021)

Kombo and Tromp (2018) observe that a Cronbach's $\alpha > 0.7$ implies that the research instrument provides a relatively good measure. The SPSS for windows reliability program was used to determine the reliability of research instruments. In this study, the Cronbach alpha value was above 0.7, which indicated adequate convergence and internal consistency.

3.12 Procedure for Data Collection

The researcher initiated the research process by drafting a letter to the Director of Postgraduate Studies at Masinde Muliro University of Science and Technology, seeking consent to proceed with the research study. Subsequently, an application for a research permit was submitted to the National Council of Science and Technology (NACOSTI) to obtain authorization for conducting the study among landowners in Likuyani Sub County. Upon receiving the research permit, the researcher sought clearance from the county Ministry of Lands officer to visit the selected respondents for the study.

Prior to commencing the actual study, the researcher conducted introductory visits to the locations of all selected respondents. Appointment schedules were arranged with the sampled respondents to ensure adequate preparation for the study. The selection of respondents was carried out randomly to accommodate their busy schedules. Subsequently, the questionnaires were administered to the respondents at their respective locations. However, owing to the sensitive nature of the study's information, a significant portion of the work was carried out directly by the researcher.

3.13 Data Analysis and Presentation

The study incorporated a combination of qualitative and quantitative research methods to analyze the impact of land use land cover changes on maize production in Likuyani Sub County, Kenya. The data collected from various respondents, as previously mentioned, underwent a comprehensive examination. Completed instruments were gathered and organized for analysis. Quantitative data underwent analysis using descriptive statistics and were visualized through tables, bar graphs, pie charts, and choropleth maps generated using ArcMap. The collected data were coded and entered into the Statistical Package for Social Sciences (SPSS) version 20 for further analysis. Descriptive and analytical statistics were employed to interpret the obtained data. Additionally, a multiple regression analysis was conducted to quantify the strength and relationships between the variables.

Conversely, qualitative data, stemming from open-ended questions, were scrutinized to identify and categorize themes, categories, and patterns relevant to the study objectives, following the approach suggested by Mugenda and Mugenda (2018). In alignment with Kothari (2018) and Mugenda and Mugenda (2018), the linear regression model was deemed suitable for this study. The research data underwent analysis utilizing descriptive statistics, and the interrelation between variables was examined through a general linear regression model.

Model 1; $Y= \beta_0+\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$

Where: Y = Dependent Variable (student's discipline) Independent variables which include;

X_1 is spatiotemporal land use land cover changes, X_2 is impact of land use land cover change and, X_3 is Impact of land use land cover change.

In the model, β_0 represents the constant term while the coefficients β_1, $\beta 2$, and β_3, were used to measure the sensitivity of the dependent variable (**Y**) to unit change in the predictor variables X_1, X_2, and X_3.

ϵ is the error term which captures the unexplained variations in the model. When moderation is introduced i.e. Model 1 plus government regulation as a moderating factor;

Model 2; $Y= \beta_0 + \beta_1 X_1 * M + \beta_2 X_2 * M + \beta_3 X_3 * M + \epsilon$

Where β_0 = a constant

β_0, β_1, β_2, and β_3 are the regression coefficients

ϵ = the stochastic term

M is government regulation as a moderator.

3.14 Ethical Considerations

The researcher made sure that the information that respondents submitted would remain private. The study made sure that participants had the right to privacy and were shielded from harm—both psychological and physical. The respondents were given enough information about the study's goal that was both clear and sufficient for them to make an informed decision about whether or not to participate.

3.15 Summary

This chapter addressed the study design, study population, study area, sample and sampling process, data collection tools, data collection process, data analysis, and the underlying assumptions of the research methodology. Furthermore, the research design utilized for this study was deliberated.

3.16 Limitations of the study

The study was to some extend be limited to the following factors:

i) Questionnaires may not provide opportunities for the researcher to ask clarification of answers given by the respondents, in case some questions were not answered the researcher may not get an explanation from the respondents as to why some questions are incomplete and the researcher may not be able to predict if the respondents have answered the questions until after the collection of the instruments. To solve this problem, the researcher ensured that the questions are simple and clear so that the respondents answer them accurately.

ii) The study population reduced as some declined to take part in the study while others did not return the questionnaires. The researcher dealt only with those respondents who were willing to take part in the research as per the research ethics.

iii) The Landsat images acquired had a coarse spatial resolution of 30m which posed a challenge in identifying some of the features. This was mitigated by applying Google Earth images with a higher spatial resolution thus enabling the researcher to identify and separate the features. Ground visit and verification was also applied while picking GPS points.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter provides the findings regarding the mapping of land use land cover change within the study area from 1997 to 2017, utilizing Landsat and Sentinel 2A images captured at five-year intervals. The analysis aimed to ascertain the influence of land cover changes on land dedicated to maize production. The statistical data extracted from error matrices played a crucial role in identifying and interpreting trends in land use land cover changes spanning from 1997 to 2017. Subdivision of land into small parcels not viable for any sustainable maize cultivation deduced from digitized RIM maps and records on land subdivision depict how far land subdivision has affected area under maize production. These are land parcels with acreage less than a third of an acre as per information obtained from the agricultural officers. The data from Survey of Kenya land subdivision records and results from questionnaires and discussions with Agricultural officers helped in formulating the causes of reduced land under maize production in Likuyani Sub County.

4.2 Spatiotemporal Land use land cover change analysis

4.2.1 Determining LULC

The examination of the 1997 Landsat 7 classified choropleth map of Likuyani Sub County yielded valuable insights into the distribution of land cover classes within the study area, achieving a classification accuracy of 80.47%.

The land cover categories and their respective extents were observed as follows: Forest occupied 13.66% of the area, Grass/Shrub and Farm land covered 14.97% and 26.75%, respectively. Bare land represented 23.06% of the total area, while Buildings accounted for 4.15%. Swamp areas comprised the smallest land cover at 4.14%.

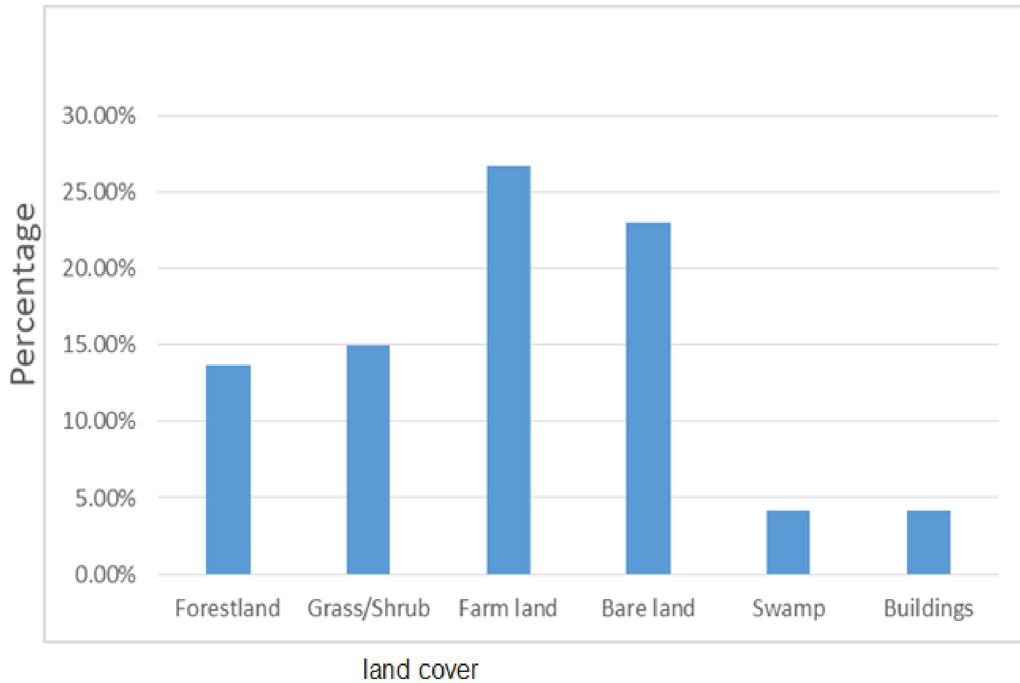


Figure 4.1: Land use land cover classes in percentage cover for 1997

Source: (Field Data, 2021)

Different types of land use and land cover changes (LULCC) are influenced by the complex interactions between environmental, economic, and sociocultural factors (Geist and Lambin, 2014). The Earth's land surface is under pressure from these interactions (Reynolds *et al.*, 2017), especially when they combine with other phenomena including water scarcity, biodiversity loss, and climate change (Maitima *et al.*, 2019). As a result, there is a rise in poverty, climatic fluctuations, and habitat destruction (Bremner *et al.*, 2016).

The effects of these shifts are frequently more severe in developing nations where local residents mostly depend on natural resources for their livelihoods (Safriel, 2017). Due to the growing global population and its associated needs, it is anticipated that human-induced changes in land use, resulting from a variety of activities, will continue (Lambin *et al.*, 2018).

It's critical to comprehend change dynamics and how they impact and interact with human society in the present and the future when creating interventions that maximize beneficial effects on the environment (Adger *et al.*, 2015). Effective natural resource management methods and the favorable acceptance of management practices depend on the integration of human perception on these interventions. The Figures 4.2 (a and b) represent land covers in Sango and Soy settlement schemes in the year 1997. Figures 4.2 (a) represents the classified map of Soy settlement scheme and Figure 4.2 (b) that of Sango settlement scheme in the year 1997. In both maps the black color in the legend is a software generated color of those pixels that are not classified. Dark green, pink, blue, green and brawn represent forest, bare land, swamp, grass/shrub and buildings land cover. In figure 4.2b, yellow represents farmland while the same land cover is represented by the color beige in figure 4.3a.

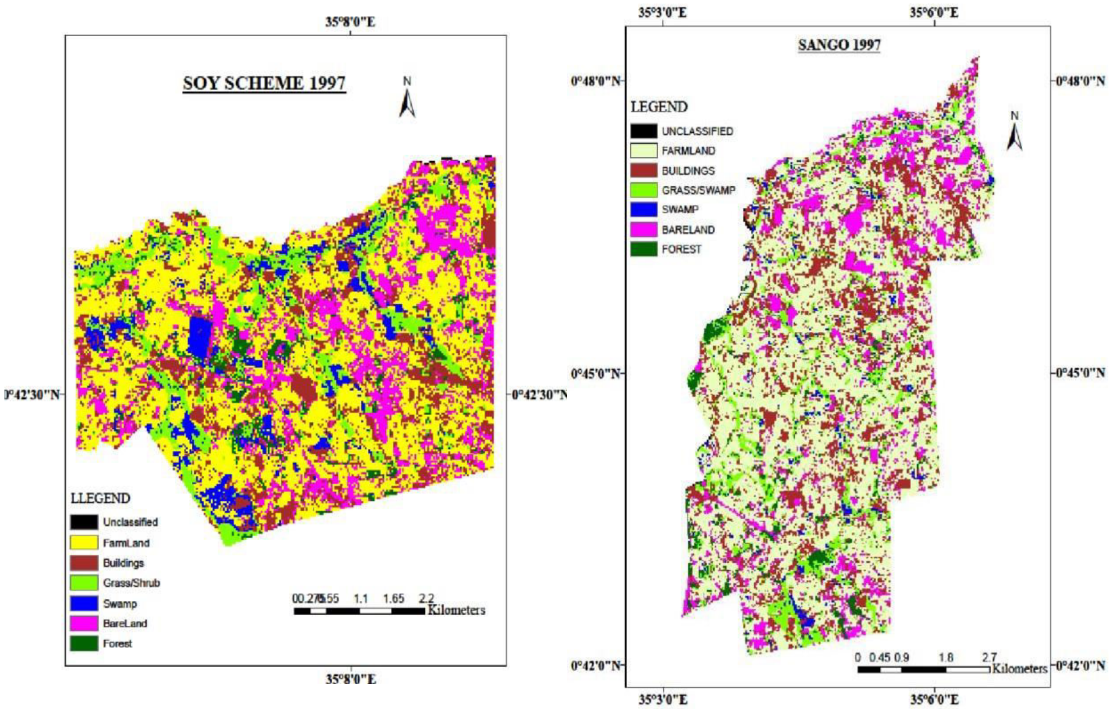


Figure 4.2 (a and b): Classified Map of Soy and Sango scheme in 1997

Source: Landsat 5 image (1997)

Land cover change under maize production classes extracted from the classified map are also presented in figure 4.3. Figures 4.3a represents the classified map of Sergoit settlement scheme while Figure 4.3b represents Nzoia settlement scheme in the year 1997. In both maps the black color in the legend is a software generated color of those pixels that are not classified. Dark green represents forest cover and grey represents buildings in both maps. In figure 4.3a, light brawn represents farmland, brawn represent bare land, blue represents swamp and green represents grass/shrub land cover. In figure 4.3b, yellow represents bare land, brawn represents grass/shrub land cover, green represents swamp, and color pink represents farmland.

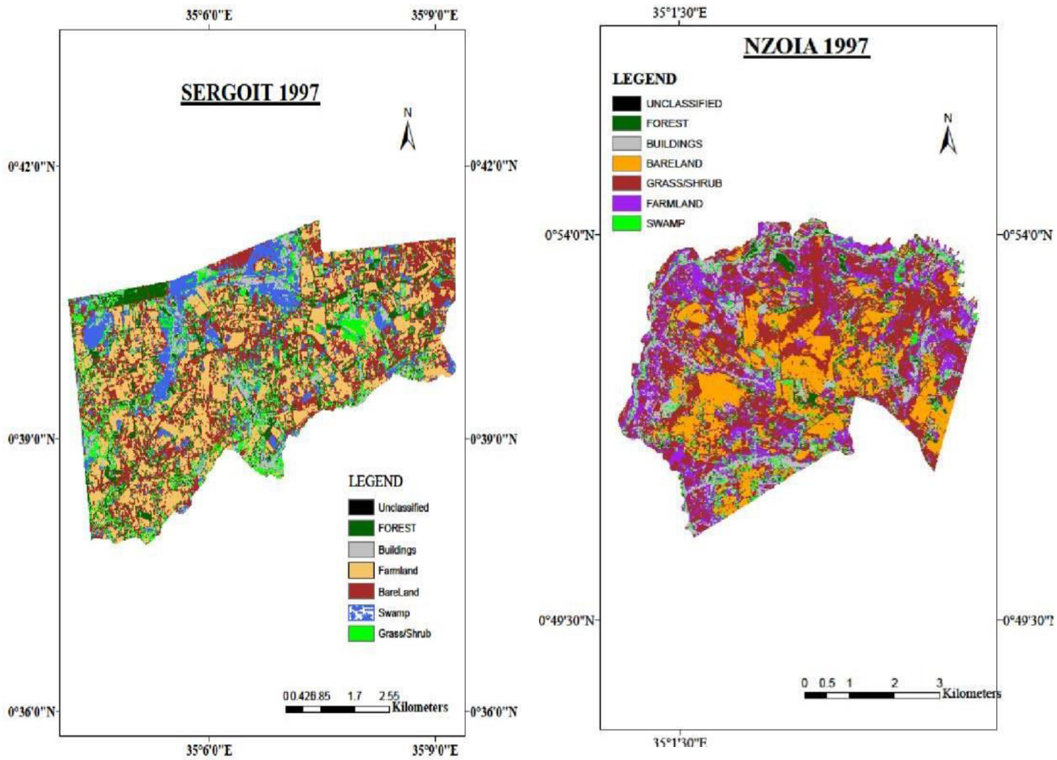


Figure 4.3 (a and b): Classified Map of Sergoit and Nzoia scheme in 1997

Source: Landsat 5 image (1997)

Figure 4.4 represents the classified map of Likuyani Sub County in the 2002. The land cover classes in this this map are represented by colors as; blue represents swamp, light pink bare land, yellow is farmland, green grass/shrub, dark green represents forest and brawn represents buildings land cover.

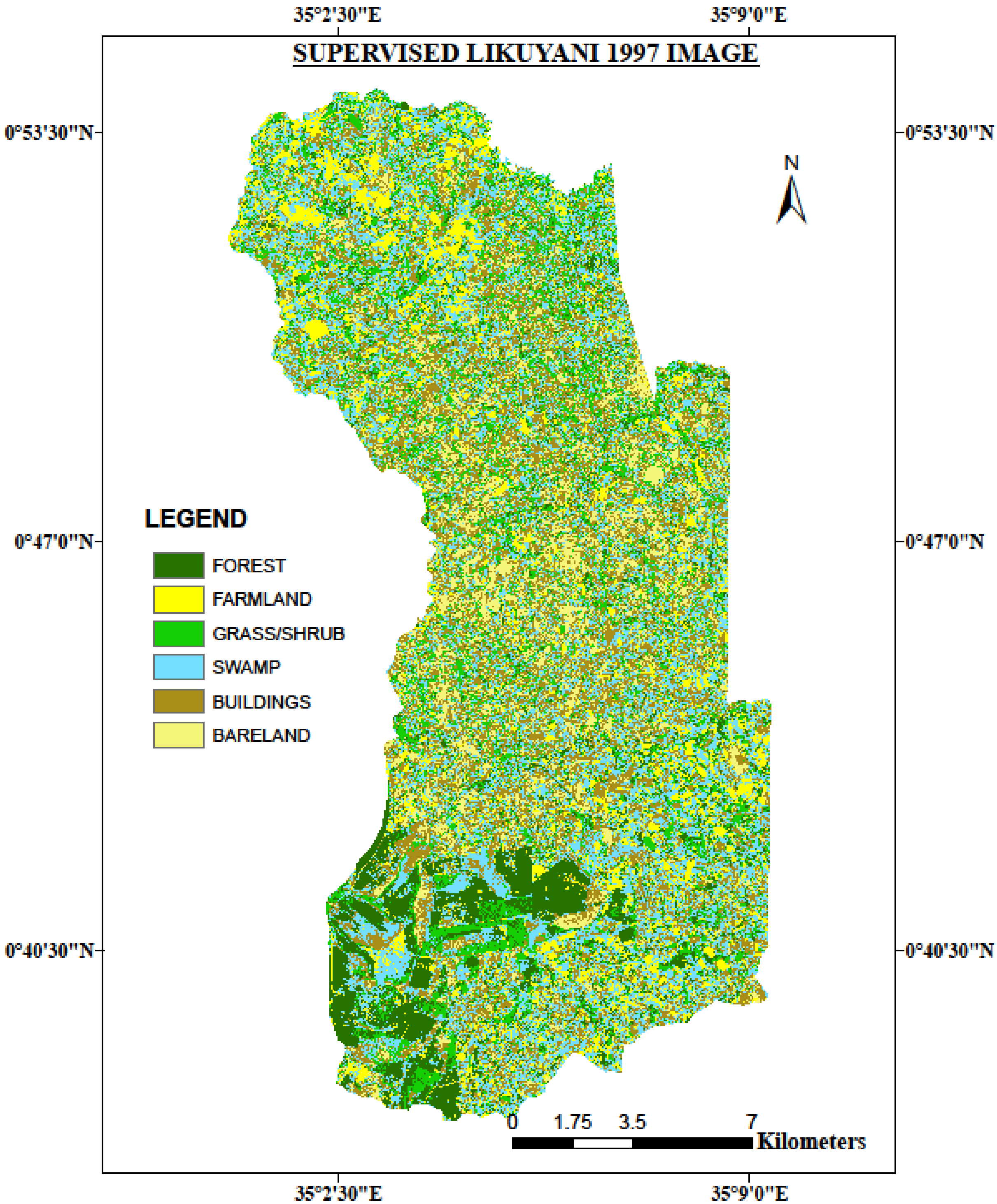


Figure 4.4: Classified Land use land cover Map of Likuyani Sub County 1997

Source: Landsat 5 image (1997)

4.2.2 Land cover change types in 2002

The Likuyani sub County categorized map from 2002 as indicated in Figure 4.5 and a bar chart entailing the land cover change results for each category of maize production as indicted in figure 4.6.

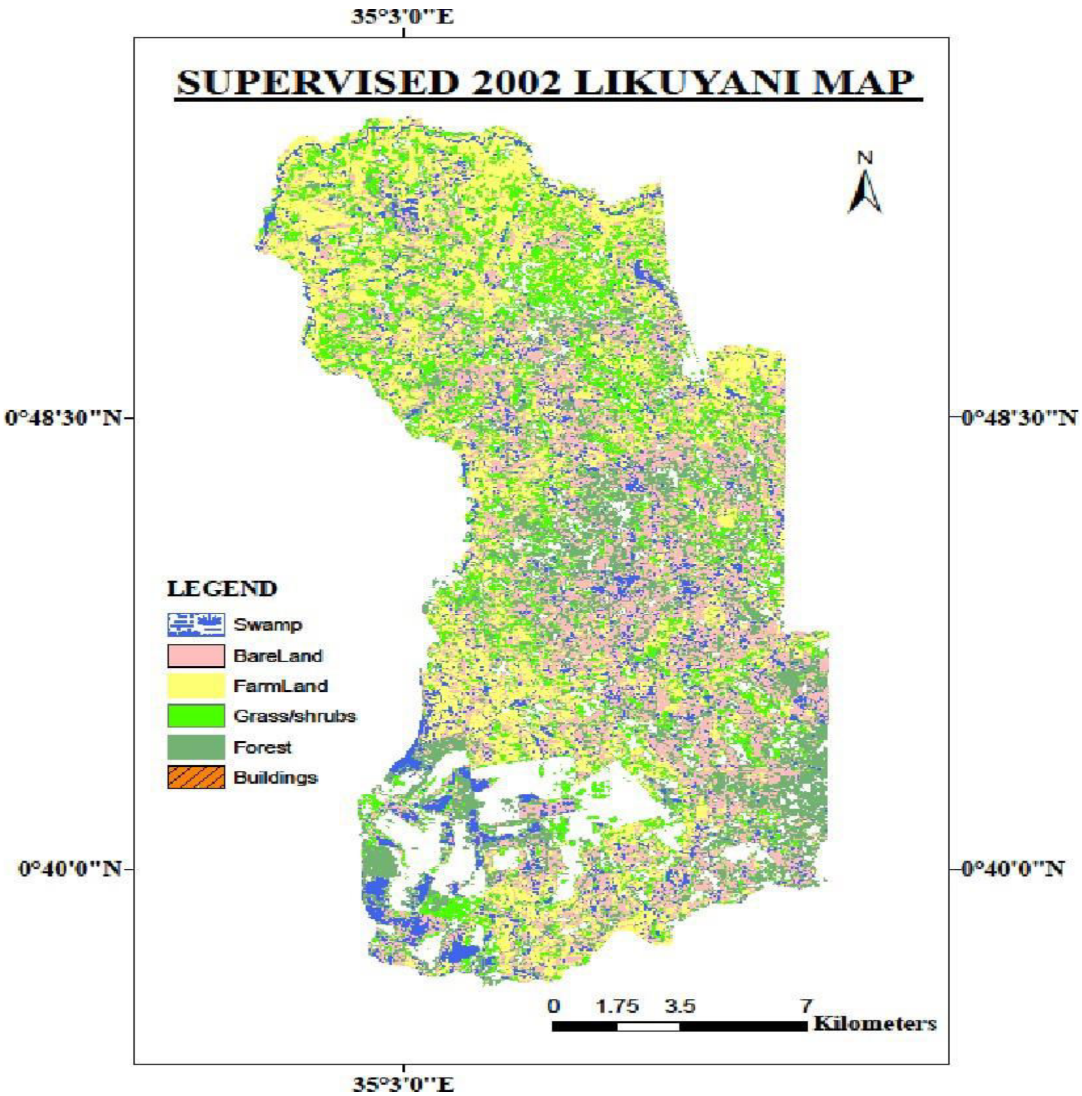


Figure 4.5: Classified map of the study area for the year 2002

Source: Landsat 8 image (2002)

Information obtained from the error matrix analysis of the Landsat 8 image taken in 2002 revealed changes in land cover types within Likuyani Sub County. During the image capture, approximately 21.83% of the area was classified as Bare Land, primarily due to ongoing plowing activities in the region. Agricultural land, representing 24.4% of the Sub County, was prevalent. Forest cover accounted for 11.42% of the land, while Grass/Shrubs covered about 13.0%. Buildings and swamp areas constituted 7.54% and 3.45% of the total land cover, respectively

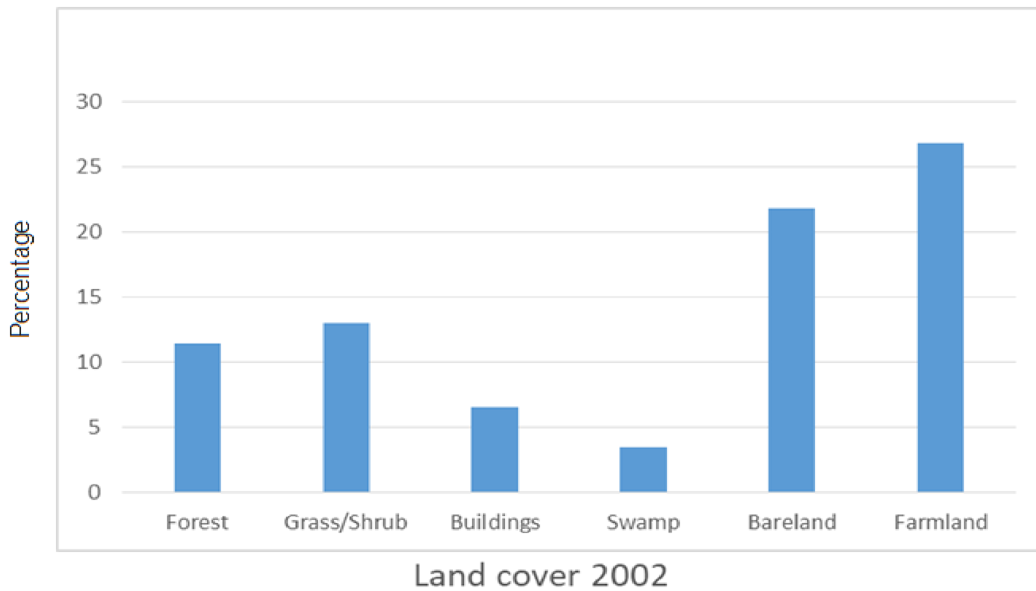


Figure 4.6: Likuyani Land cover change under maize production in the year 2002

Source: Field Data, 2021

4.2.3 Land use change in the four Settlement schemes in the year 2002

Figure 4.7 summarizes the image classification for the 2002 settlement schemes of Sango, Soy, Sergoit, and Nzoia.

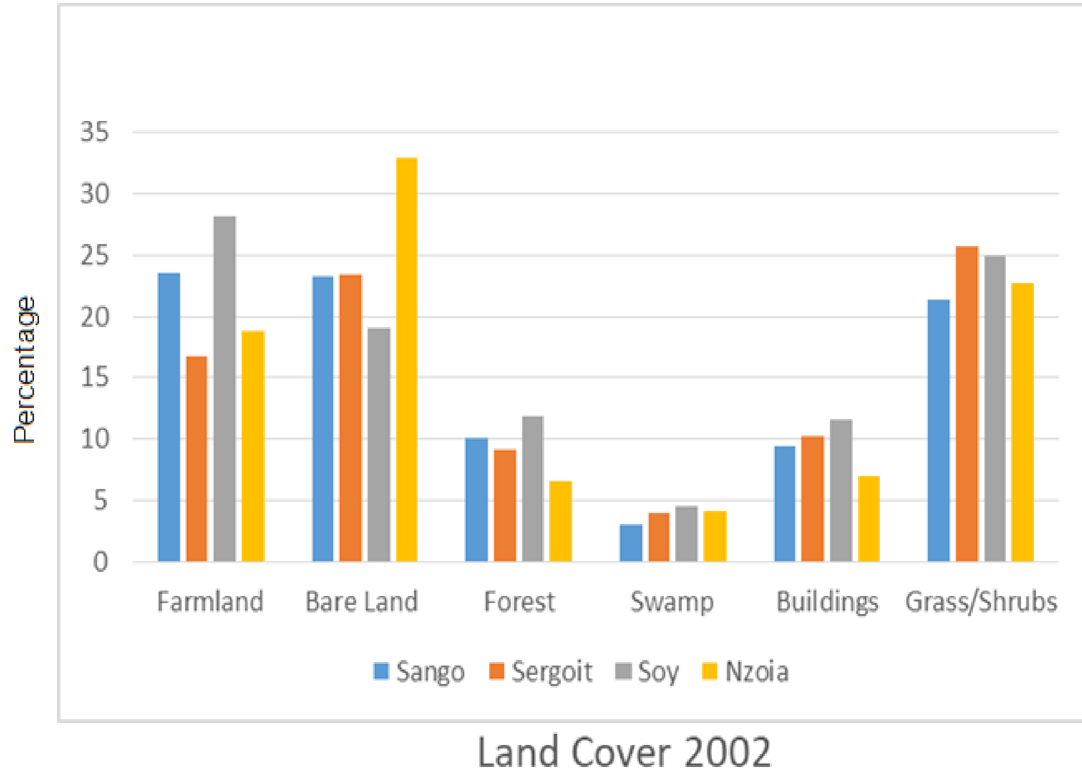


Figure 4.7: Land cover categories for Sango, Sergoit, Soy and Nzoia in 2002

Source: Field Data, 2021

During the image acquisition period in 1997, the percentage of farmland varied across the settlement schemes: Sango accounted for 23.5%, Sergoit 16.81%, Soy 28.81%, and Nzoia 18.77%. Bare land cover was notable, constituting 23.23% in Sango, 23.44% in Sergoit, 19.03% in Soy, and 32.89% in Nzoia settlement schemes. An examination of the land use and cover in Sango, Sergoit, Soy, and Nzoia during 1997, based on classified maps, revealed distinctive landscape compositions. Bare land predominated as the primary land cover category across all schemes, while Swamp held the smallest area.

Nzoia stood out with the largest expanse of bare land, whereas Soy had the least. Conversely, Sergoit and Soy exhibited the most significant coverage of swamp compared to Sango, which had the smallest swamp area. Regarding land utilization during the image capture, Nzoia showed the highest farming area, followed by Sango. Sergoit and Soy displayed relatively similar extents of farming areas. Moreover, Sango had the largest portion earmarked for building structures, followed by Sergoit, Soy, and Nzoia.

4.2.4 Coefficient of Determination of spatiotemporal LULC

The outcomes indicated in Table 4.1 provides an R-square value of 80.2%, suggesting that approximately 80.2% of the variance in the dependent variable (Land under maize production) can be explained by the independent variable (Land use land cover changes). This implies that around 19.8% of other factors not included in this model are influencing land under maize production. Furthermore, the significance of the moderating term, with a P-value of 0.068 (>0.05), suggests that spatiotemporal land use land cover changes play a moderating role in the overall impact of the explanatory variable on changes in land under maize cover in Likuyani sub-county.

Table 4.1: Coefficient of Determination of spatiotemporal LULC

Coefficient of Determination										
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.768[a]	.802[b]	.519	.109	.802	51.173	1	285	.068	.256
a. Predictors: (Constant), land cover classes										
b. Dependent Variable: land cover classes										

Source: Field Data (2021)

Consequently, the study refutes the null hypothesis that "There were no significant spatiotemporal land use land cover changes in Likuyani Sub County between the years 1997 and 2017."

4.2.5 LULCC dynamics between the years 1997 and 2002

Data from the 2002 categorized image of Likuyani sub County showed that the classifications of land cover had changed. The difference in each category's percentage value between 1997 and 2002 represents the change in land cover. The Likuyani Sub County's land cover change is compiled in Table 4.2 below.

Table 4.2: Land cover change for Likuyani Sub County

			Class			
Year	Forest	Grass/Shrubs	Farm/Land	Bare/Land	Buildings	Swamp
1997	13.66	14.97	26.75	26.06	4.15	4.14
2002	11.42	13.0	24.4	21.83	6.54	3.45
Increase			4.29		1.39	0.3
Decrease	1.04	3.97		0.96		

Source: Field Data (2021)

According to the data in Table 4.2, there was an increase in Forest and grass/Shrub cover by 1.04% and 3.97% respectively. Additionally, Bare land expanded by 0.96%, while Farm/Land showed a growth of 4.29%. This change might be partly due to some areas previously classified as Grass/Shrubs, possibly related to the introduction of sugar cane, which was classified as Grass during the image capture and classification process. Moreover, Buildings increased by 1.39%, and swamp areas experienced a slight rise of 0.3%. The data on land subdivision indicates a notable increase, which coincides with the observed rise in building areas.

4.2.6 LULC classes in Likuyani Sub County in 2007

During the image capture in 2007, the classified cover in Likuyani Sub County showed that Forest accounted for 10.87%. Farmland covered 21.22%, while Grass/Shrubs occupied 10.72%. Additionally, swamp areas covered 4%, Bare land constituted 20.83%, and buildings comprised 7.69% of the total classified cover. Figure 4.23 visually represents the various land cover classes in Likuyani Sub County for the year 2007

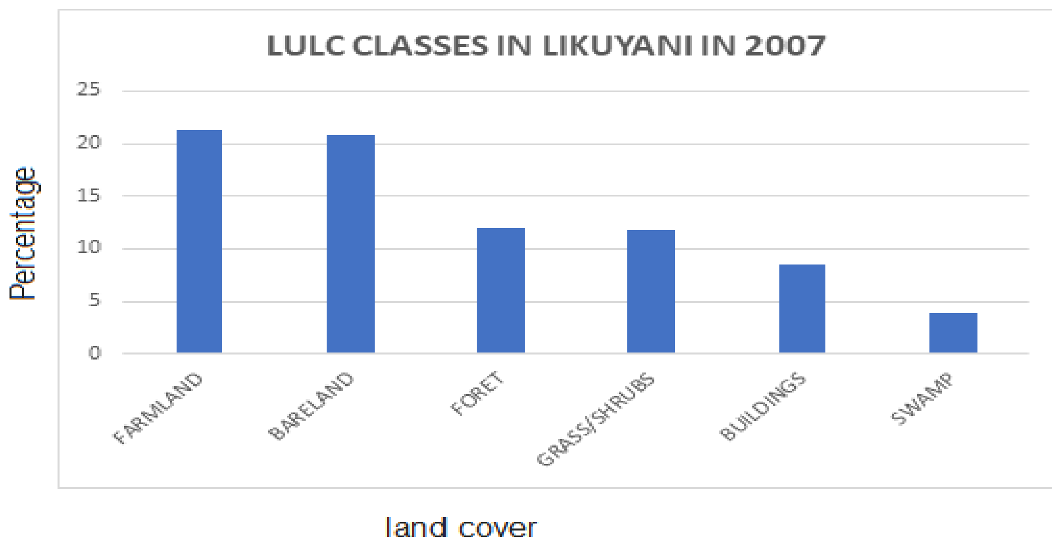


Figure 4.8: LULC classes in Likuyani sub county in the year 2007

Source: Field Data, 2021

Figure 4.9 represents the classified map of Likuyani Sub County in the 2007. The land cover classes in this this map are represented by colors as; blue represents swamp, brawn bare land, pink represents farmland, green grass/shrub, dark green represents forest and brawn represents buildings land cover.

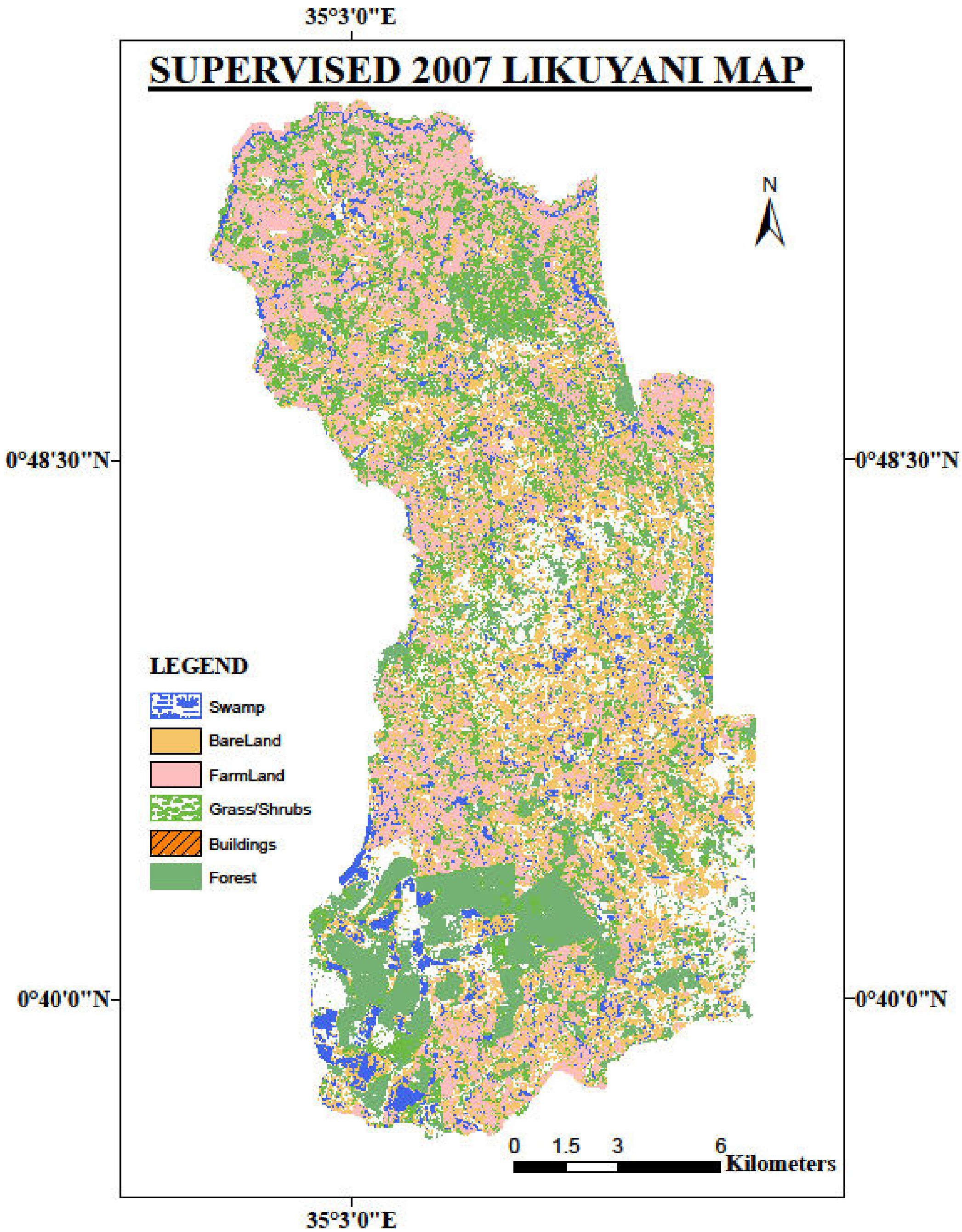


Figure 4.9: Classified map of Likuyani in 2007

4.2.7 LULCC dynamics between the years 1997, 2002 and 2007

The alterations in Land Use and Land Cover Change (LULCC) within Likuyani Sub County from 1997 to 2002 and 2007 are summarized in Table 4.9. Farmland decreased from 26.7% in 1997 to 24.4% in 2002, further reducing to 21.22% in 2007. These variations are likely due to the conversion of farmland to bare land when it was plowed. Swamp cover remained relatively stable, with a minor increase of 0.55% over the fifteen-year period. The Shrub/Grass category experienced an overall decline of 2.28% during this period, potentially shifting to become farmland or areas for buildings. Buildings consistently increased by 1.15% as the population grew between 1997 and 2007, according to data from KBS (Kenya Bureau of Statistics). Table 4.3 details the land cover changes observed in Likuyani Sub County between 1997, 2002, and 2007.

Table 4.3: Land cover and changes in percentage between the years 1997, 2002 and 2007 in Likuyani Sub County

Year	Bare Land	Forest	Grass/Shrubs	Farmland	Buildings	Swamp
1997	23.06	13.66	14.97	26.75	4.15	4.14
2002	21.83	11.42	13.0	24.4	6.54	3.45
Increase					2.39	
Decrease	1.23	2.54	1.97	2.35		0.69
2007	20.83	10.87	10.72	21.22	7.69	4
Increase					3.54	
Decrease	2.23	2.76	4.25	5.53		0.14

Source: Field Data (2021)

Figure 4.10 represents rates of land cover changes from 1997 through 2002 to 2007 in Likuyani sub County land cover.

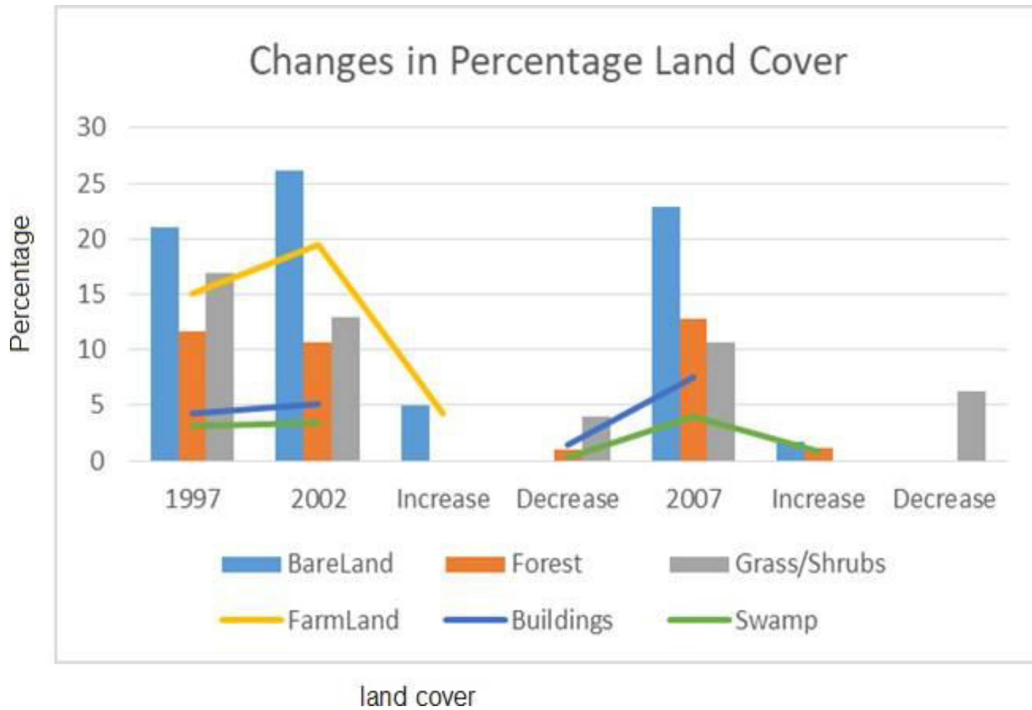


Figure 4.10: Rates of change in land cover between the years 1997 and 2007 in Likuyani Sub County

Source: Field data, 2021

4.2.8 LULCC in Sango, Sergoit, Soy and Nzoia Settlement Schemes in 2007

In various locations within Likuyani sub-county, contrasting patterns in Land Use and Land Cover Change (LULCC) were observed, indicating an upward trend in the expansion of buildings at the expense of farmland. The increase in farmland areas seems to have encroached upon grass/shrub areas. Nonetheless, when considering the perceptions of the entire sample of local communities, a significant change in the landscape's land use classes was evident.

Similar observations were made by Kairu (2016) and Terer *et al.* (2015), who noted that the expansion of cropland tended to favor riparian land due to favorable environmental conditions such as high soil moisture, fertile soils, and the presence of freshwater. These findings align with Pisannelli *et al.*'s (2012) study in rural and mountainous areas of Central Italy, confirming that community members can discern both positive and negative changes through their prolonged interaction with the environment. Young *et al.* (2016) emphasize humanity's capability to modify environments based on their knowledge and expectations. Human perceptions and attitudes toward the environment are reflective of their experiences and long-term interactions, underscoring the importance of designing effective strategies based on local understanding and appreciation of environmental dynamics (De Meo *et al.*, 2016).

Regarding land cover distribution in settlement schemes, farmland covered 21.13% in Sango, 11.33% in Sergoit, 23.1% in Soy, and 10.01% in Nzoia. Bare land comprised 26.52% in Sango, 18.52% in Sergoit, 23.11% in Soy, and 27.22% in Nzoia. Forest cover accounted for 8.77% in Sango, 9.95% in Sergoit, 11.8% in Soy, and 7.02% in Nzoia. Buildings occupied 4.89% in Sango, 5.77% in Sergoit, 6.21% in Soy, and 4.11% in Nzoia, while Grass/Shrub was observed at 17.66% in Sango, 20.76% in Sergoit, 16.88% in Soy, and 25.6% in Nzoia. Comparing the land cover data to that of 2002, it is evident that buildings consistently increased in all four settlement schemes, while bare land showed an increase in Sango and Nzoia, whereas the other land cover classes demonstrated a decrease during the same period.

Land cover classes in the four settlement schemes are illustrated in Figure 4.11.

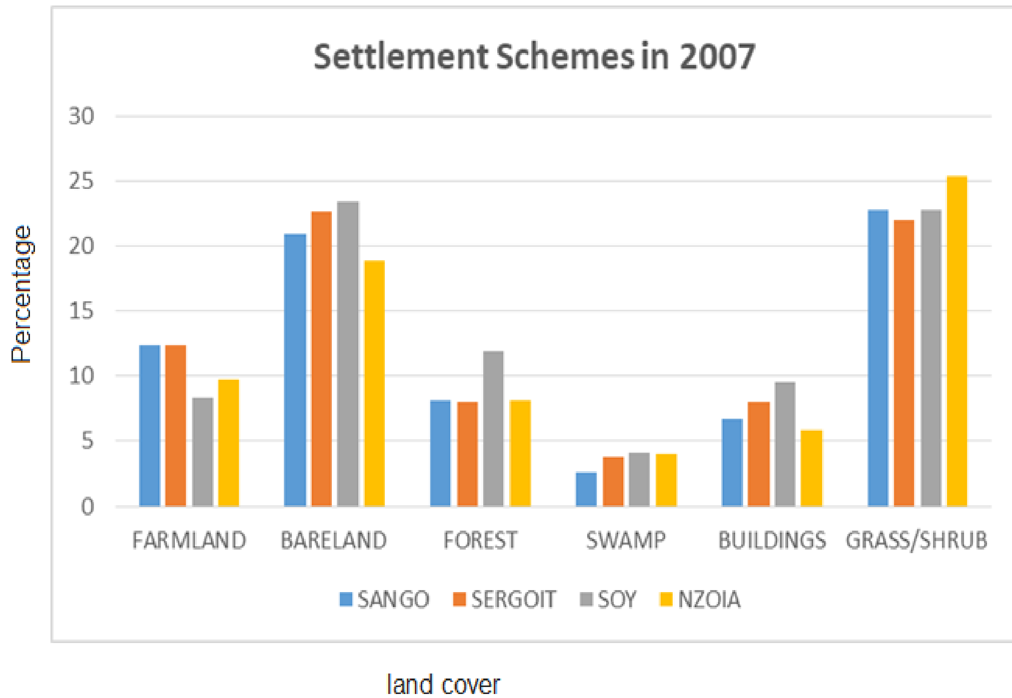


Figure 4.11: Settlement Schemes in 2007

Source: Field Data, 2021

Classified land cover maps of the Sango, Sergoit, Soy, and Nzoia settlement plans from which the land cover data was obtained from. Figure 4.12a and 4.12b represent classified maps of Sergoit and Sango settlement schemes in the year 2007 respectively. In both images swamp land cover is represented by the color blue, farmland cover is represented by yellow color and bareland is represented by color brawn. Grass/shrub land cover is represented by light green in figure 4.13a, and green in figure 4.13b. Forest is represented by light green while in figure 4.13b, it is represented by dark jungle green. Buildings land cover is represented by color brawn in figure 4.13b, and dark pink in figure 4.13a.

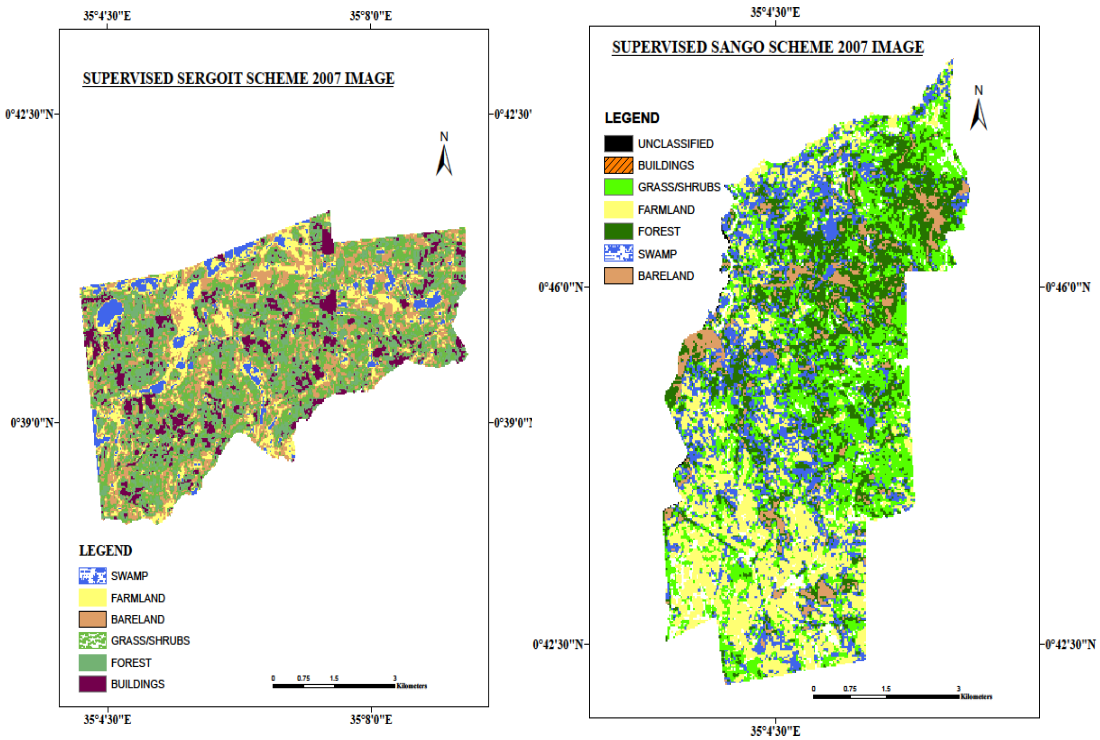


Figure 4.12 (a and b): Sergoit and Sango scheme 2007

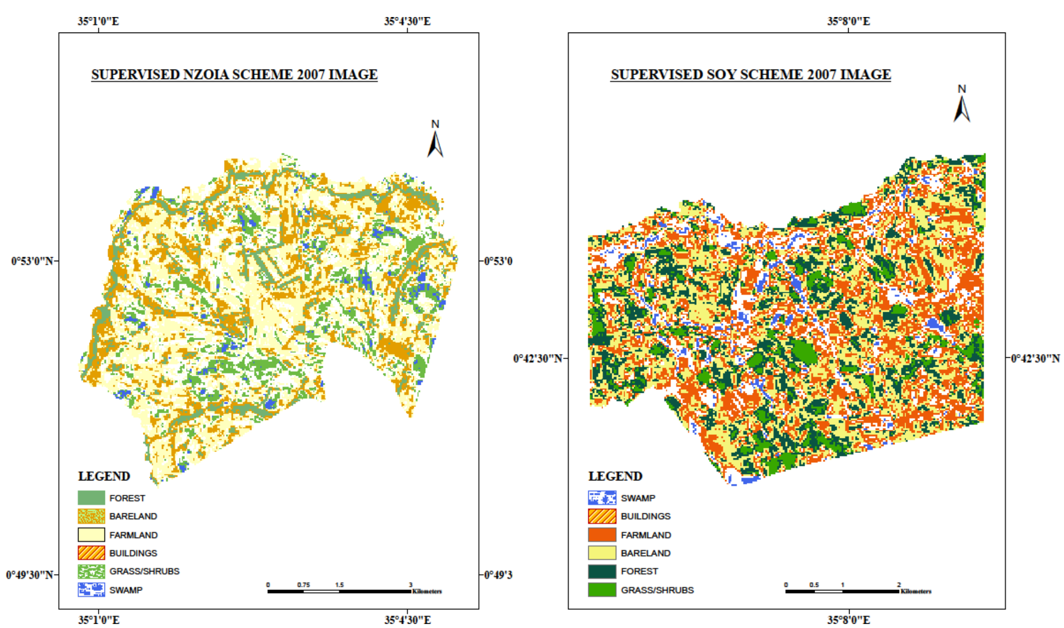


Figure 4.13 (a and b): Land cover classes in Nzoia and Soy Scheme 2007

4.2.9 LULCC dynamics between the years 1997 and 2007 in the four settlement schemes

In the Sango settlement system, the percentage of forest cover decreased significantly, from 12.44% in 1997 to 8.77% in 2007. The steadily declining amount of forest cover might be explained by the growing population, which encouraged the clearing of forest areas to make way for farms. In Sango, the total reduction in forest cover was 3.67%. Similar trends were observed in the Sergoit, Soy, and Nzoia settlement schemes, with forest cover diminishing by 1.96%, 2.64%, and 1.01%, respectively.

Among these schemes, Soy experienced the most substantial decline in forest cover, accounting for a reduction of 2.64%, while Nzoia had the least decline, standing at 1.01%. According to data from the Survey of Kenya, Soy exhibited higher instances of land subdivision compared to the other schemes. This higher rate of land subdivision in Soy could be linked to its proximity to the main Eldoret/Kitale highway. Conversely, the Nzoia scheme, situated farther away from major highways, recorded fewer cases of land subdivision and consequently experienced lower loss in forest cover. Figure 4.14 Represents forest cover changes between the years 1997 and 2007.

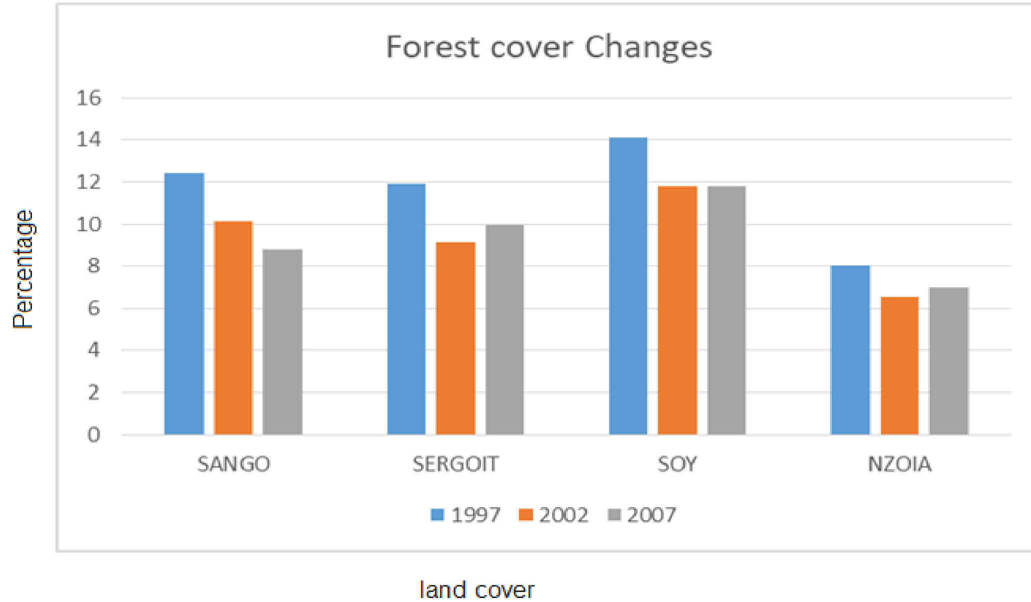


Figure 4.14: Forest cover change between the years 1997 and 2007

Source: Field Data, 2021

The Grass/Shrub category exhibited a decline across all the settlement schemes, with Sango experiencing the most significant decrease of 14.21%, whereas Nzoia recorded the smallest change of 2.22%. This decline in the Grass/Shrub category, which is widespread throughout the entire area, reflects the clearing of these areas for agricultural purposes and construction. Particularly, regions undergoing more land subdivision, indicative of population growth, saw a more pronounced change in land use.In Nzoia, there was initially a reduction in Grass/Shrub cover in 2007, which subsequently increased again in the same year. Ground visit data and information sourced from the Likuyani Agriculture and Food Authority Yearbook of Sugar Statistics 2020 revealed that the land had been converted to sugarcane cultivation.

The software classified sugarcane as part of the Grass/Shrub category, explaining the increase in this land cover classification. Figure 4.15 indicates Grass/shrub cover changes.

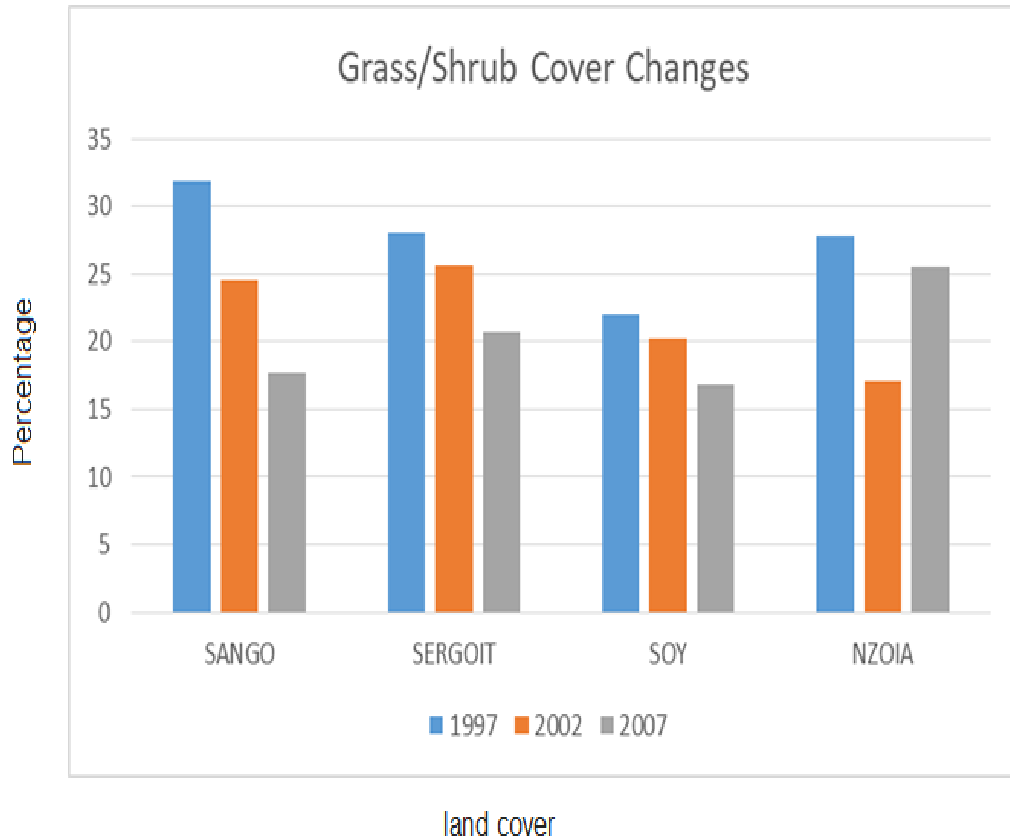


Figure 4.15: Grass/Shrub cover changes between the years 1997 and 2007

Source: Field Data, 2021

The expansion of buildings was observed across all four settlement schemes during the specified period. Soy and Sergoit Settlement schemes experienced the most significant increase in building area due to their accessibility from the Kitale/Eldoret highway. Conversely, Nzoia, with less accessibility compared to the other schemes, had the smallest increase in the area covered by buildings.

The expansion of buildings typically aligns with population growth, often resulting from land subdivision activities. Records from the Survey of Kenya indicate that Nzoia had the least number of subdivisions among the four schemes, which correlates with the minimal change observed in building cover in this area. Figure 4.16 Provides details of the area under Buildings cover change for the period of fifteen years which begins from 1997 to 2007.

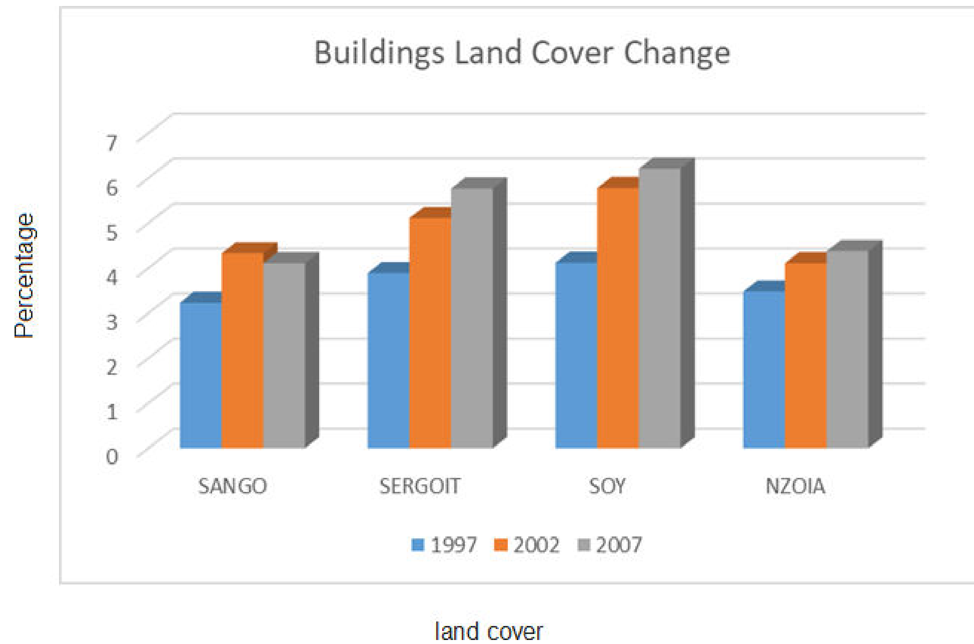


Figure 4.16: Building cover change from 1997 to 2007

Source: Field Data, 2021

Between the years, there were varying modifications to farmland, the amount covered in vegetation, and unplowed land at the time of image capture. This is because bare ground and farms can be substituted for one another. All of the plowed farmland is represented by bare land. Unplowed, barren land will be designated as farmland at the same time.

There is a rise in barrel and a decrease in farmland in New Zealand. These two categories have decreased overall, which suggests that less land is being used for the production of maize. The Sergoit Settlement, Soy, and Sangoit plans all exhibit the same situation.

4.2.10 Land cover classes in Likuyani Sub County in 2012

At the time of image acquisition, the land cover categories in Likuyani are represented in Table 4.4 indicates Forest cover captured at 12.72%, Grass/Shrubs at 9.77%, Buildings was 8.53%, Swamp 3.87%, Farmland 20.22% and bare land covered 14.33%.

Table 4.4: Land cover classes distribution in Likuyani in 2012 by percentage

Classes	Percentage
Forest	11.88
Grass/Shrubs	9.77
Buildings	8.53
Swamp	3.87
Farmland	20.22
Bare land	14.33

Source: Field data, 2021

The analysis of the six land cover classes revealed several trends between 1997 and 2012. The data showcased a continual rise in Buildings, increasing by 4.38% during this period, which correlates with population growth and escalating land subdivision activities recorded in the Sub County. Forest cover exhibited a fluctuating pattern, decreasing from 1997 to 2002 but steadily increasing from 2002 through 2007, and by 2012, it had risen from 10.78% to 11.88%. This augmentation was influenced by an upsurge in Blue gum tree farming, a land use classified as forest cover by the remote sensing satellite sensor.

Bare land, characterized by areas without vegetation at the time of image capture, experienced a decline from 23.06% in 1997 to 18.33% in 2012. It's noteworthy that this category interchanged with Farmland as plowed land transformed Farmland to Bare land and vice versa. Consequently, Farmland reduced from 26.75% to 20.22% by 2012. Moreover, Grass/Shrub cover increased from 10.72% in 2007 to 11.77% in 2012, corresponding with the intensified cultivation of sugarcane within the Sub County during this period. Figure 4.17 provides land cover categories in Likuyani Sub County in the year 2012. Figure 4.17 represents classified map of Likuyani Sub County in the year 2012. The land cover categories are represented in the legend as farmland, color pink, bareland color brawn, grass/shrubs color speckled green, forest dark green and swamp blue.

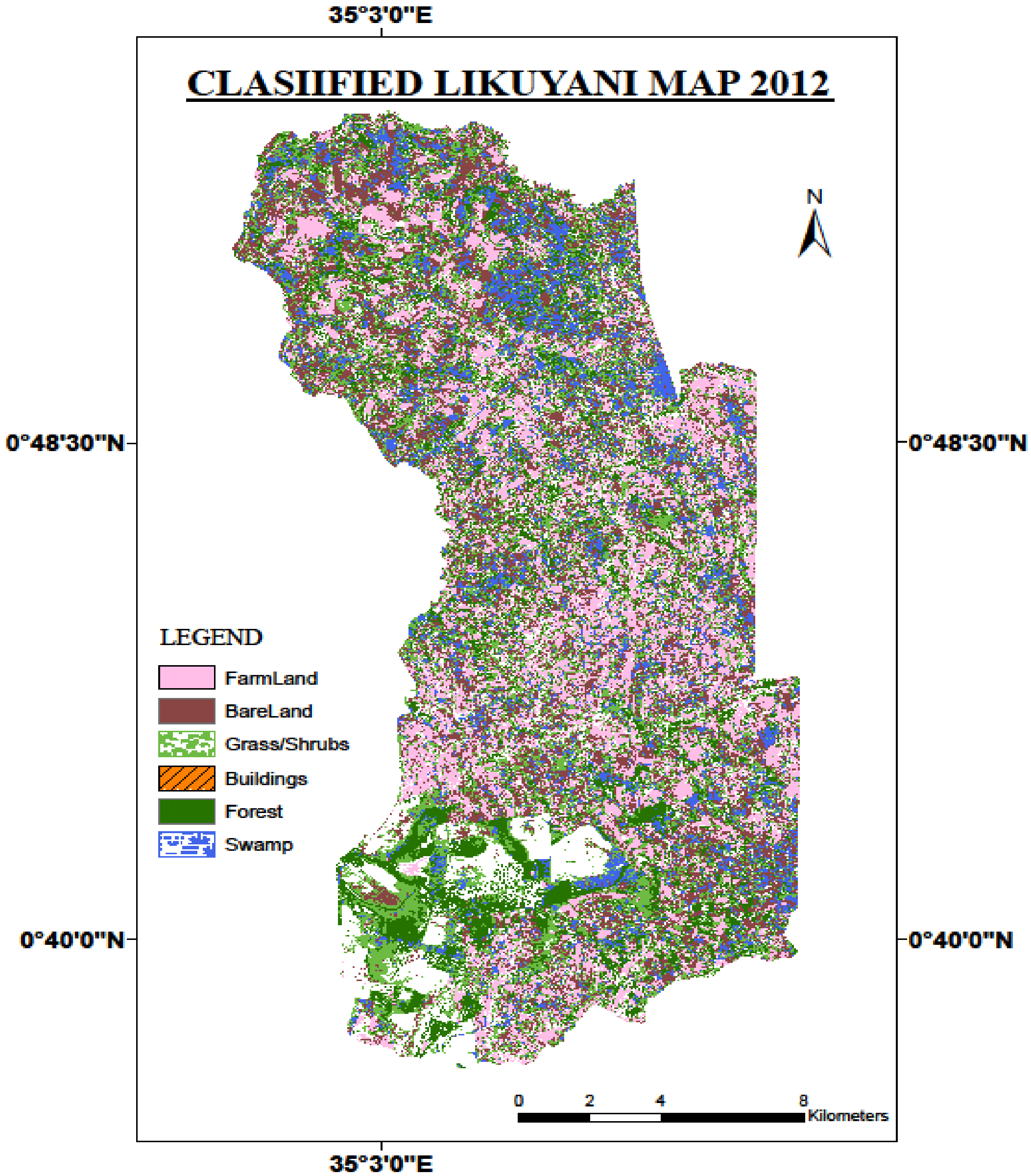


Figure 4.17: Likuyani land cover classes in 2012

Source: Researcher, 2021

4.2.11 Land cover in Sango, Sergoit, Soy and Nzoia settlement schemes in 2012

Notable changes were found in 2012 when the categorized image data in Likuyani Sub County was analyzed. Sugarcane fields, which were frequently included in the Grass/Shrub category, are mostly to blame for the noticeable increase in land cover in this category. All settlement proposals showed a steady rising trend in building areas. Between 2007 and 2012, Sergoit had the most rise (1.01%), while Sango had the lowest gain (0.34%). Within Sango settlement scheme, Farmland decreased by 12.43% from 1997 to 2012, whereas bare land increased by 4% during the same period, rising from 19.23% to 23.88%. Similarly, in Sergoit, Farmland reduced by 4.52%, while bare land increased by 5.44%. Notably, Soy experienced the highest loss in Farmland, dropping by 15.71%, accompanied by a 9.17% increase in bare land cover. Meanwhile, in Nzoia, Farmland decreased by 12.52%, while bare land increased by 6.02%. The substantial increase in bare land across all settlement schemes in 2012 was primarily due to extensive plowing activities in preparation for maize planting. For instance, Nzoia exhibited a significant reduction in Farmland, recorded at 20.88% in 1997, decreasing to 8.34% in 2012, indicative of the land cover changes observed during this period. Land cover for the four settlement schemes are presented in Figure 4.18.

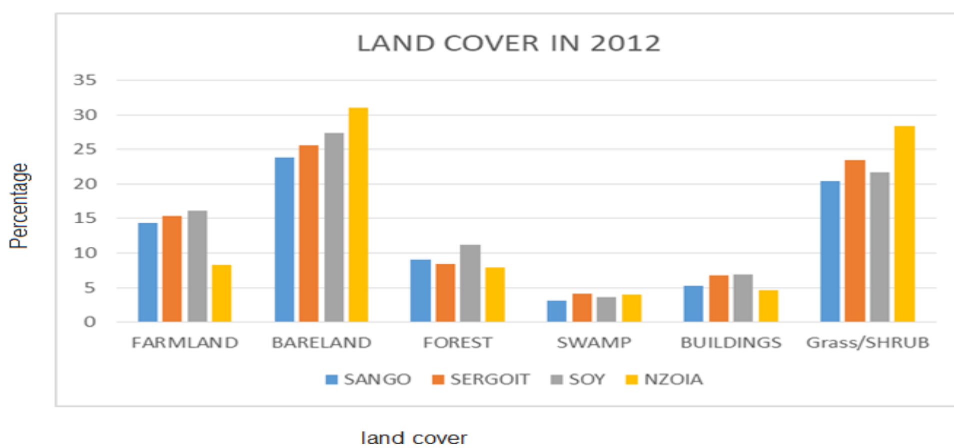


Figure 4.18: Land cover for Sango, Sergoit, and Soy and Nzoia settlement schemes

Source: Field data, 2021

Figure 4.19a, represent the classified map of Nzoia settlement scheme in the year 2012. In the legend swamp is represented by the color blue, forest by jungle green, bareland by yellow color farmland by magenta, grass/shrub by speckled green and buildings by brawn. Figure 4.19b, represents classified map of Sergoit settlement scheme Landsat 8 image of the year 2012. Land cover classes were represented by colors as; buildings brawn, forest green, grass/shrubs specked green bareland dirty green, farmland magenta, and swamp blue.

The figures 4.19 a and b are a indicates land cover in the four settlement schemes for the year 2012.

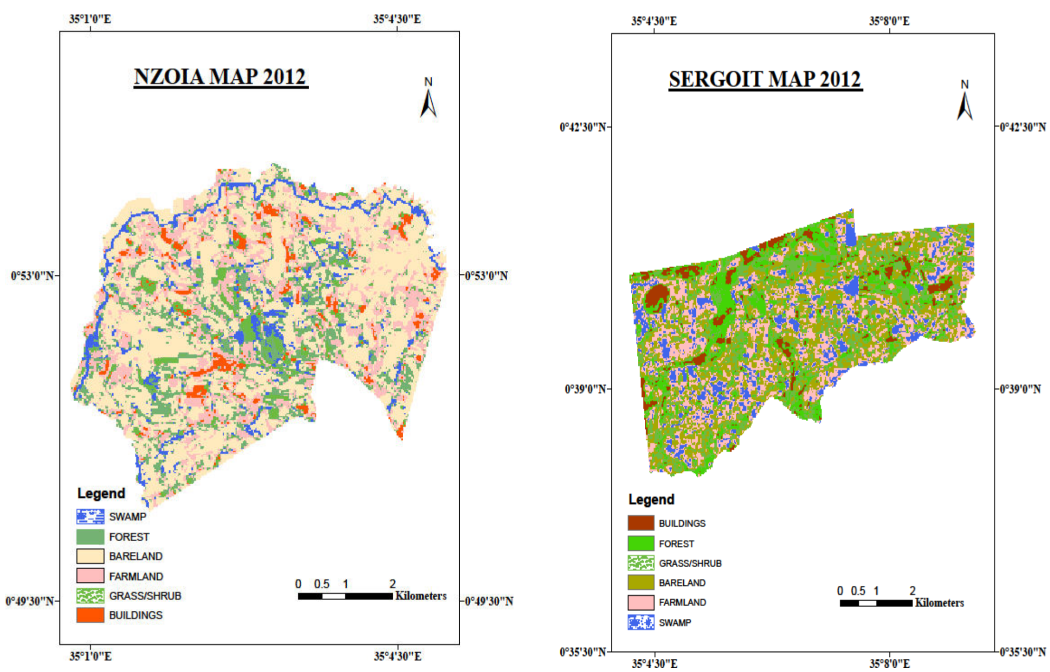


Figure 4.19 (a and b): Nzoia and Sergoit scheme 2012

Figure 4.20a, represents Landsat 8 classified map of Soy settlement scheme in the year 2012. Green represents forest cover, brawn represents buildings cover, pink resents farmland dark brawn represents bareland dirty green represents grass/shrub and swamp is represented by the color blue. Figure 4.20b, represents Landsat 8 classified image of Sango settlement scheme of the year 2012. Land covered by swamp is represented by blue color, buildings are represented by speckled brawn, farmland is represented by dark brawn, bareland is represented by green, grass/shrubs is represented by speckled green and forest is represented by green color.

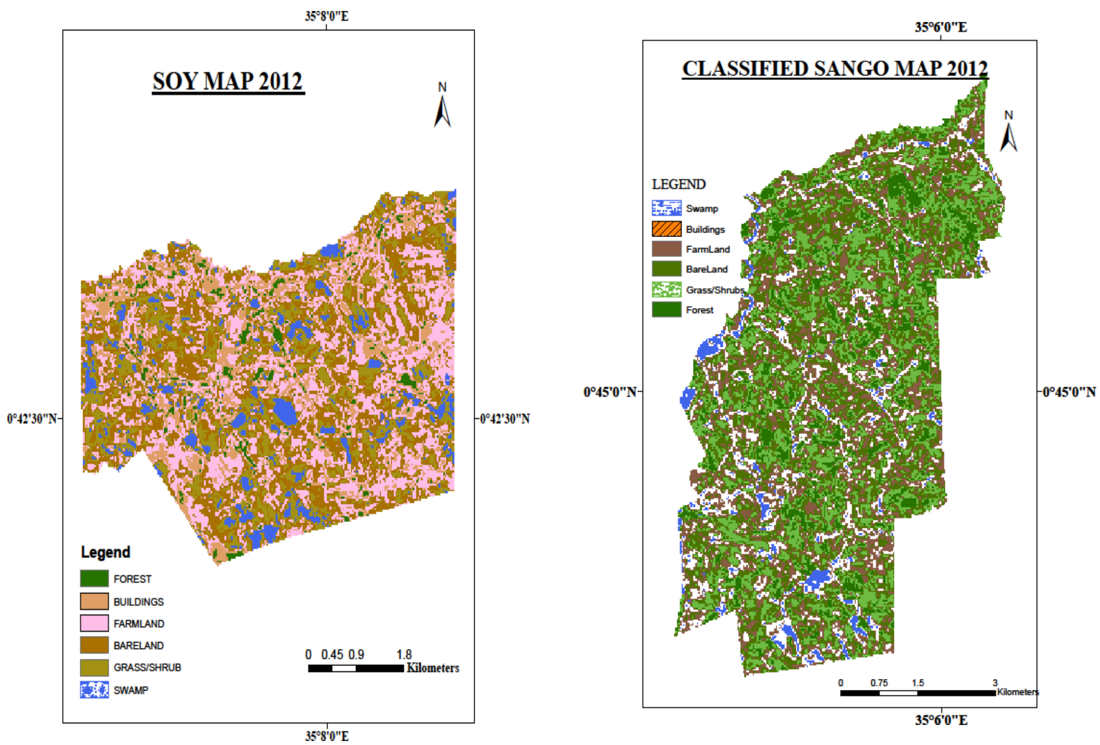


Figure 4.20 (a and b): Classified Soy and Sango scheme 2012

4.2.12 LULC in Likuyani Sub County in 2017

Over the course of twenty years, there was a notable increase in Buildings cover, reaching 9.01%. Concurrently, Forest cover exhibited a consistent rise from 13.66% to 14.72% throughout the study period. Interestingly, the rise in forest cover was observed in areas previously categorized as Grass/Shrub and Farmland due to the continuous expansion of blue gum tree farming practices. During this period, Farmland decreased to 19.47%, while bare land increased to 27.14%. The increase in bare land can be attributed to a substantial portion of farmland that remained unplowed. When considering the overall changes in Farmland and Bare land from 1997, there was a noticeable reduction in these two classes, which primarily represent areas utilized for maize production.

Moreover, the land cover under swamp increased by 0.75%, attributed to increased rainfall experienced in the preceding year (as observed in the field) The land cover classes for 2017 are represented in the Sentinel 2A classified image in Figure 4.21. Land cover forest is represented by green color, bare land is represented by yellow color, farmland magenta, grass/shrubs speckled green, swamp is represented by blue and buildings land cover by hacked brawn.

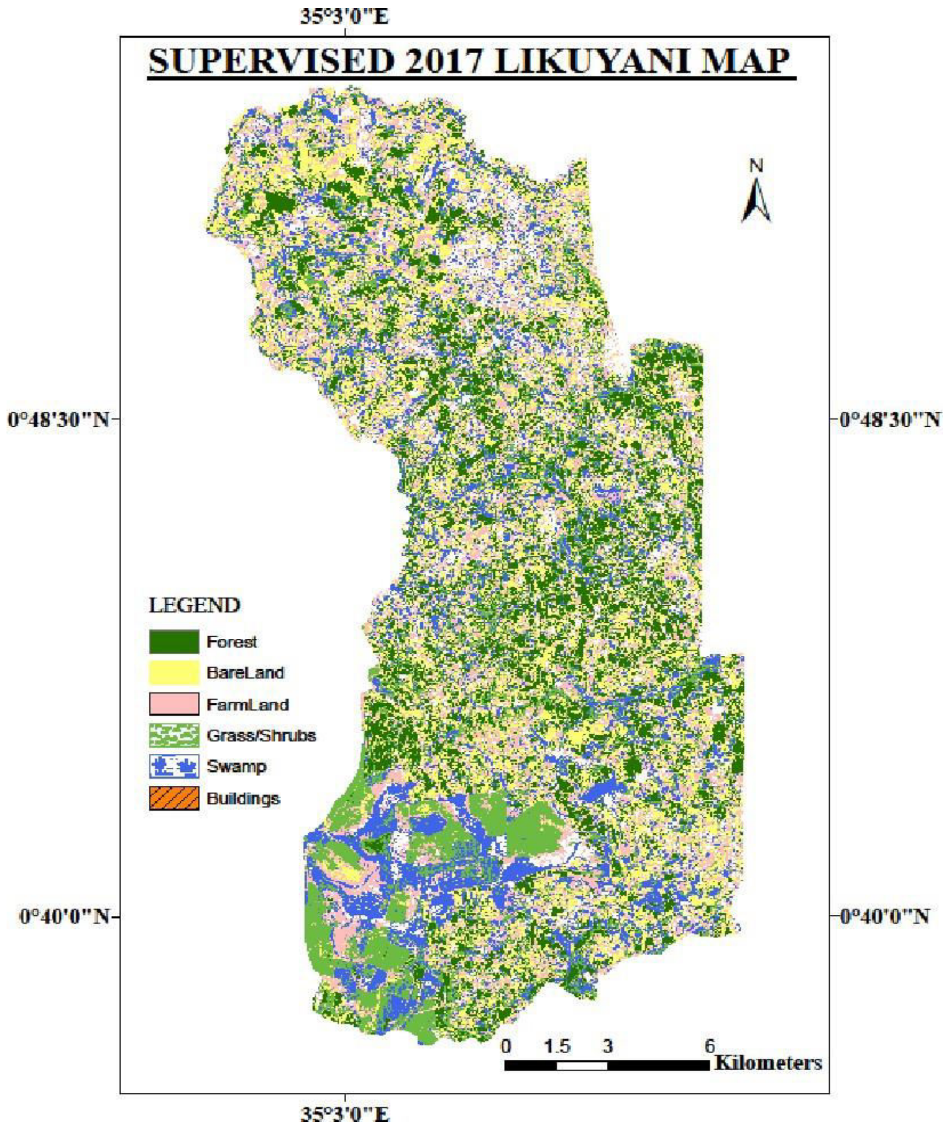


Figure 4.21: LULCC classes for the year 2017

Land cover change under maize production classes in Soy and Sergoit settlement schemes in 2017. Examination of land cover alterations in the chosen four settlement schemes indicated a considerable upsurge in housing construction across all schemes, albeit more restrained in Nzoia compared to the remaining three. The growing population necessitated additional housing, leading to increased land subdivision, impacting Farmland and bare land classifications. Moreover, there was an evident augmentation in the Grass/Shrub category within all four schemes, attributable to the expansion of sugarcane farming. The summarized depiction of land use cover changes is presented in Figure 4.22.

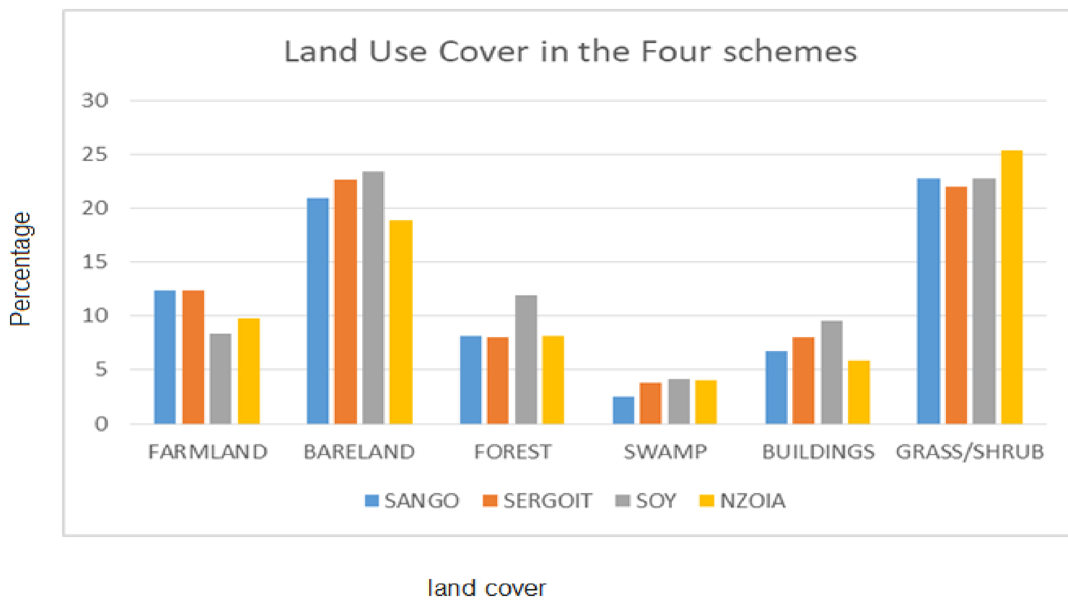


Figure 4.22: Land use cover in Sango, Sergoit, Soy and Nzoia Settlement schemes in 2017

Source: Field Data, 2021

Figure 4.23a, represents a false color Sentinel 2A classified map of Soy settlement scheme. In the legend, the color green represents forest cover, grey represent grass/shrub, amber represents bareland maroon represents buildings blue represents swamp and pink represents farmland. Figure 4.23b, represents a Sentinel 2A classified false color map of Sergoit settlement scheme. The classified features are represented by the color green representing forest, blue representing swamp, amber representing bareland. And beige representing farmland.

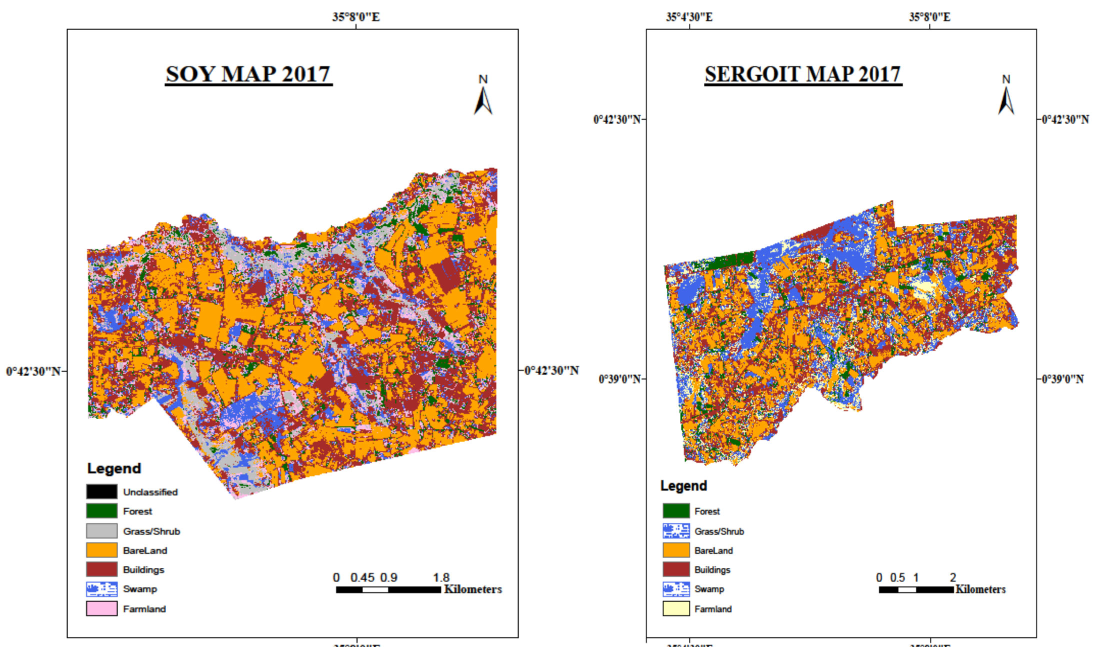


Figure 4.23 (a and b): A Soy and Sergoit scheme 2017

Figure 4.24a, represents a Sentinel 2A classified false color map of Sango settlement scheme. The classified features are represented by the color green representing forest, blue representing swamp, amber representing bareland. And beige representing farmland and maroon represents buildings. Figure 4.24b, represents a false color Sentinel 2A classified map of Nzoia settlement scheme. In the legend, the color green represents forest cover, speckled green represent grass/shrub, brawn represents bareland maroon represents buildings blue represents swamp and yellow represents farmland.

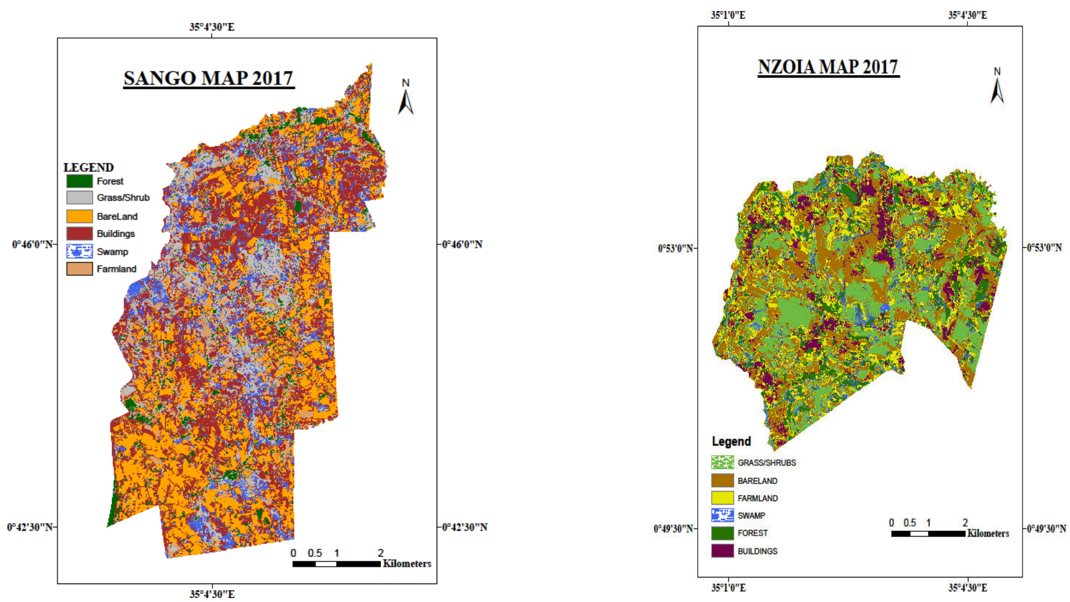


Figure 4.24 (a and b): Sango and Nzoia scheme 2017

4.2.13 LULC dynamics between years 1997 and 2017

Despite not growing continuously, the forest cover saw a net increase of 1.06% in 2017 throughout the research period. From 13.16% in 1997 to 11.42% in 2002, the amount of forest cover first declined, and then it dropped even further to 10.86% in 2007. Nonetheless, there was an upward trend starting in 2007 and it reached 14.72% in 2017.

The forest ranger at the Nzoia forest station stated that the main cause of the notable decrease in forest cover between 2002 and 2007 was the harvesting of mature trees within the forest. Furthermore, during this time, some farmers' trees that had reached maturity were harvested. The Grass/Shrub category showed a decrease of 1.97% from 14.97% in 1997 to 13.00% in 2002. However, by 2007, this category had started to steadily increase and reached 16.78% in 2017. The overall increase in Grass/Shrub cover from 1997 to 2017 was 1.81%. Most of the land cover transformation from Grass/Shrub to other categories like farmland and buildings contributed to the earlier reduction in this category.

The surge in this category from 2012 to 2017 was linked to the introduction of sugarcane farming in numerous parts of Likuyani Sub County, where the software classified sugarcane as part of the Grass/Shrub category. Bare land increased by 4.08% from 23.06% in 1997 to 27.14% in 2017, while farmland increased by 7.28% during the same period. This increase in bare land and farmland was the largest alteration in land cover within the study area. Given their interrelated nature forming the land under maize production, their combined cover indicated a reduction of 3.2%. Buildings cover witnessed a gradual rise from 4.15% in 1997 to 9.01% in 2017, marking an overall increase of 4.86%, almost doubling its coverage. Swamp land cover remained relatively stable, with minimal fluctuations observed between the study years. Reports from ground visits suggested an above-average rainfall in 2016, enabling the sensor to detect more swamp areas compared to previous years, resulting in an overall cover increase of 0.75%.

Conversely, farm land cover decreased by 2.44% from 14.23% to 11.79%. The most substantial reduction in farm land cover occurred between 2007 and 2017, coinciding with an increase in the area's population. Records from KBS indicated a rise in Likuyani population from 91,210 in 1999 to 125,137 in 2019, directly associated with an escalation in settlement and a reduction in agricultural land. The overall reduction in farmland cover was 2.32%.

4.2.14 Trends in land cover changes

There are notable fluctuations in the land under maize farming over the years which have in turn affected maize production. The percentage under cover under farmland was initially higher than that of bare land. However, farm land has been steadily reducing while bare land has been steadily increasing as shown in figure below. The highest gap was in the year 2017 where there was a sharp rise on the land that was bare and a drop in percentage of farm land meaning that most of the land that was originally under cultivation was bare.

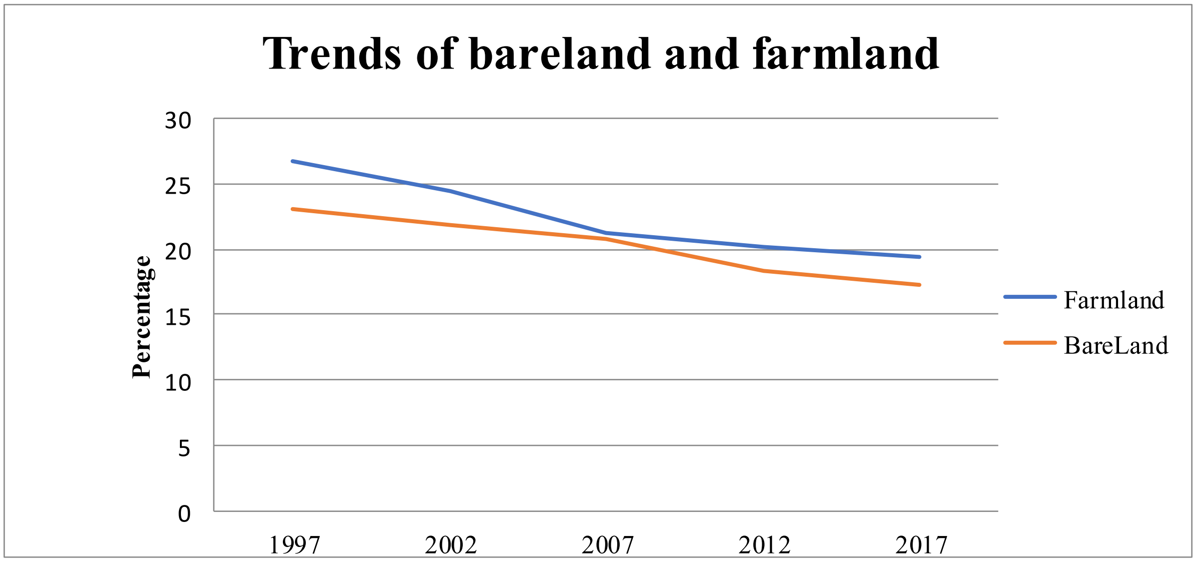


Figure 4.25: Comparison between the trends in bare land and farmland

Source: Field Data, 2021

Over time, variations in the proportions of land falling into different groups are apparent. The area covered by grasslands and shrubs decreased steadily between 1997 and 2007, then began to rise again until 2012, when both saw a notable increase. While still making up a minor portion of the total, swamps saw a slight decline in 2012 and a notable increase in 2017. On the other hand, from 1997 to 2017, the proportion of land covered by buildings increased consistently without experiencing any notable variations.

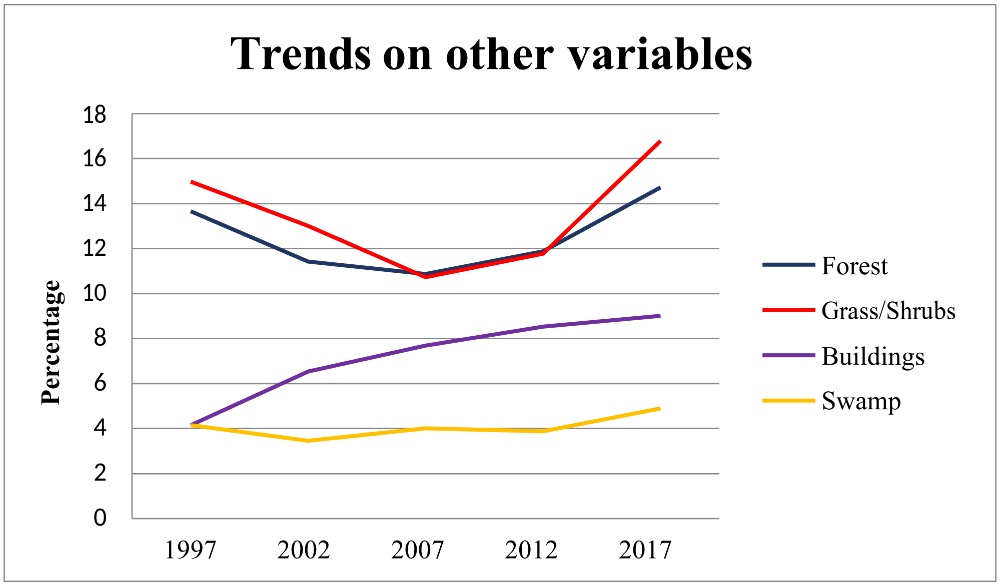


Figure 4.26: Trends of change in percentage of land under forests, grass/shrubs, buildings and swamps

Source: Field Data, 2021

4.2 Causes of LULC on different Land cover classes

The primary objective of the study was to evaluate the repercussions of land use and land cover changes on different land cover classes by analyzing the percentage variations in each land cover category. Throughout the study duration, an observable exchange occurred between areas classified as Farmland and Bare land. Plowed Farmland was recognized as bare land, while unplowed land was identified as Farmland. These two classifications collectively constitute the land allocated for maize production, and alterations in these categories directly impact the land utilized for maize cultivation. Any changes, whether an increase or decrease, in these two categories signify a direct impact on the area of land devoted to maize production.

The data extracted from the error matrices, depicted in the bar chart presented in Figure 4.27, revealed that the Buildings category had the most substantial influence on land designated for maize cultivation. To obtain these results, the data from the error matrices was calculated by dividing the accurately classified figures located in the error matrix's diagonal by the total reference points. The outcome was then multiplied by 100 to yield the percentage representation of that specific land cover class for that year. Further details regarding these outcomes are provided in Figure 4.27.

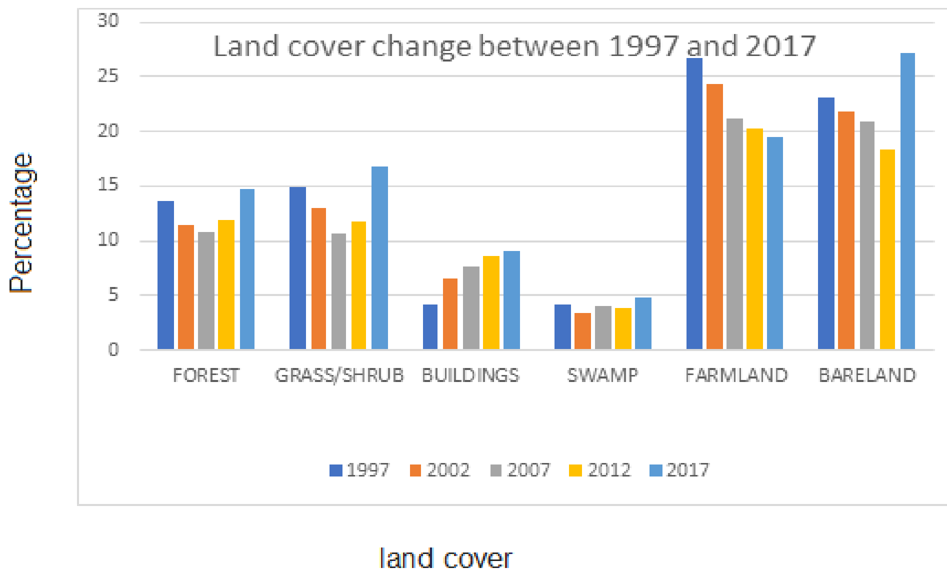


Figure 4.27: Percentage of land cover classes from 1997 to 2017

Source: Field Data, 2021

The data from Figure 4.28 illustrates the land cover distribution across Likuyani Sub-County. In 1997, Forest cover accounted for 13.66%, Grass/Shrub for 14.97%, bare land for 23.3%, Farmland for 26.75%, Swamp for 4.14%, and Buildings for 4.15%.

Over time, Buildings increased notably by 4.86%. This rise correlates with the substantial population surge in Likuyani, as recorded by the Kenya National Bureau of Statistics (KNBS) from 91,210 in 1999 to 152,055 in 2019. This population expansion directly influences the increase in constructed buildings. As these buildings encroach upon Farmland, there's a corresponding reduction in the land area available for cultivation, as summarized in Table 4.3. By 2017, the area under buildings more than doubled to 9.01%, indicating the most substantial negative impact on land designated for maize production. Concurrently, Forest cover increased from 13.66% to 14.72%.

Upon visual inspection of the choropleth maps from 1997 and 2017, observations revealed changes in farmlands transitioning into forest covers. Ground assessments confirmed that certain landowners had opted to plant trees for income generation. These farmers, who didn't reside on the land, viewed tree planting as an income source and a means to protect their land from encroachment. The Grass/Shrub category showed a gradual reduction from 14.97% in 1997 to 10.72% in 2007, then increased to 16.78% by 2017. This land cover shift was predominantly attributed to its conversion into farmland and settlement areas due to population growth, which was substantiated by questionnaire data. The surge observed from 2012 to 2017 was due to the introduction of sugarcane farming.

The analysis of temporal and spatial land use and land cover changes in Likuyani Sub-county over the last two decades underscores the significant impact of population growth and settlement development around urban regions. Vast regions previously occupied by Grass/Shrub, notably long the riparian areas, have been transformed into croplands and settlement in the upstream section of the study area. This mediated by the availability of guaranteed water for irrigation and fertile soils for farming.

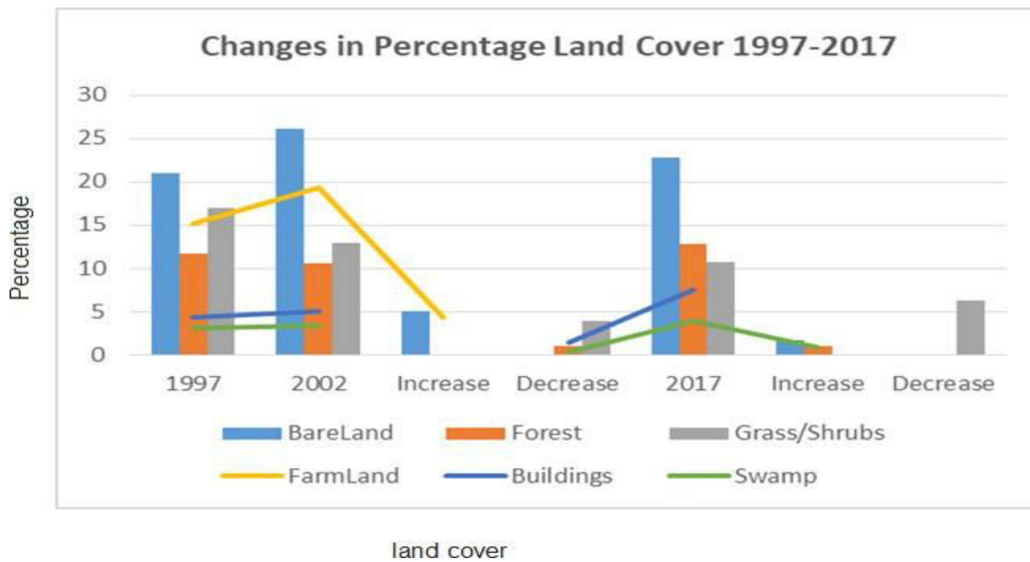


Figure 4.28: Changes in Percentage of land cover and 1997 to 2017

Source: Field data, 2021

4.2.1 Coefficient of Determination of the causes of land use change on land cover classes

The study sought to determine the coefficient of determination on the impact of LULCC on land cover classes as summarized in table 4.5**.**

Table 4.5: Coefficient of Determination of impact of LULC on land cover classes

Coefficient of Determination										
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.590[a]	.559	.283	.093	.559	54.094	1	285	.061	1.037
a. Predictors: (Constant), land cover classes										
b. Dependent Variable: land cover classes										

Source: Data (2021)

The outcomes illustrated in Table 4.5 indicate an R-squared value of 55.9%, suggesting that approximately 55.9% of the variations in the dependent variable (Land under Maize production) can be explained by the independent variable (impact of LULC). Consequently, this implies that there exist other unaccounted factors amounting to 44.1% that influence Land Use Land Cover Change (LULCC) but are not considered in this model. Moreover, the moderating term demonstrates significance with a P-value of 0.061, slightly above the 0.05 threshold. This signifies that LULCC serves as a moderator in influencing the overall effect of explanatory variables on land cover changes within Likuyani sub-county. As a result, the study rejects the null hypothesis that posited, "Land use land cover has no significant impact on land cover classes between the years 1997 and 2017."

4.2.3 Implications of LULC in Likuyani Sub County

The study aimed to assess the repercussions of land use land cover changes in Likuyani Sub County, which included examining the extent of land subdivision within the area into parcels deemed unsuitable, less than half an acre in size, for sustainable maize production. Utilizing digitized RIM (Record of Information on Microfiche) maps of the chosen four settlement schemes, valuable insights were obtained regarding the degree of land subdivision present in the region. Table 4.6 provided below presents a summary encompassing the sizes and count of land parcels during the schemes' inception, the number of subdivided parcels per settlement scheme at the time of RIM acquisition, parcels smaller than half an acre per settlement scheme, and the percentage of subdivisions per settlement scheme.

Table 4.6: Number of Land parcels at inception, after subdivision, Number of parcels less than half an acre and percentage subdivision per settlement scheme.

Table 4.6: Settlement scheme distribution and allocation

Settlement Scheme	Number of Allocated land parcels	Parcels Subdivision After subdivision	No of land Parcels less than half Acre	Percentage Land subdivided
Sango	540	1335	156	247
Sergoit	190	929	63	489
Soy	156	831	113	533
Nzoia	237	412	24	174

Source: Data (2021)

The data extracted from Table 4.6 reveals notable observations regarding land subdivisions in the study area. Sango settlement scheme displayed the highest count of initially allocated parcels at the inception of the scheme. Additionally, it also exhibited the greatest number of subdivided land parcels, particularly those below half an acre in size. Sango, characterized by gently sloping plains and situated just 8 km from the nearest access point to the Eldoret-Kitale highway, has drawn considerable interest from potential land buyers. This accessibility has significantly contributed to the rise in land subdivision within this scheme. Figures 4.29, 4.30, 4.31, and 4.32 present the digitized RIMs for the selected schemes, offering a visual representation of the land subdivision patterns observed. Figure 4.29 entails land subdivisions from the initial 540 parcels to 1335 parcels in Sango scheme

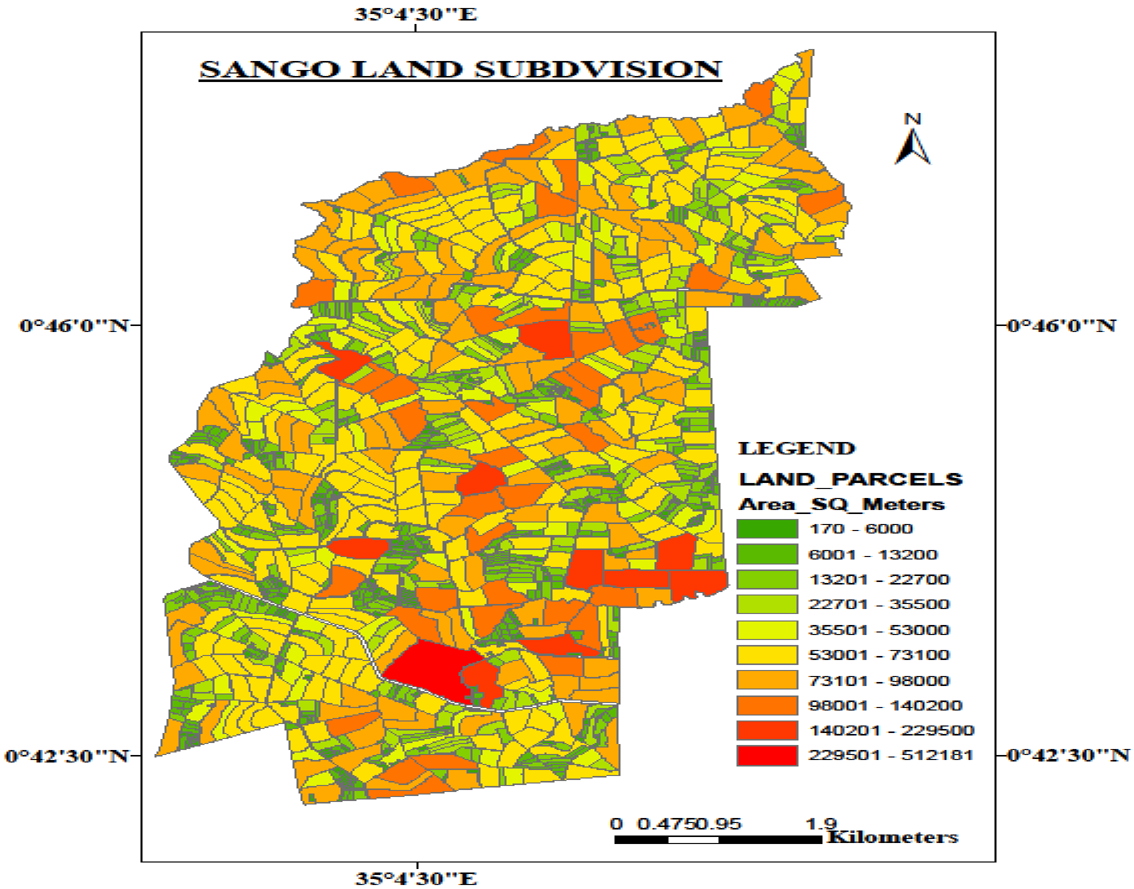


Figure 4.29: Sango settlement scheme

Source: Data, 2021

Figure 4.29 represents the map of Sango settlement scheme land registered subdivisions as per the year 2017 in color ranking. The color ranking from green through yellow to red. The color scheme rates the plots from the smallest in area to the largest in square meters. The smallest being deep green and the largest deep red. It can be seen the smallest land parcel has an area of 170square meters and the largest parcel has an area of 512181 square meters. The dominant color is yellow ranging between 35501 and 53000 square meters. Much of those colored green are located along roads. The least number of land parcels are those in red. This depicts most of the land has undergone subdivision in Sango settlement scheme as per the year 2017. Since land subdivision goes in tandem with population, it can be inferred that the population of Sango did increase within the study period. This is also supported by the KBS data of 1999 and 2019. Figure 4.30 presents the map of Nzoia scheme after land subdivision from the initial 237 parcels to 412 parcels.

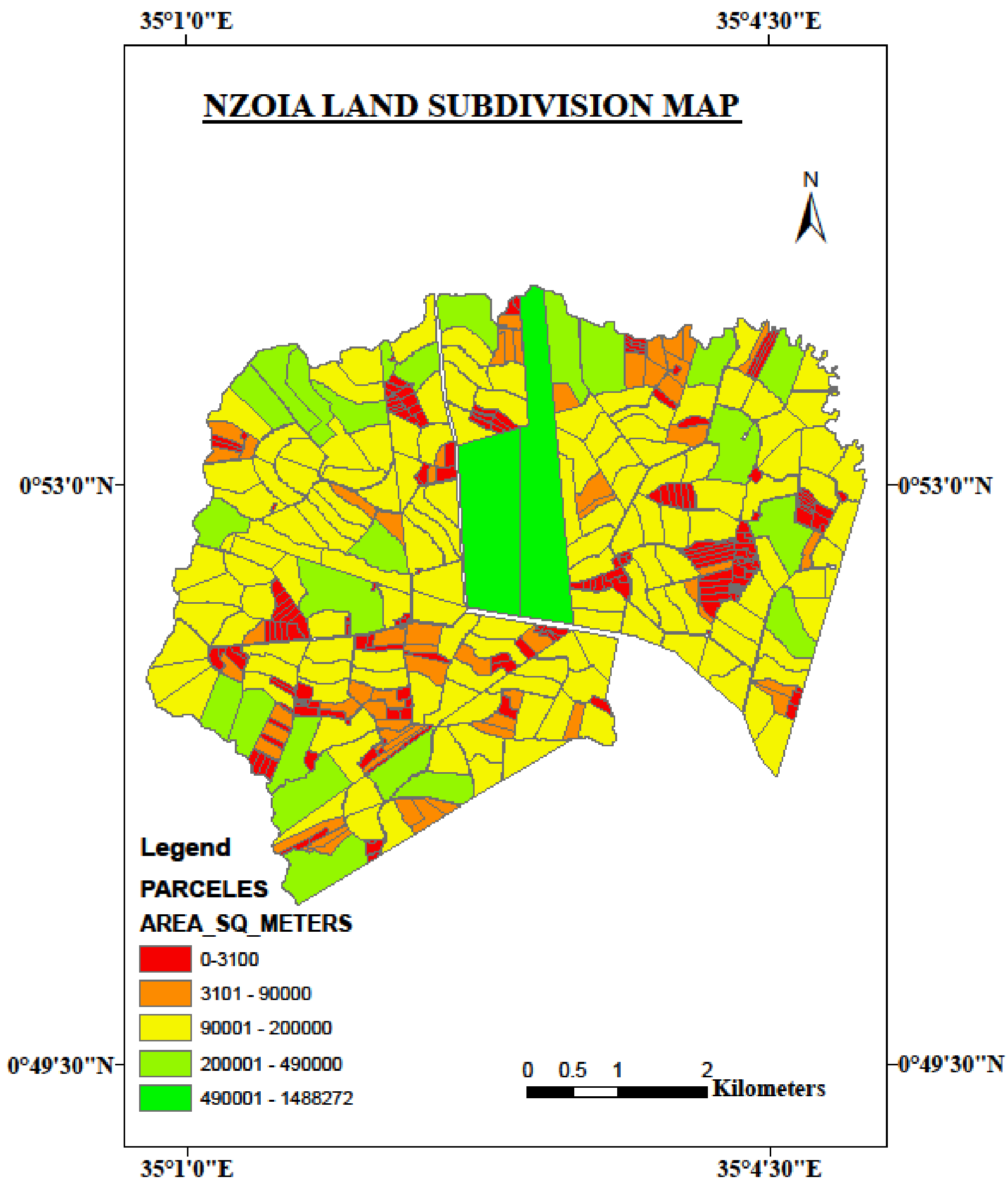


Figure 4.30: Nzoia settlement scheme after subdivision

Source: Data, 2021

Figure 4.30 represents the map of Nzoia settlement scheme registered land parcels in color ranking as per the year 2017. The acreages are presented in color ranking from red through yellow to green. Red representing land parcels with the smallest acreage and green representing land parcels with the largest acreage in the region. The yellow is dominant in Nzoia settlement scheme ranking between 90001 and 200000 square meters. Nzoia settlement scheme had the largest size in land parcels allocations and least land subdivisions. The large land parcels ranked in green are the few and those ranked in red as the smallest in area are mostly located along main roads. Figure 4.31 presents the map of Sergoit scheme after land subdivision from the initial 190 parcels to 926 parcels.

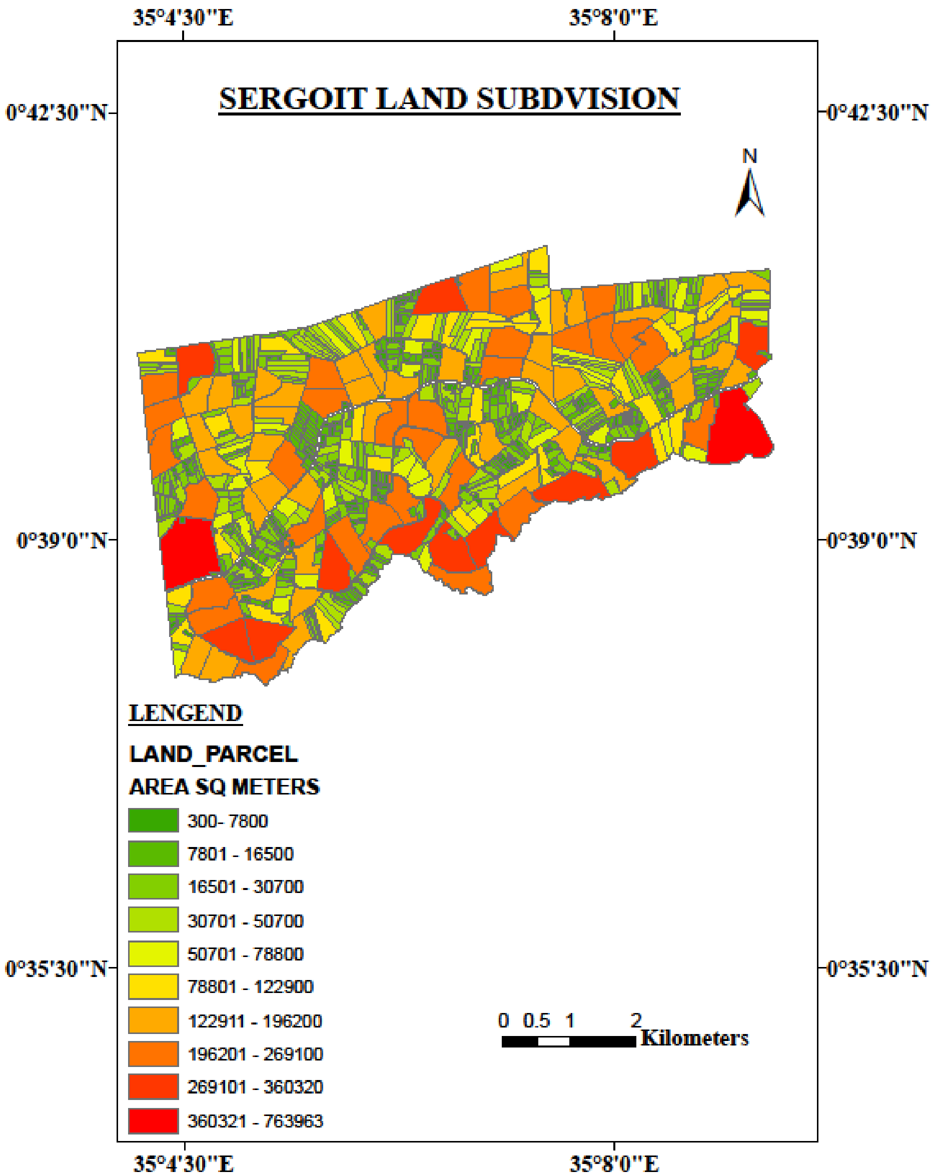


Figure 4.31: Sergoit Scheme after subdivision

Source: Data, 2021

Figure 4.31 represents registered land subdivided parcels of Sergoit settlement scheme with area of the subdivided land parcels ranked in color from green through yellow, brawn to red. Deep green is ranked smallest in area and the green color fades as area increases to yellow. The yellow color fades in correspondence in increase in area which ends in deep red as highest ranked area. In Sergoit, the color green is dominant. This indicates the land is highly subdivided in small parcels ranked between 300 and 7800 square meters. Figure 4.32 presents the map of Soy scheme after land subdivision from the initial 157 parcels to 821 parcels.

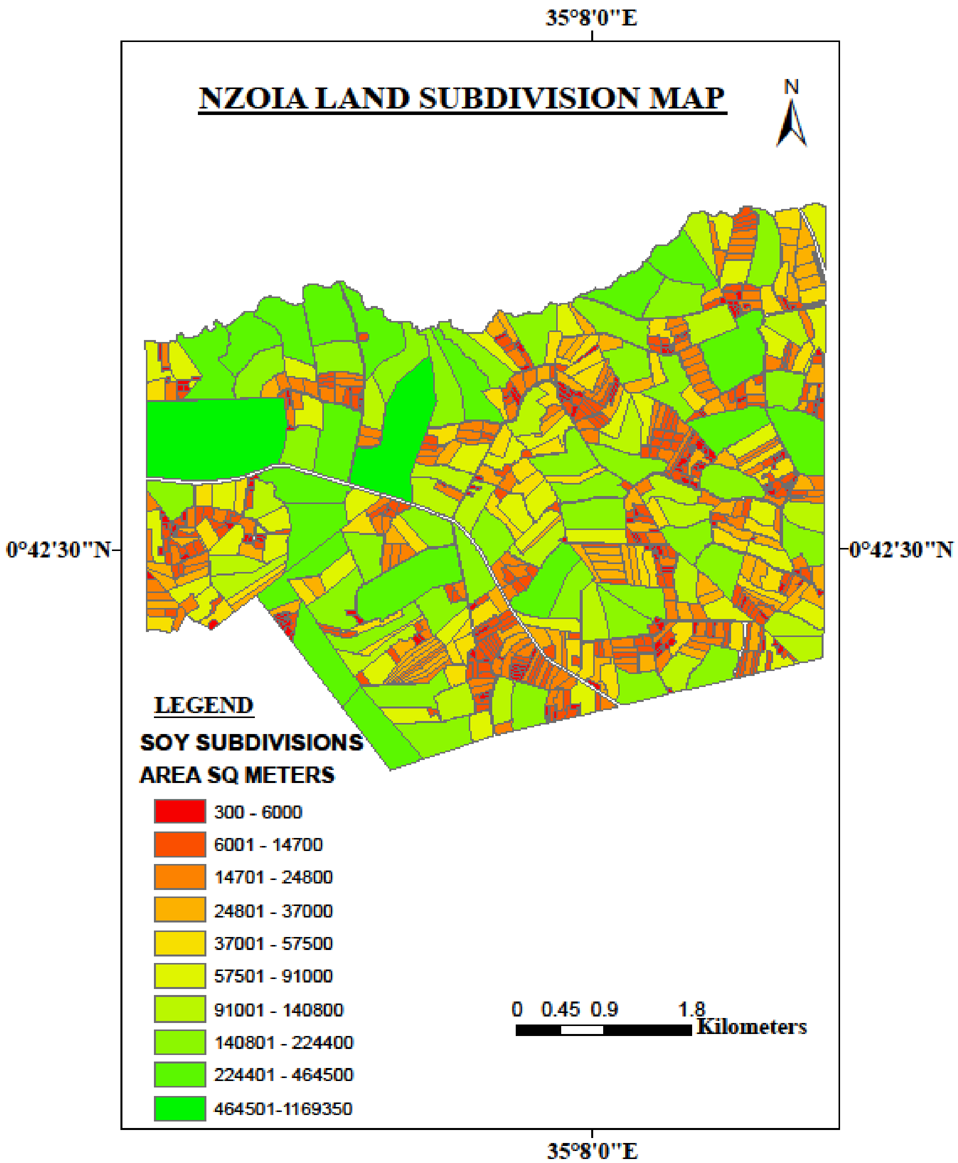


Figure 4.32: Soy Scheme after being subdivided

Source: Data, 2021

Figure 4.32 represents the map of Soy settlement scheme land parcels registered as per the year 2017. Land subdivision is dynamic and keeps changing. The land parcel acreages is ranked from red through brawn to green. Deep red represents the smallest parcels in acreage and fades as the area increases to brawn. Brawn also fades with increase in area towards red with deep red standing for the land parcels with largest area in the Soy settlement scheme. From data collected in the field in form of questionnaires and observations confirmed that indeed land subdivision was taking place at a high scale in the study area. Verbatim with the area chief and agricultural officer affirmed that land subdivision and conversion of land from maize cultivation to sugar cane plantations had reduced the area of land under maize in the Sub County.

The Soy settlement scheme emerges as the most subdivided, recording a substantial percentage of subdivisions at 53.3%. Situated adjacent to the main Eldoret-Kitale highway and housing Soy town, this region faces significant encroachment from urban expansion. As urbanization encroaches upon agricultural land, particularly in the vicinity of Soy town, land values closer to urban centers increase, leading to a transformation of agricultural land into commercial areas, offices, and shops. Maize production remains feasible only in the interior farms away from the urbanization influence.

Sergoit settlement scheme closely follows Soy at 48.9%. Situated adjacent to the Soy settlement scheme and bordering the Turbo forest and Eldoret-Malaba highway, Sergoit faces similar environmental challenges as Soy, resulting in considerable land subdivisions. Residents in Sango settlement scheme highlighted that what was once a single property between 1970 and 1980 is now divided among multiple households, indicating a significant increase in land subdivisions over time. In the Soy scheme, around 133 land parcels were smaller than half an acre, rendering them unsuitable for productive crop cultivation, including maize. Contrarily, Nzoia settlement scheme records the least subdivision rate at 17.4%. Unlike other schemes, Nzoia is situated farthest from main highways and towns, historically lacking easy accessibility due to poor road networks. However, recent improvements in infrastructure, including roads and rural electrification, have led to increased accessibility and improved living standards. These developments have affected land market prices, attracting speculation and potentially influencing land subdivision trends.

4.2.4 Determination of alterations in usage of land and coverage in Likuyani Sub County (1997 to 2017)

According to the study's findings, which are shown in Table 4.7 above, variations in the dependent variable (land under maize production) can account for roughly 83.6% of the variance in the independent variable (causes of LULCC).

This implies that 16.4% of the factors influencing LULC use are not included in this model and instead influence the use of LULC. Furthermore, the moderating term's P value of 0.070>0.05 indicates its relevance. This suggests that in the Likuyani sub-county, LULCC moderates the overall effect of the explanatory variable on land under variations in the cover of maize. Table 4.7 below presents the regression analysis on the implications of land use land cover changes on land under maize production

Table 4.7: Coefficient of Determination on causes of LULCC on land under maize production

Coefficient of Determination										
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.609[a]	.836[b]	.709	.513	.836	58.684	1	285	.070	.129
a. Predictors: (Constant), causes of LULCC										
b. Dependent Variable: Land under Maize production										

Source: Data (2021)

Thus, the hypothesis that "Land use land cover change has no significant implications on land under maize production" was rejected by this study. The primary catalyst behind land use changes in Likuyani sub-county has been the expansion of cropland, chiefly observed along riparian lands due to their favorable conditions such as water availability for irrigation and suitable environments for farming. This expansion mirrors similar scenarios seen in various developing countries. For instance, in Brazil, European exploitation of forest areas for rubber, coffee, and sugar cane production led to a reduction in forest cover. Studies conducted elsewhere have also highlighted the impact of agricultural expansion on forestland.

Kundu *et al.* (2018) evaluated Land Use and Land Cover Change (LULCC) in Mau Forest over about four decades, revealing an increase in agricultural areas at the expense of forests. The degradation and deforestation were notably significant due to unplanned forest exploitation in various forests like Aberdares, Mt. Kenya, Mt. Elgon, and the Mau complex (Ayuyo and Sweta, 2015). Factors contributing to cropland expansion also include the rapid increase in both native and immigrant populations leasing and acquiring land for farming purposes. Studies by Jorgenson and Burns (2017) in developing countries and Kioko and Okello (2019) within the Amboseli ecosystem link rural population growth to changes in land use.

This trend aligns with findings by Mbau (2013) on the implications of land use and land cover changes on human-wildlife conflict in the semi-arid Amboseli ecosystem. Changes in livelihoods and an increasing immigrant population have been identified as additional drivers of land use change (Okello et al., 2018). Baaru (2018) and Mbau (2018) both observed similar phenomena where proximity to markets influenced land use changes in Kenya and Tanzania. Further examples include studies by Mwavu and Wirkowski (2018) in Budongo forest and Kathumo (2017) in Gucha River catchment, illustrating the clearing of forest areas for agriculture and settlement. Similar patterns of forest clearance for farming and settlement were noted in the Mau Forest complex (Ayuyo and Sweta, 2016).

4.3 Determinants influencing LULCC in the maize-producing areas

4.3.1 Land ownership by farmers

According to the study results shown in Figure 4.34 above, the majority of respondents have owned land for less than ten years. This is supported by the fact that 150 respondents (or 53%) indicated as much on the questionnaire, 86 respondents (30%) indicated they had owned land for between 11 and 30 years, and 50 respondents (17%) have owned land for more than 30 years. Figure 4.33 indicates land ownership and for how long

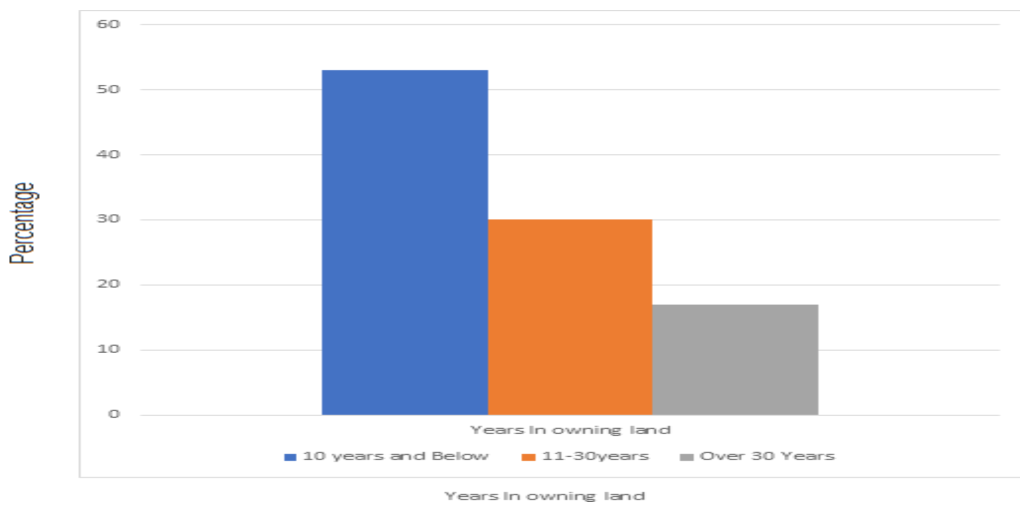


Figure 4.33: Period of land ownership

Source: Field data, 2021

As a result, this suggested that the respondents had a great deal of expertise with issues pertaining to land covering and use.

4.3.2 Types of crops been cultivating on farm

The researcher sought to find out the type of crops the respondents have been cultivating on their land. Table 4.8 presents the type of crops cultivated by farmers in Likuyani Sub County.

Table 4.8: Types of crops being cultivated

Crops	Frequency	Percentage
Maize	195	67
Eucalptus spp	36	12
Others	55	21
Totals	286	100

Source: Data (2021)

The findings from Table 4.8 indicate that a significant majority of the respondents in the study area engage in maize cultivation. Specifically, 195 individuals, constituting 67% of the respondents, confirmed their involvement in maize cultivation. Additionally, 55 respondents (21%) cultivate other crops, whereas 36 respondents (12%) cultivate *Eucalptus* spp.

The field survey conducted across the four selected settlement schemes involved interviews with selected individuals, on-site observations of existing land cover, and the collection of GPS points to assess image accuracy post-classification. Interviews aimed to gather insights into the decisions influencing land use change and their impacts on maize production. Only individuals residing on their farms for 20 years or more were interviewed to align data with the study period. According to questionnaire results, 100% of long-term residents had engaged in maize cultivation at some point in the past. However, over time, there has been a consistent decline both in the area of land under maize production and the number of individuals cultivating maize. The study sought to determine if farmers preferred cultivating crops other than maize. Findings revealed that 30% of respondents favored cultivating crops other than maize, while 70% still preferred maize cultivation. This indicates that despite the declining trend, maize production remains the most favored crop in the study area.

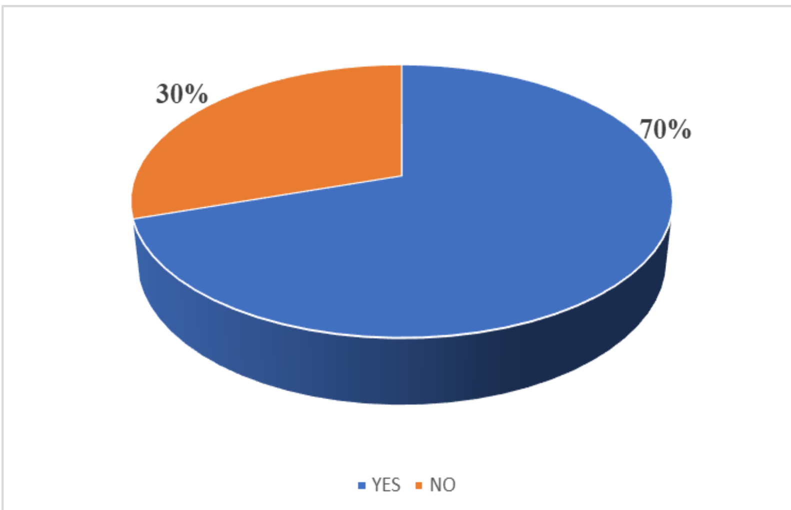


Figure 4.34: Percentage preference for maize cultivation to other crops

Source: Field Data, 2021

The data depicted in Figure 4.34 illustrates that a significant majority of respondents, constituting 70%, are engaged in maize cultivation, while 30% indicated their non-involvement in maize farming. The primary reason for favoring other crops was attributed to market forces.

The Government's agency, the Cereal and Produce Board (CPB), traditionally served as the primary maize buyer from farmers, purchasing their entire maize produce. However, the CPB's capacity to buy all maize from farmers had diminished, presenting a challenge as selling maize became more difficult due to limited market availability. Among the respondents interviewed, 80% preferred other crops due to perceived higher profit margins. For instance, the cultivation of sugarcane gained popularity as it boasted a ready market with convenient harvesting and direct transportation from the farm. Additionally, 7.14% of respondents observed reduced maize yields, while 12.86% expressed an interest in exploring new crops. The variability in climate was also noted to adversely affect maize production, leading to occasional losses for farmers in certain years.

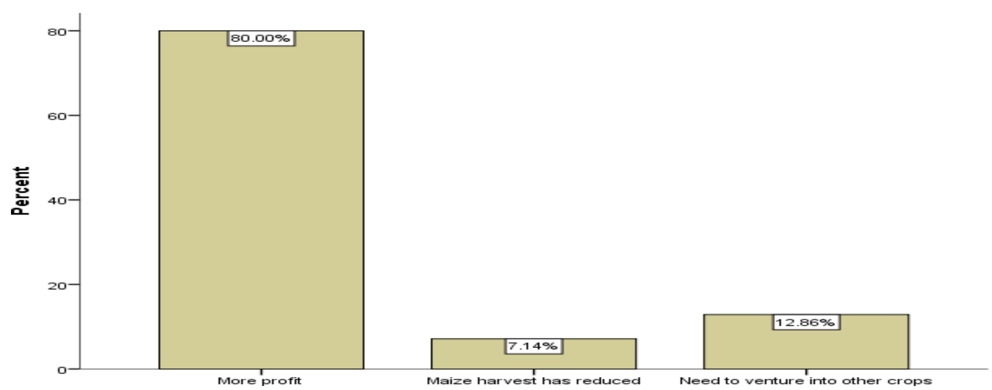


Figure 4.35: Reasons as to why people prefer crops other than maize

Source: Field data, 2021

The data from Figure 4.35 illustrates the reasons behind the respondents' preferences for cultivating crops other than maize. An overwhelming 80% of respondents indicated a desire to shift away from maize cultivation toward crops with higher market values.

Around 12% expressed an interest in cultivating new crops unfamiliar to the study area to diversify away from the dominance of maize. Notably, 96.67% of respondents still preferred maize cultivation, corroborating observations of numerous farms engaged in sugarcane cultivation. Conversely, only 3.33% showed an interest in cultivating blue gum trees, a species that typically takes around eight years to mature and finds application in housing construction, fencing, and manufacturing electric poles. Farmers with larger landholdings typically planted these trees on portions of their land or wetlands, while smaller landowners were less inclined toward blue gum tree farming.

However, conflicts arose among those farming maize near the trees, citing adverse effects on maize production. Land subdivision emerged as a significant driver of land use and land cover change, with 94.44% of respondents having subdivided their land for various purposes, including sales or family distribution, while 5.56% had not done so. Figure 4.36 outlines the reasons for land subdivision, where 48.24% cited family heirs who subsequently sold portions of their land for diverse needs. Another 35.29% of the subdivisions were aimed at distributing land among family heirs. This trend of subdividing land into smaller parcels has had a detrimental impact on maize production in the region.

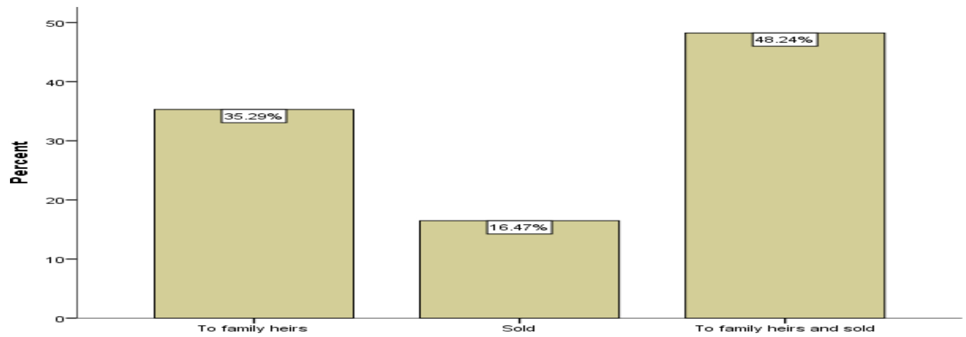
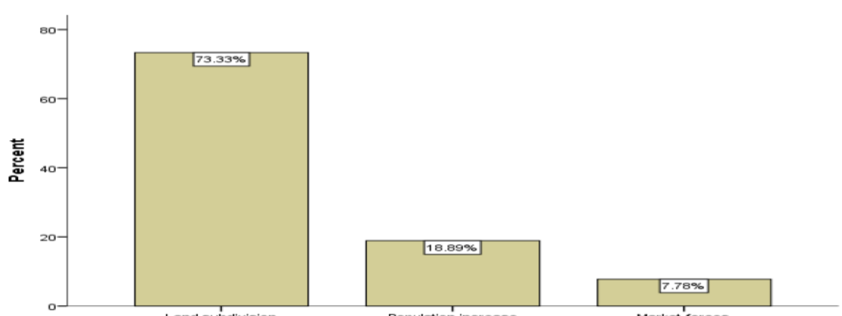


Figure 4.36: Percentage of reasons for land subdivision

Source: Field data, 2021

Land subdivision trends are consistent with patterns in satellite image data that show changes in land cover, as was previously mentioned. According to 73.33% of respondents, it seems to be the main factor causing the change in maize production. Subsequently, population growth was shown to be the second important factor, accounting for 18.89% of the stated causes, and price variations



for 7.78%.

Figure 4.37: Causes of shift from maize production

Source: Field Data, 2021

Results from the respondents indicated that, number of land parcels have increased but sizes of the parcels and area under maize cultivation greatly reduced as the total land area remained constant.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter serves as a summary encompassing the findings, conclusions, recommendations, and suggestions for further research derived from the study. It also identifies additional areas that require further investigation and exploration.

5.2 Summary of the findings

This study focused on six different land use and land cover classes (Forest, Farmland, Grass/Shrub, Swamp, Bare land, and Buildings) and used Landsat and Sentinel 2A imagery over five different years (1997, 2002, 2007, 2012, and 2017). The goal of the study was to identify changes in land use within Likuyani Sub County between 1997 and 2017, especially with regard to land used for maize cultivation. The analysis revealed that the Buildings category, which is strongly correlated with population growth, is the main driver of changes in land use. Four separate phases were used to categorize these changes: 1997–2002, 2002–2007, 2007–2012, and 2012–2017.

The research area's area under maize cultivation has changed, albeit at varying speeds and magnitudes depending on the various classification categories, Bare land is the plowed land that is waiting to be planted with maize, and part of farmland is the unplowed area that will soon be plowed to form land under maize production. Combined gives a total of 10.20%. This corresponds to a 0.155% yearly decline over a twenty-year timeframe.

Building cover increased from 4.15% to 9.01% over the same time span, according to calculations. When compared to all land covers, the land cover of buildings had the highest yearly rise rate (0.24%), translating to a total increase of 4.86% which translates to annual rate of 0.243%. During the research years, there was a yearly 0.1% increase in the land cover of grass and shrubs. This land cover declined significantly over the first three quarters of the research, primarily as a result of population growth that increased land subdivision and the building of habitational homes. This land cover began to increase with the introduction of sugarcane growing because the software misclassified the sugarcane cover as grass. Throughout the course of the study, there has been a noticeable inverse link between the amount of land used for maize cultivation and the land covered by buildings.

In the first era, the amount of land used for maize production fell while the land cover of buildings climbed; in the second period, the amount of land used for maize cultivation fell by 3.68% while the land cover of buildings increased by 0.85%. The substantial rise in the area covered by buildings can be linked to factors such as population growth, increased habitation, better infrastructure, and urban sprawl, which resulted in the conversion of more farmland to settlement.

Furthermore, there is a clear inverse relationship between the amount of grass and shrub cover and the growth of built-up areas. The amount of grass and shrub cover decreased by 4.25% in the first half of the study period (from 1997 to 2007), but it increased by 6.06% in the second half (from 2007 to 2017).

Concurrently, the land area occupied by buildings showed increases of 1.32% in the second half and 3.54% in the first half of the study period, totaling a 4.86% increase in the land cover of buildings, while the substantial rise in grass/shrub land cover aligns with a considerable increase in building land cover and the expansion of sugarcane farming during the same period. These findings are consistent with data on sugarcane production and population growth, which indicates a marked population increase between 2009 and 2019 compared to the period between 1999 and 2009. The transformation of grassland and shrubland into residential buildings to cater to the burgeoning population and agriculture may underlie the observed decline in grassland/shrub cover.The influence of forest cover on the area utilized for maize cultivation appeared minimal. Over the initial phase of the study (1997 to 2007), there was a decline of 2.79% in forest cover, which then saw an increase of 3.85% in the subsequent phase. The growth in forest cover during the latter period was attributed to farmers introducing blue gum tree cultivation in specific sections of their land. Notably, the reduction in forest cover during the initial phase was due to the extraction of older trees from Turbo Forest, rather than a transformation of the forest's land cover into a different classification.

The breaking up of the land into smaller sections and the expansion of habitation, which naturally occurs after the property is subdivided, jeopardized the area under maize cultivation. This indicates that the number of homesteads that were initially on a piece of land has increased, which has led to a decrease in the area used for maize cultivation.

These facts are corroborated by the outcomes of digitalized RIMs land parcels, from which GIS spatial analysis techniques can be used to quantify the sizes and number of subdivisions for each plan. The digitized RIMs' results showed that land subdivisions were more noticeable in the vicinity of important thoroughfares and metropolitan centers. The settlement plans for Soy and Sergoit were particularly impacted. These results were confirmed by running SQL queries on the digital data and land subdivision data from Kenyan records of the Kakamega Survey.

5.3 Conclusions

5.3.1 Spatial and temporal alterations in LULCC within Likuyani Sub County from 1997 to 2017

Findings show that human activity is the primary cause of land use change that impacts area producing maize in the Likuyani sub-county. In the studied area, settling and diversifying from the main crop—maize—are important human activity. Throughout the research period, new immigrants were drawn to the area by the chance to purchase land and the rich soils surrounding agricultural land. These factors are primarily linked to the growth of towns and the destruction of forests. One of the main ways that humans altered the environment was by converting land to farms. It was clear that there had been a substantial shift in the Sub County's land-use and land-cover, with farmland covering 26.75% of the area in 1997 compared to 19.47% in 2017.

Nonetheless, the percentage of land covered by forests rose from 13.66% in 1997 to 14.72% in 2017. The spatiotemporal LULCC coefficient of determination yielded a significant value (p 0.068>0.05), suggesting that the LULCC in Likuyani from 1997 to 2017 was noteworthy.

5.3.2 Influence of LULCC on various land cover classes in Likuyani sub-county from 1997 to 2017

Nevertheless, the research findings also indicate that, from the perspective of local residents, alterations in land use and cover have yielded positive outcomes. For communities residing close to agricultural lands, the advancement of sugar cane production has resulted in increased employment opportunities. Moreover, the expansion of settlements has facilitated improved access to essential services such as schools and healthcare, while also fostering new investment avenues in the area. On the flip side, the demand for more land for food cultivation and settlements due to immigration has adversely impacted the region in terms of land use and cover. Failure to address this issue could lead to further detrimental effects on the ecosystem's integrity and livelihood sustainability. It's essential to strike a harmonious equilibrium between development and the supply of environmental services.

The local community effectively correlated various benefits and challenges with alterations in land use and land cover. A positive consequence highlighted was the heightened production of sugar cane, while the negative impact revolved around the expansion of agricultural and settlement areas in the study zone. This study showcased the effectiveness of utilizing remote sensing and participatory GIS to address issues stemming from shifts in land use and cover. Leveraging contemporary technologies empowered the local community to map and deliberate upon their primary land use concerns in ways that were previously unattainable. This facilitated the validation of information through direct observations. Engaging with land users directly provided swift feedback for expedited decision-making, particularly on critical matters requiring prompt attention. The study aptly exemplifies how GIS and remote sensing techniques can be employed for mapping land use changes and engaging local communities in understanding the reasons and impacts of such transformations.

5.3.3 Causes of LULCC affecting land under maize production in Likuyani Sub County between 1997 and 2017

According to the study's findings, Kenya's most fertile sub-county, Likuyani sub-County, adds to the nation's breadbasket by growing maize. There are several issues facing the sub county that have an impact on the area used for growing maize. The most noteworthy ones include the growing population, land subdivision, the shift from maize to other crops. Population growth has resulted in much smaller lots and more structures, which has decreased the amount of land used for growing maize and the region's total yield.

By manipulating the data from remote sensing, it was possible to see a general trend of rising structures and falling crop land. Moreover, there was a notable decrease in the cover of grass and shrubs during the first half of the research period, followed by a modest rebound in the second half. The primary forces behind population growth, reduction in the amount of land used for maize farming.

The research area was undergoing various changes in land cover, which indicated a decrease in the amount of land under crop production, according to the results of the image classification. The amount of land used for settlement and the amount of land left over for maize farming are significantly impacted by population growth. It is evident that growing population and settlement are strongly correlated with areas adjacent to developing towns and metropolitan centers that are experiencing significant rates of land subdivision.

In Likuyani Sub County, land subdivision patens were successfully explored using GIS. When applied to the digitalized RIMs maps, Structured Query Language (SQL) offered a clear graphical representation of the sizes and spatial areas negatively impacted by the land subdivision. The primary land cover categories at various research areas were assessed using questionnaires and site visit observations in comparison to remote sensing data.

There was a correlation and agreement between the results from the questionnaire and ground observations and those from remote sensing and GIS. Additionally, the ground inspections revealed an increase in sugarcane farming, a ground cover that was difficult to distinguish from remote sensing photos due to their imprecise spatial resolution. Information from the 2020 Food Authority Yearbook and Agriculture. Coefficient for determination of Causes of LULCC on land under maize production gave a significant value p 0.070>0.05.

The study reached the following conclusions:

i. Likuyani Sub County land usage has had a considerable shift in land cover, primarily due to population growth, land subdivision, and increased settlement. This is adversely affecting the extent of land used for maize cultivation and causing substantial changes. The amount of land used to grow maize has decreased by 3.17%. Overall, there is less area under cultivation and more land occupied by structures.

ii. The population of the Likuyani sub-county is growing, which is a factor in the demand for housing and the subdivision of property. This is a result of changes in land usage, which affects the amount of land available for crop cultivation.

iii. Employing GIS and remote sensing technologies facilitated the comprehensive assessment of the drivers behind land use and land cover alterations, unveiling their direct impacts on the area designated for maize production. The study revealed a continuous evolution in land use within the research area, signaling potential threats to the land dedicated to maize cultivation, as corroborated by structured questionnaires and meticulous on-site observations.

5.4 Recommendations

The study's findings led to the following suggestions being made:

i. Leveraging the extensive historical data available through remote sensing can be instrumental in monitoring fluctuations in land cover across the entire maize production area. This approach stands to enhance land management practices, ensuring the optimal utilization and preservation of land for maximizing maize yield
ii. In places intended for the nation's food production, such as Likuyani Sub County, legislation should be passed to curb spatiotemporal land use land cover changes subdivision of land beyond acreage that cannot maintain tangible maize and food production
iii. A participatory planning strategy that incentivizes families to establish a home on a specific plot of land designated for encouragement.
iv. Area should stop producing crops other than maize, such as crops that substitute for it. The primary offender in this situation is sugarcane growing. The National Cereal and Produce Board (NCPB), a body within the government, works to guarantee that farmers who grow maize have access to subsidized inputs and a ready market. This is because farmers are being driven to grow other crops that are thought to be more profitable than maize due to low earnings and high input

5.5 Suggestions for further research

This include the following:

i. Since maize is still the main staple grain in the nation, there is a need to evaluate the effects of increased sugarcane farming on land used for maize production.

ii. Using high spatial resolution imagery, evaluate how land subdivision and population growth affect food production.

REFERENCES

Aboud (2019) Economic growth in arid and semi-Arid lands of Kenya.

African Agricultural Status Report. (2014). Climate Change and Small Holder Agriculture in Sub-Saharan Africa.

Agrawal and Yedama, (2017). Fighting Hunger. Things that really matter

Alemmeta, A. A., & Singh, K. N. (2017). The Implications of Land Use and Land Cover Changes for Rural Household Food Security in the Northeastern Highlands of Ethiopia: the case of the Teleyayen Sub-warershed.

Ambwere, S. (2003). Policy Implications of Land Subdivision in Settlement Areas: A Case Study of Lumakanda Settlement Scheme.

Anupam. (2017). Tutorial on Accuracy Assessment: Unit 14.

Ayieko, P. O., Wawire, N. W., & Ombuki, C. (2013). The Response of Maize Production in Kenya to Incentives. *International Journal of Development and Sustainability Online. 2(2). doi:2168-8662*

Aykut , A., & Necdet, T. (2010). Comparing Different Satellite Image Classification Methods: An Application in Ayvalik District, Western Turkey.

Ayuyo, I and Sweta, L. (2014) Land cover dynamics in Kirisia Forest Ecosystem, Samburu County. Kenya. *Advances in Remote sensing Journal. VOL. 5 No 3*

Baaru, (2011) Assessment of changes in land use and land cover changes and soil Erosion risk factors in Kathe Kakoi Catchment, Machakos County. Kenya.

Bacc, (2015). Second Assessment of Climate Change for the Baltic Sea Basin. *Regional Climate Studies*

Biswajit, P. (2017). Modelling factors that affect water system flows.

Bronstert, A., Balabukh, V., Valentina, K. Burger, G., Didovets, L., (2017). Climate change impact on regional floods in the Carpathian region. *Journal of Hydrology; Regional Studies. Volume 22*

Chumo, M. K. (2013). Determining Factors that Affect Maize Production in Turbo Constituency, Kenya.

Chune, S. S. (1997). The Changing Land Use Pattern in a Million Acre Settlement Scheme and its Implications on Household Income Generation from Agriculture: *The Case of Naitiri scheme in Bungoma District.*

CIDP (2018) Kakamega County Integrated Development Plan 2018-2022

Cline-Cole, Maconachie, Daniel, J., (2018) Wood Energy Interventions and Development in Kano, Nigeria

DeMeo, T., Ryan, H., Chris, R., June, K., Steve, A., Mike, S., Mark, S (2016) Expanding our und Understanding of Forest structural restoration needs in practice. *Journal Northwest Science 92(1):18-35* *https://doi.org/10.3955/046.092.0104*

Deichmann, (2016). Digital Technologies and Agriculture in Developing Countries. *Journal of Agriculture and Economics. Volume 47. http://doi.org/10.1111/agec.123.00*

Di Gregorio and Jansen (2018) A new concept for land cover classification systems. Food and Agriculture Organization. Environment and Natural resource services GCP/RAF/ITA Africover-East Africa project Soil Resources Management and conservation services.

ESRI. (2014). *ERDAS Imagine Guide Book.*

FAO, F. a. (2015). Regional Overview of Food Insecurity in Africa. Accra. Hoge, G. H. (2013). Professional Land Surveyors and Engineers Journal.

Horvat, Z. (2012). Change Detection in Land Use Land Cover Change (LULC) in Medimurje County, Croatia between 1978, 1992 and 2007 Using Landsat Imagery. Retrieved from bacc.ing.tech.inf.

Geist and Lambin (2014) Proximity and underlying causes of Forest cover changes in Peninsular Malaysia. *https://doi.org/10.108/j.forpol.2014.05.007*

Hussein , A. O. (2009). Land Use and Land Cover Change, Drivers and Impacts: A Comparative Study form HKuhar Michael and Lenche Dima and A wash Basins of Ethiopia.

Gumindonga, (2017). Satellite inspired hydrology in Uncertain future: H SAF and HEPEX Workshop.

Hoge, G. H. (2013). Professional Land Surveyors and Enginners Journal.

Horvat, Z. (2012). Change Detection in Land Use Land Cover Change (LULC) in Medimurje County, Croatia between 1978, 1992 and 2007 Using Landsat Imagery. Retrieved from bacc.ing.tech.inf.

Hussein, A. O. (2009). Land Use and Land Cover Change, Drivers and Impacts: A Comparative Study form HKuhar Michael and Lenche Dima and Awash Basins of Ethiopia.

IUCN, (2018). Red list of endangered Species. *(International Union for Conservation of Nature annual report 2018).*

Indian, P., Pramit, V., and Rughubansh, A.S., (2017). Rural Development and LULCC in Rapidly Developing Agrarian South Asian Landscape. *Remote Sensing Applications Society and Environment. Volume 14. Pages 138-147.*

Joseph, G., & Jeganathan , C. (2006). Fundamentals of Remote Sensing book. Retrieved from http://www.ccrs.nrcan.gc.ca/resource/ tutor/fundam/chapter1/01_e.php

Joseph, G., & Jeganathan , C. (2006). Fundamentals of Remote Sensing book. *Retrieved from http://www.ccrs.nrcan.gc.ca/resource/tutor/fundam/chapter1/01_e.php*

Kabubo, M. J., Linderhof, V., Kruseman , G., Atieno, R., & Mwabu, G. (2010). Poverty- Environmental links: The Impact of Soil and Water Conservation and Tenure Security on Household Welfare in Kenya. *Journal of Development and Agricultural Economics, 2(1). doi: 041-053*

KALRO. (2021). Demand driven research for food security and income. Nairobi: Kalro, org.com.

Kairu A.W (2016) Environmental and land use cases in Kenya

Kathumo, V. M (2011) Assessment of Land use Land Cover changes in River Gucha Catchment. Kenya

Kihima, M. V. (2017). The Impact of Land Subdivision and Fragmentation on Rural Development: *A Case Study of Vihiga County.*

Kiplimo, L. B., & Ngeno, V. (2016). Understanding the Effect of Land Fragmentation on Farm Level Efficiency: An Application of Quantile Regression-Based Thick Frontier Approach under maize production in Kenya.

Kioko and Okello, (2010) Land cover and Environmental changes in semi-arid and Rangeland, Southern Kenya. School of field studies, center for wild life Management studies Journal. Box 27743-00506 Nairobi Kenya

Lambin, E. F. (2001). The Cause of Land Use and Land Cover Change: Moving Beyond the Myth. Global Environmental Change, Netherlands.

Leemans, J., Sarah, A. Christopher, B. and Shea, M. (2017). Classifying the full range of strategies used in implementation of Science practices. Implementation science 125(2017)

Lewis. (2013). Economic Impact of Climate Change under maize production in Kenya

Lillesand, T.M., Kiefer, R.W. Chipman, J. (2017). Remote Sensing and Image Interpretation

Lu, D., Hailing , J., & Lingbin, Y. (2018, May 7-10). Spatiotemporal Change of Vegetation Coverage and its Driving Forces Based on Landsat images: A Case Study of Chugchun City. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII(3).

Lusch, D. P. (2015). Digital Image Processing and Analysis.

Maina , P. M. (2012). The Role of Land Use and Land Cover Changes and GIS in Flood Risk Mapping in Kilifi County, Kenya.

Majumder, B. (2011). Land use land and cover change detection study of sukinda valley using remote sensing and GIS. 30.

Mallupattu, P. K. Sreenivasula, R, (2020). Analysis of land use land cover change using GIS and remote sensing data at urban area, Tirupat, India. Hidu pupblishing cooperation, science world Journal. Volume 2018 Article I/D 268623

Marien, T. (2018). Mapping Land Use and Land cover Change in Kalmar, Sweden Using Object- based Change Detection.

Matima, J., Mugatha, Simon, M., Robbins's., louis, N., Gachambi, Majule, A., Derik, P/.Linkages between land use changes and biodiversity across East Africa.

Mather, A.S, Needle, C. (2019). Relationships of population and Forest Trends. *Geographic journal 166, 2-13 https;//dol.org/10.1111/j.1475-4959.2000.tb00002.x*

Mathew, H, Gabriel, S, Christian, S, Luke, O, (2021). Hydroclimatic analysis of rising water levels in the Great Rift Valley lakes of Kenya. Journal of Hydrology; Regional studies volume 35; 100857

Mbau, S. David, W, Wasonga, O and Kimiti, K, (2013) Community perception on spatiotemporal Land use change in the Amboseli Ecosystem Southern Kenya. *Department of land resource Management and agricultural Technology. University of Nairobi Box 30197 Nairobi Kenya*

Ministry of Agriculture. (2009). Agricultural SectorDevelopment Strategy (ASDS). Government Press.

Mittermeier, R. Marcus, V.M.O., Antonio, M.S.O., Augustino, F.N.G., Paulo, E.O, and Anderson, T.S.F. (2020) Recognizing Brazilian Gerrado Enclaves by Modelling Geoenvironmental Parameters. *Journal of Geographic Information Systems. Volume 12 no 2*

Mutunga, N., & James, O. (2003). Annual Harvest Assessment. Kenya: July 2002- 2003.

Mwavu, E. and Witkowski, E (2008) Land use and Land changes (1988 to 2002) around Budonga Forest Reserve North West Uganda. *Implications of Forest and woodland Sustainability Land degradation and Development Journal 19,606-622*

Mwendwa, P, Giliba, R.A (2013). Climate change Impacts and Adaptation Strategies in Kenya. *Chinese journal of Population and Environment 10(4):22-29.*

Myers, S.S., Mathew, R., Smith, S.G., Christopher, D., Giolden. (2017). Climate change and Global food systems. *Harvard University volume 38.259-277 http:// doi.org/10.1146/annurev-puplhealth-031816-044356*

Mzusu, M.K, Zhang. W, Kapute, P. Wei, X., (2019). The Impact of LULCC on Nkula Dam in the Middle Shire River Catchment. Malawi. Earth Observations and Geospatial analysis. Doi.5772/intechopen.89452

Ndambuki, F. K. (2014). Assessing the Impacts of Environmental Changes on the Water Resources of the Upper Mara, Lake Victoria Basin.

Ndirangu, S. W. (2017). An Evaluation of the Effects of Land Fragmentation and Agro- Ecological zones on Food Security and farm efficiency: T e case of Embu County in Kenya.

Needle, Mather A. S and Coby L (2018). Relationship of population and Forest Trends. *Geographic Journal*

Nelson, S. A., & Siamak, K. B. (2019). Image Processing and Data Analysis with ERDAS IMAGINE. *Tylor and Francis Group 2019 copy.*

Niroula, G. S., & Thapa, G. B. (2007). Impacts of Land Subdivision on Input Use, Crop Yield and Production Efficiency in the Mountains of Nepal. *Land Degradation and Development, 18(3), 237-248.*

Njiru. (2016). Hydrological Information for Dam site selection by Integrating Geographic Information System GIS and Analytical Hierachical Process (AHP). Nairobi.

Noe, R.A., Hollenbeck, J.R., Gerhat, B and Wright, P.M (2018). Human resource management. Gaining a competitive Advantage. *(11th Edition). New York McGraw-Hill*

Norrington, G., Thornton, D.N., (2011). Climate change Financing and Aid Effectiveness. Tanzania case study

Ogechi, B. A., & Waithaka, E. H. (2014, October). Land Use Land Cover Changes and Implications: A Case Study of Keumbu Region Kisii County, Kenya. *International Journal of Science and Research (IJSR), 3(10).*

Ojwang', G. O., Agatsiva, J., & Situma, C. (2010). Analysis of Climate Change and Variability Risks in the Smallholder Sector: The Case of the Laikipia and Narok Districts Representing Major Agro-ecological Zones in Kenya.

Onono, P. A., Wawire, N. H., & Ombuki, C. (2013). The Response of Maize Production in Kenya to Economic Incentives. *International Journal of Development and Sustainability, 2(2).*

Oumer, H. A. (2009). Land Use and Land Cover Change, Drivers and its Impact: A Comparative Study from Kuhar Michael and Lenche Dima of Blue Nile and A wash Basins of Ethiopia.

Peacock, R. (2014). Accuracy Assesment of Supervised and Unsupervised Classification Using Landsat Imagery of Little Rock. Impact of Climate on Maize/ Food Production.

Pisanelli, A., Chiocchini, F., Cherubini, L., Lauteri, M., (2016) Combining Demographic Land use dynamics with local communities perceptions for analyzing socio- economical systems. *A case study in a mountain area of Italy. Forest Bio geosciences and Forestry Volume 5, issue 3 page163-170. https://doii.org//0.3832/ifor0615-005-Research gate Articles.*

Poongothai, E. (2018). Applications of Fuzzy Sets and Artificial Intelligence

Prisley, S. P., & Smith, J. L. (2012). Using Classification Error Matrices to Improve the Accuracy of Weighed Land-Cover Models.

Quentin, F. B., Jim, C., Julia, C., Carole, H., & Andrew, S. (2006). Drivers of Land Use Change, Final Report. Matching Opportunities to Motivations. *Royal Melbourne Institute of Technology, Department of Sustainability and Primary Industries.*

Randal, S. (2011). Image Classification Tutorial. Regional Centre for Mapping of Resources for Development Remote Sensing Training. (2014). Renny, C. (2008). Effects of land use and land cover changes on the hydrology of weruweru-kiladeda sub-catchment in pangani river basin, Tanzania.

Rogan, J., & Chen, D. (2004). Remote Sensing Technology for Mapping and Monitoring Land Cover and Land-use Change. *Progress in Planning, 301-*

325.

Reynolds, C., Robert, J., Fletchr Jr, Celinc, M., Samantha, M., (2017) Inconsistent effects of landscape heterogeneity and land use on animal diversity in an agricultural mosaic: Multi scale and multi taxon investigation

Robert, N. and Mwaniki, D., (2021) The Global Urban Monitoring Approach taken by UN-HABITAT

Rosegrant, W., Nelson, M., Jawoo, R Robertson, D., (2008). Climate change. Impact on Agriculture and costs of adaptation

Rudel, T, and Roper, J., (2016) Deforestation and Coca Cultivation rooted in the twentiesth century. (Journal of Bioscience volume 66)

Sadik, N. (2002). Population Growth and the Food Crisis. Retrieved from htttp: //www.fao.org Science, A. A. (2019). *Retrieved from https://www.science.org.au.learning*

Science, A. A. (2019). *Retrieved from https://www.science.org.au.learning*

Siddhartho, P. S. (2013). Analysis of land use and land cover change in Kiskatinaw river watershed: a remote sensing, gis & modeling approach. East Eisenhower: *Pro Quest LLC 2014.*

Stacy A. C. Nelson and Siamak Khorram. (2019) Image Processing and Data Analysis with ERDAS IMAGINE. CRC Press Taylor & Francis Group 6000 Broken Sound Parkway NW, Suite 300 Boca Raton, FL 33487-2742 © 2019 by Taylor & Francis Group, LLC

Smith, R. B. (2011). Image Classification Tutorial.

Soare, E., Irina, A. C., Vasilia, A. V., & Livia, D. (2018). World Market Research on Maize. The Economist on East Africa Drought. (2009).

The Economist on East Africa Drought. (2018). *Research Methodology. Methods and T techniques. New Delhi: 2nd Ed. New Age International (P)* Ltd. New Delhi, India.

The Encyclopedia of the Earth. (2016). Earth Portal.

Thomas M. Lillesand, Ralph W. Kiefer Jonathan W. Chipman (2016) Remote sensing and Image *Interpretation. University of Wisconsin-Madison 6th Edition. Book printed and bound by R. R. Donnelley-Crawfordsville.*

University Corporation for Atmospheric Research (UCAR). (2010). Flash Flood Early Warning System Reference Guide, United States of America. *http://www.meted.ucar.edu/hazwarnsys/ffewsrg/FF_EWS.frontmatter.pdf.*

USGS. (n.d.). Mapping, Report Sensing and Geospatial Data.

Walker, W.D., Magdalena, S., Masakazu, T., (2018). Benefits and negative impact of citizen science applications to water as experienced by communities.

Wanjala, J. M. (2016). Determinants of Maize Yields among Small Scale Farmers in Trans Nzoia West Sub County. Tran Nzoia, Kenya.

Wanjala, R. W. (2012). Impact of Human Population on Land degradation in Former Lugari District Kakamega County. Kenya.

Wu, Z., Liu, M., & Davis, J. (2005). Land Consolidation and Productivity in Chinese Household Crop Production. 16, 28-49.

Young, O. (2019) Impact of LULCC on Forested Land in Yongping valley.

Xiang, T. Zhang, J. Yasucun, J. Chen, H. When, L., (2018). Potential Bands of Sentinel-2A Satellite for Classification Problems in Precision Agriculture. International *Journal of Automation and Computing.*

Xiaoning, G., Lars, G. M., & Sachiko, T. (2009). FAO.

APENDICES

APPENDIX I: INTERVIEW GUIDE

1) Are there any changes in unit per parcel of land owned by households? Yes ( ) No ( )
2) If yes, how is the size of land parcels changing among different households?
3) Have you noticed any change in land use and land cover in your locality?
4) What are the major land use changes that have occurred in your locality?

APPENDIX II: QUESTIONNAIRE

IMPACT OF LAND USE/LAND CHANGE COVER TO MAIZE PRODUCTION

1. How long you been owning the farm?
   10 years and below☐ 11 to 30 years☐ over 30 years☐

2. What type of crops have you been cultivating on your farm?
   I, Maize☐ ii, Blue gum Trees ☐ iii, Others ☐

3. For how long have you been cultivating maize?
   I, 10 years and below☐ ii, 10 to 30 years☐ iii, Over 30 years☐

4. Did you at one point prefer any other crop cultivation other than maize?
   Yes ☐ No ☐

   If yes, why did you prefer other crops?
   More profit ☐
   Maize harvest has reduced ☐
   Need to venture in new crops. ☐

5. Which crop would you prefer to cultivate instate of maize?
   Blue gum Trees, ☐ Sugar cane ☐

6. Have you subdivided your land?
   Yes ☐ No ☐
   If yes, what purpose?
   to family heirs☐ Sold ☐ Family heirs and sold ☐

7. How many acres of land did you cultivate before the decision?

   Under 5 acres ☐ 10 to 20 acres ☐
   5 to 10 acres ☐ More than 20 acres ☐

8. How many acres of land are you currently cultivating?

   Under 5 acres ☐

   5 to 10 ☐

   10 to 20 20 acres and above ☐

9. Have you increased or reduced acreage under maize cultivation?

Increased ☐ Reduced ☐

If reduced, explain

i) subdivided part of the land……………………………………………………

ii) ventured into other crops……………………………………………………

iii) Left the land idle……………………………………………………………

10. If maize prices improve, are you likely to fully resume maize cultivation. Choose one below (Very likely 100% More likely 75% Less likely 50%, 0% Not likely)

Very likely ☐ more likely ☐

less likely ☐ not likely ☐

11. What is the future of maize production in Likuyani Sub County according to your opinion?

Will be overtaken by other crops ☐ Will still dominate after some years ☐

Maize has no future in Likuyani Sub County ☐ Have no idea ☐

12. Are you witnessing any land use change in your area?

Yes ☐ No ☐

13. If yes to what cover
Forest ☐ Sugar Cane ☐ Settlement ☐

14. What is the smallest size of land that is sustainable for maize production?

Half acre ☐ One acre ☐ one and half acre ☐

15. Among the elements mentioned, which one causes a major shift in maize production?

Land subdivision ☐ Population increase ☐ Market forces ☐

APPENDIX III:2007 LANDSAT 8 ERROR MATRIX

	A	B	C	D	E	F	G	H
1	**CLASSIFIED**	**FOREST**	**GRASS/SHRUB**	**BARELAND**	**BUILDINGS**	**SWAMP**	**FARMLAND**	**TOTAL REFERENCE POINTS**
2	FOREST	211	24	0	0	0	0	235
3	GRASS/SHRUB	52	177	0	9	15	26	279
4	BARELAND	3	0	377	71	1	2	454
5	BUILDINGS	3	7	67	193	11	3	284
6	SWAMP	0	19	0	5	66	23	113
7	FARMLAND	7	12	17	3	12	235	286
8	TOTAL CLASSIFIED POINTS	276	239	461	281	105	289	1651
9								
10	Total Correct Referenced Points	1259						
11	Total True Referenced Points	1651						
12								
13	Percentage overral accuracy	76.26%						
14								
15								
16	**USER ACCURACY**		**PRODUCER ACCURACY**					
17								
18	FOREST	89.79	FOREST	76.45				
19	GRASS/SHRUB	63.44	GRASS/SHRUB	74.06				
20	BARELAND	83.04	BARELAND	81.78				
21	BUILDINGS	67.96	BUILDINGS	68.68				
22	SWAMP	58.41	SWAMP	62.86				
23	FARMLAND	82.17	FARMLAND	81.31				

APPENDIX 1V: LIKUYANI AGRICULTURE AND FOOD AUTHORITY YEAR BOOK OF SUGAR STATISTICS 2020

CANE SUPPLY FOR LIKUYANI SUB COUNTY YEAR 2016 TO 2020

	Year 2016			Year 2017			Year 2018			Year 2019			Year 2020			Total		
Sub Loc	No. of Farmers	Ton Supl	Acrea Harvested	No. of Farmers	Ton Supl	Acrea Harvested	No. of Farmers	Ton Supl	Acrea Harvested	No. of Farmers	Ton Supl	Acrea Harvested	No. of Farmers	Ton Supl	Acrea Harvested	No. of Farmers	Ton Supl	Acrea Harvested
Likuyani	0	-	0	0	0	0	1	26.14	2.46	0	0	0	0	0	0	1	26.14	2.46
Sango	57	5,109.72	169.27	59	2670.42	146.54	63	3064.94	185.36	66	1976.87	132.84	34	2550.36	111.57	279	15,372.31	745.58
Mawe Tatu	13	1,127.60	38.71	17	917.38	206.11	21	931.1	59.52	13	404.16	27.07	23	1423.03	51.45	87	4,803.27	382.86
	70	6,237.32	207.98	76.00	3,587.80	352.65	85.00	4,022.18	247.34	79.00	2,381.03	159.91	57.00	3,973.39	163.02	367	20,201.72	1,130.90

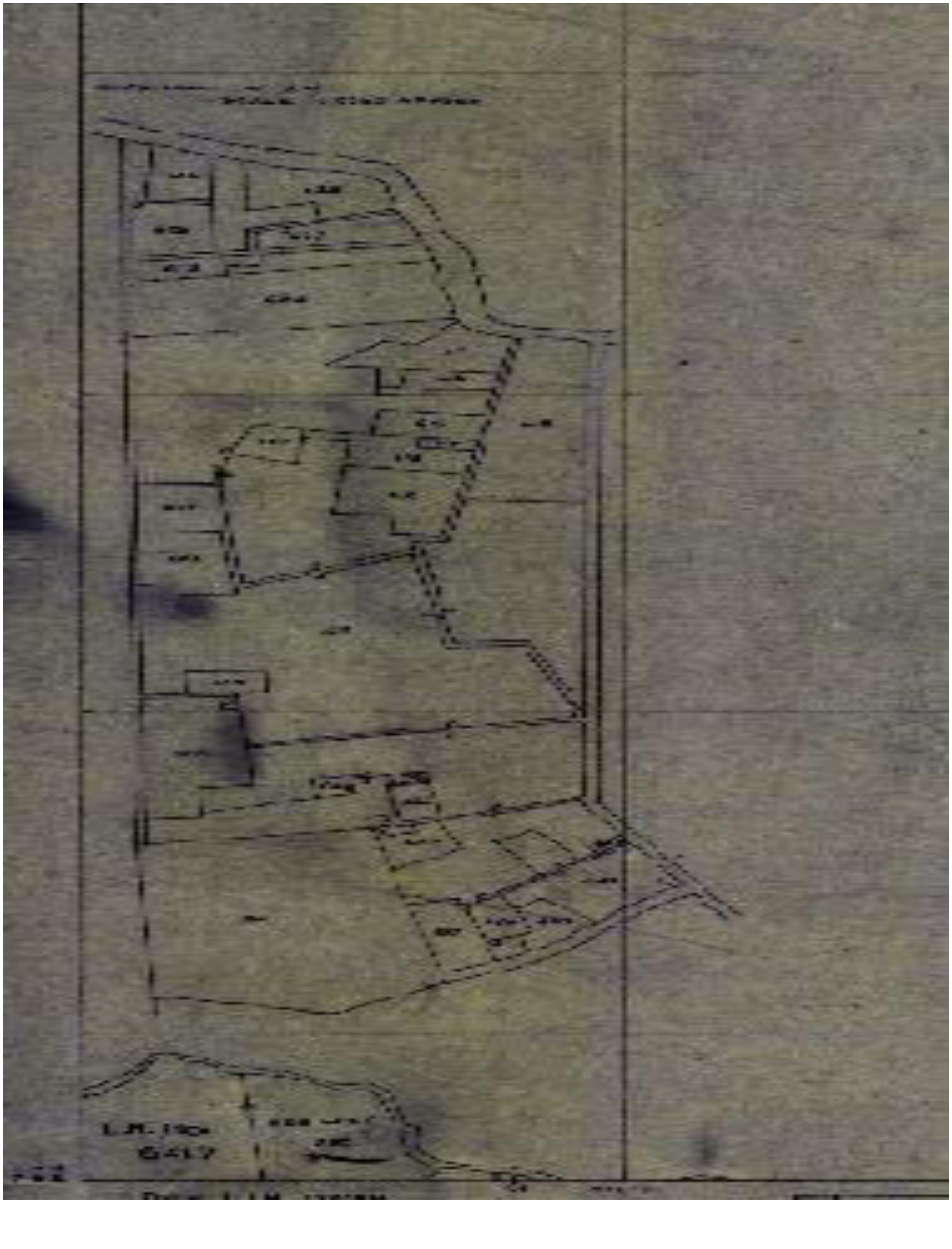
2015 1727 TONS

2016 6444 TONS

2017 5304 TONS

2018 2564 TONS

APPENDIX: V NZOIA RIM SHEET 2



APPENDIX: VI PART OF NZOIA RIM SHEET3

APPENDIX: VII PART OF NZOIA RIM SHEET

APPENDIX: VIII PART OF SANGO SHEET 1

APPENDIX: IX PART OF SANGO SHEET 2

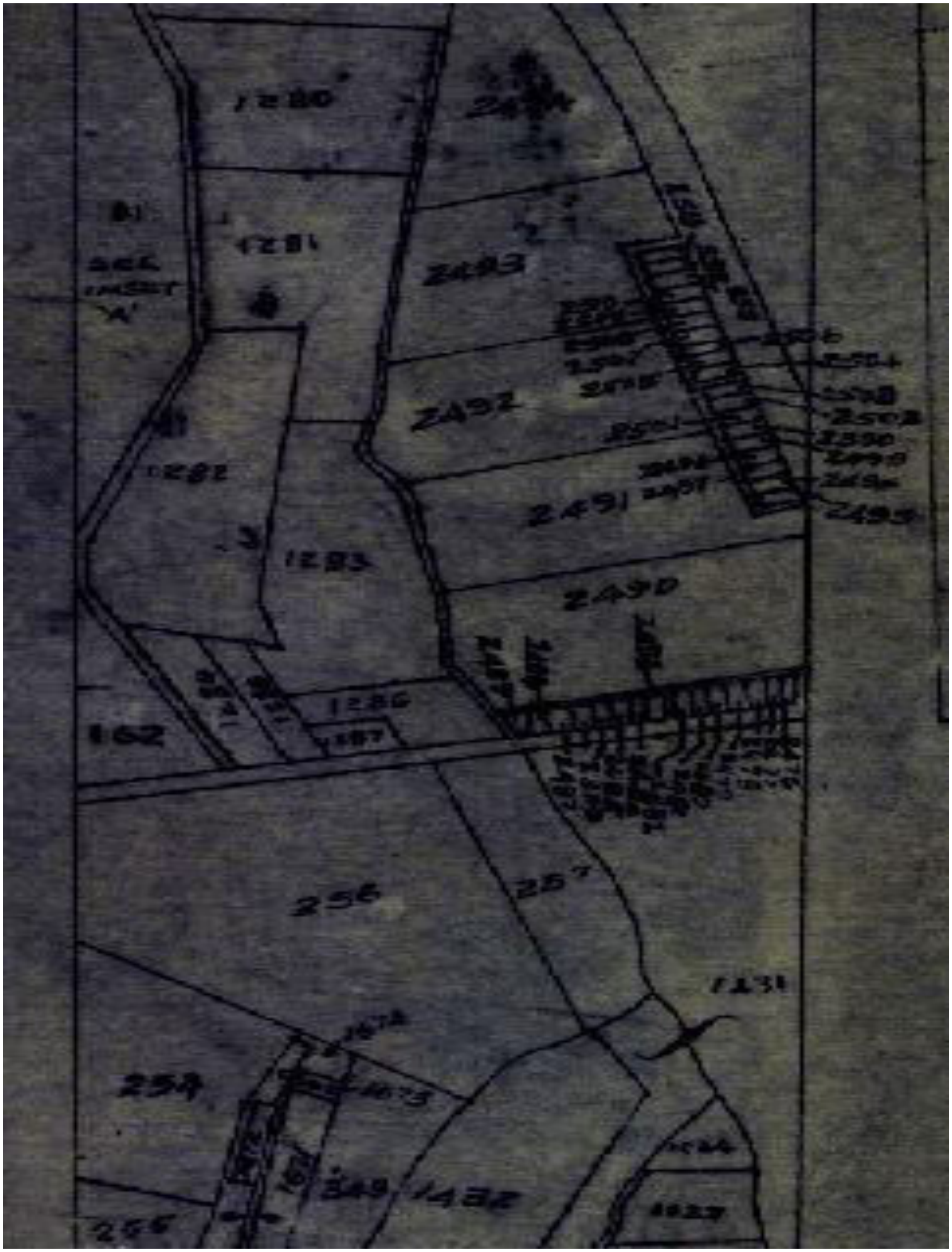
APPENDIX X: PART OF SANGO SHEET 3

APPENDIX XI: PART OF SOY SHEET 1

lots 3-4 Contract No. 70'26 Photography dated September 1966

APPENDIX XII: PART OF SOY SHEET 2

APPENDIX XIII: PART OF SOY SHEET 3

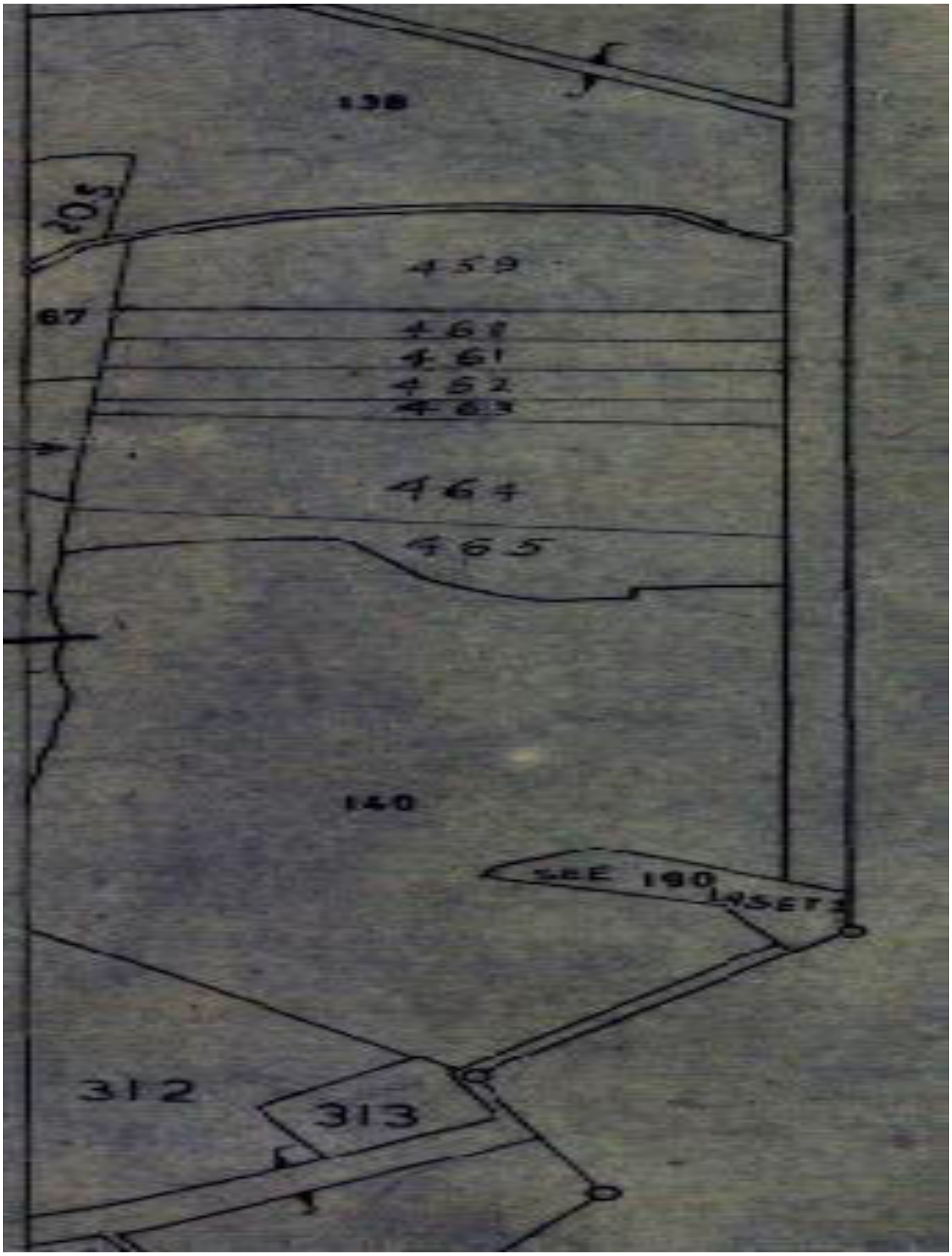


APPENDIX XIV: PART OF SOY SHEET 4

APPENDIX XV: PART OF SERGOIT SHEET 1

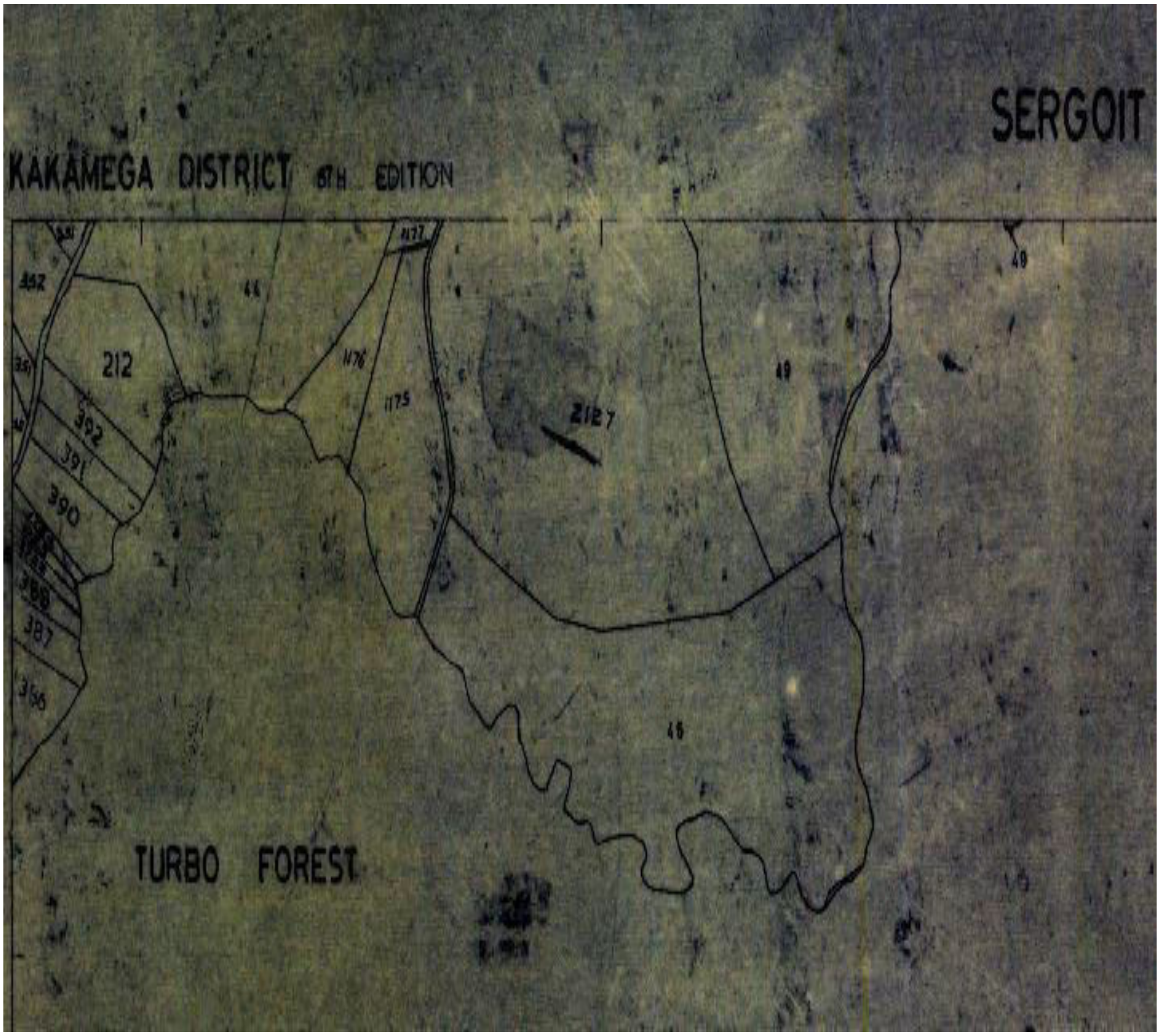
APPENDIX XVI: PART OF SERGOIT SHEET 2

APPENDIX XVII: PART OF SERGOIT SHEET 3

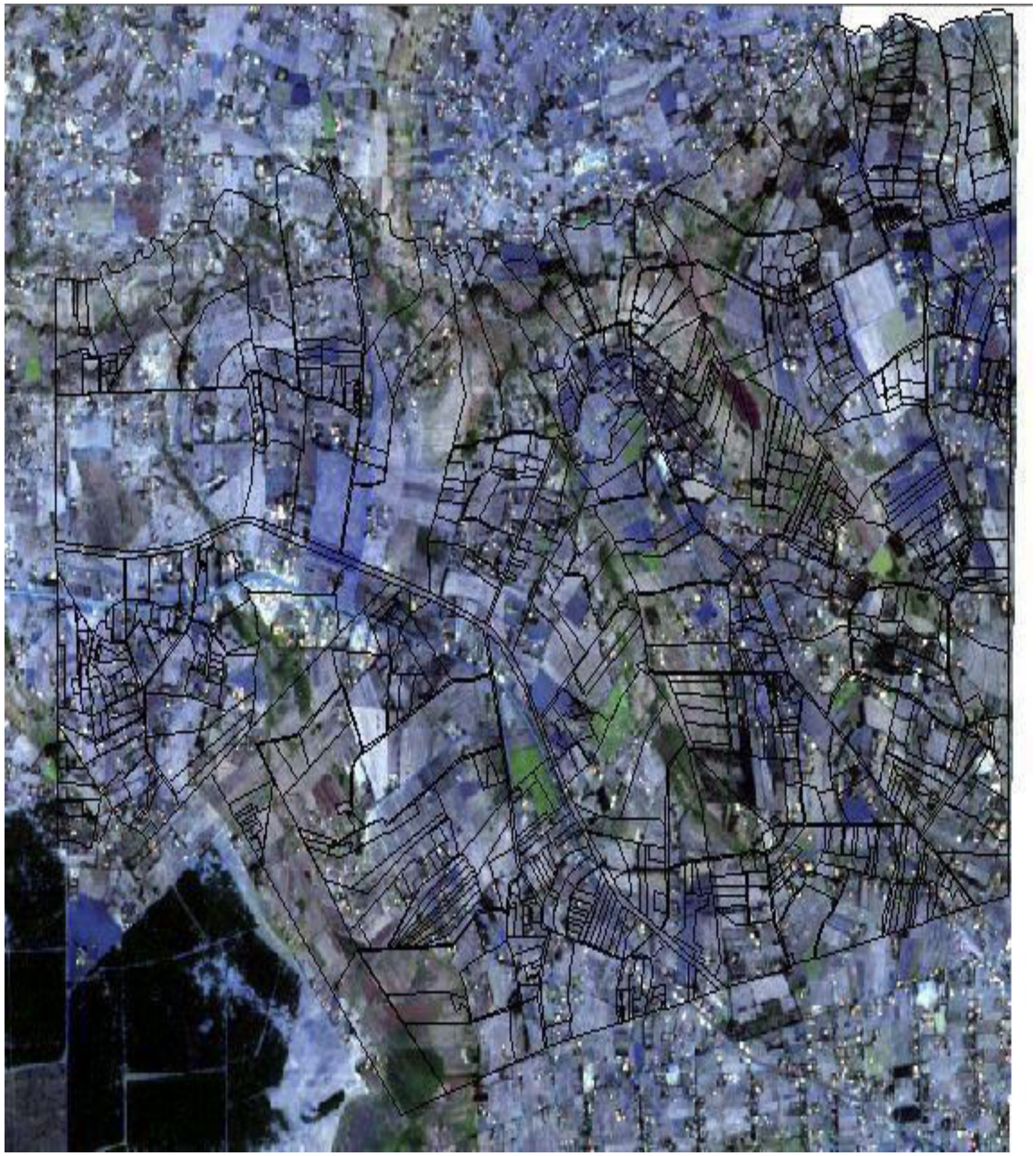


APPENDIX XVIII: PART OF SERGOIT SHEET 4

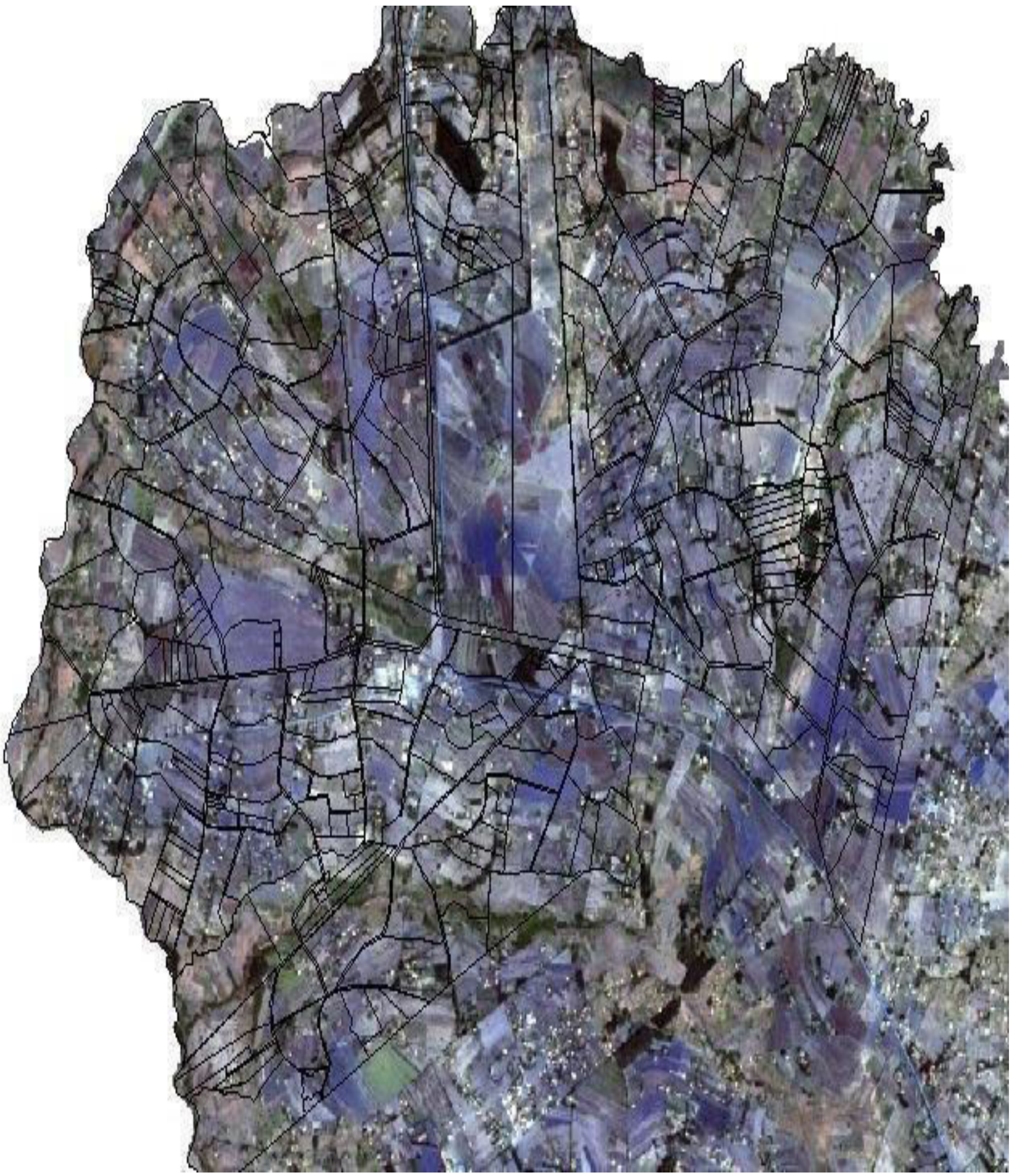
APPENDIX XIX: PART OF SERGOIT SHEET 5



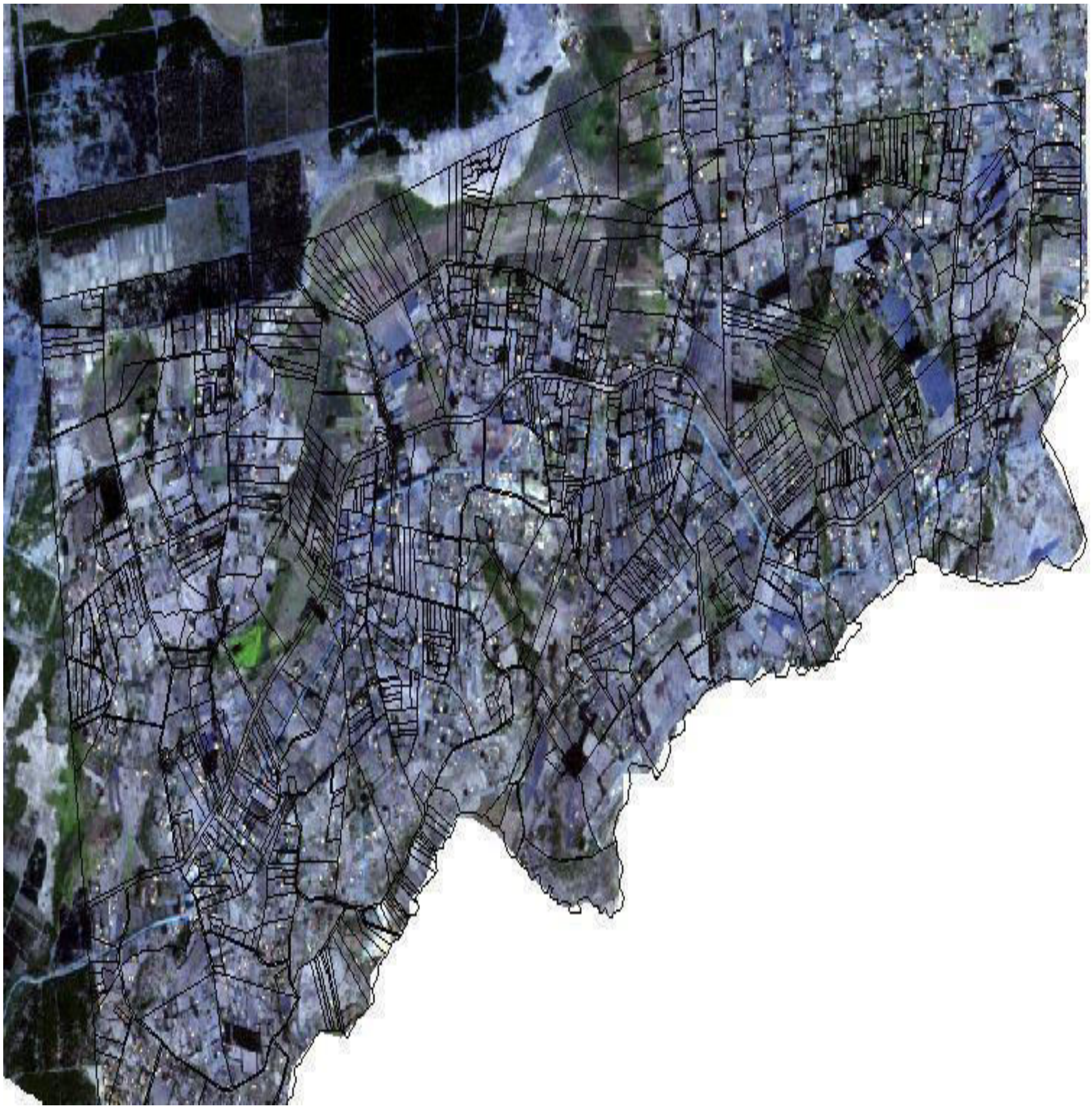
APPENDIX XX: DIGITIZED SOY SETTLEMENT SCHEME



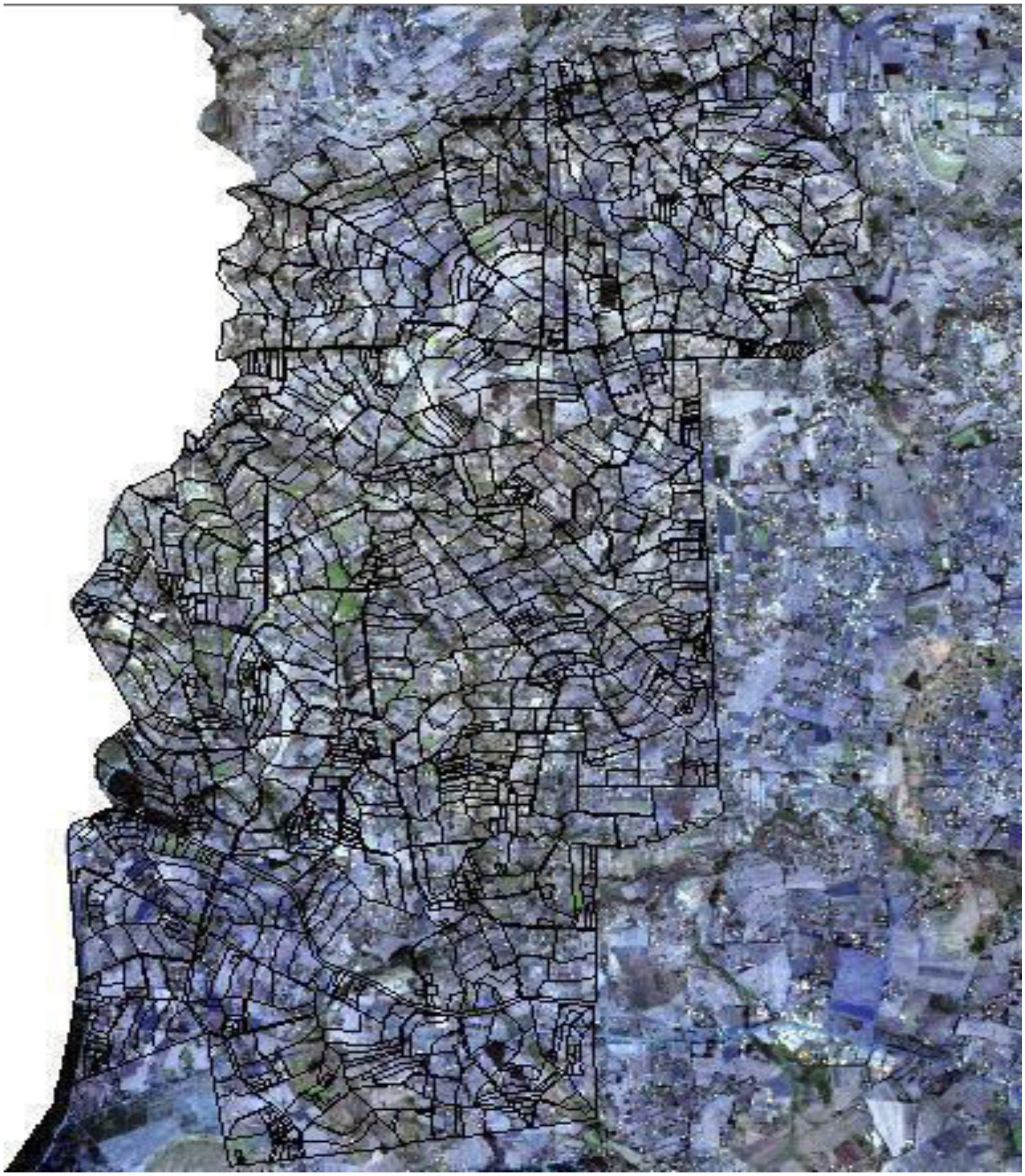
APPENDIX XXI: DIGITIZED NZOIA SETTLEMENT SCHEME



APPENDIX XXII: DIGITIZED SERGOIT SETTLEMENT SCHEME



APPENDIX XXIII: DIGITIZED SANGO SETTLEMENT SCHEME



APPENDIX XXIV: RESEARCH PERMIT

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 422002

Date of Issue: 21/June/2021

RESEARCH LICENSE

This is to Certify that Mr.. Henry Kangwana Shilibwa of Masinde Muliro University of Science and Technology, has been licensed to conduct research in Kakamega on the topic: Impact of Spatiotemporal Land use Land cover Change on Maize Production in Likuyani Sub County Kenya. for the period ending : 21/June/2022.

License No: **NACOSTI/P/21/11211**

422002

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013

The Grant of Research Licenses is Guided by the Science, Technology and Innovation (Research Licensing) Regulations, 2014

CONDITIONS

1. The License is valid for the proposed research, location and specified period
2. The License any rights thereunder are non-transferable
3. The Licensee shall inform the relevant County Director of Education, County Commissioner and County Governor before commencement of the research
4. Excavation, filming and collection of specimens are subject to further necessary clearence from relevant Government Agencies
5. The License does not give authority to tranfer research materials
6. NACOSTI may monitor and evaluate the licensed research project
7. The Licensee shall submit one hard copy and upload a soft copy of their final report (thesis) within one year of completion of the research
8. NACOSTI reserves the right to modify the conditions of the License including cancellation without prior notice

National Commission for Science, Technology and Innovation
off Waiyaki Way, Upper Kabete,
P. O. Box 30623, 00100 Nairobi, KENYA
Land line: 020 4007000, 020 2241349, 020 3310571, 020 8001077
Mobile: 0713 788 787 / 0735 404 245
E-mail: dg@nacosti.go.ke / registry@nacosti.go.ke
Website: www.nacosti.go.ke