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

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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

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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.

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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.

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ABSTRACT

Likuyani Sub -County has ideal climate and high-quality soil for farming, especially maize cultivation—a major crop in Kenya. Likuyani Sub-County has established itself as among the nation's main hub for the production of maize as a staple food crop and maize seed. 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 maize 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 objectives of the study were to: 1, Determine LULCC that occurred in Likuyani Sub County between 1997 and 2017. 2, Evaluate spatiotemporal LULCC affecting different land cover classes in respect to land under maize cultivation in the Likuyani sub-county between 1997 and 2017, and to Explore the determinants influencing LULCC in the maize-producing areas of Likuyani Sub County during the period spanning from 1997 to 2017. Sentinel 2A, Landsat 5, 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 ground points data and ground observations were used. ArcGIS 10.3, and ERDASS IMAGINE were GIS and remote sensing analytical tools that made it possible for manipulation, interpretation and presentation of secondary and primary data. Application of Microsoft Office software (SPSS), Statistical data analysis made it possible to test the hypothesis. Results from GIS showed: 1, There is significant LULCC, 2, SLULCC between different classes in relation to land under maize cultivation is significant. Buildings LC had the highest change. Subdivision, Population increase, market forces and introduction of other crops and plants were the main causes influencing LULCC in Likuyani Sub County between 1997 and 2017 Analysis showed a notable yearly decrease of 0.155% in area used for maize cultivation, in contrast to an annual growth of 0.243% in land occupied by structures. Swamps remained mostly unchanged. Regression analysis statistical techniques revealed the detrimental impact of land alterations on land under maize cultivation. The study recommends 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.

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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
CIDP	County Integrated Development Plan
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
KBS	Kenya Bureau of Statistics
KFS	Kenya Forest Services
KNBS	Kenya National Bureau of Statistics
LULCC	Land use land cover change
MSS	Multi Spectral Scanner
NACOSTI	National Commission of Science, Technology and Innovation
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
SLULCC	Spatiotemporal Land Use Land Change Coverage
SOK	Survey of Kenya
SPCA	Selective Principal Components Analysis
SPSS	**S**tatistical Package for The Social Sciences
SWIR	Short Wave Infra-Red
TM	Thematic Mapper
UTM	Universal Transverse Mercator
VNVIR	Visible and Near Visible Infrared

OPERATIONAL DEFINITION OF TERMS

ArcGIS Architecture, Engineering & Construction Geographic Information System

Bareland Land cover class representing area of ploughed land that is bare of any vegetation.

Buildings Land cover representing areas covered by constructed structures. These includes farm houses, sheds commercial areas and any other structure

Farmland Land cover class representing area of previously cultivated un-ploughed land in image classification

ERDAS Earth Resources Data Analysis system

Forest Land cover class representing areas with a continuous tree cover or thick bush

GPS Global Positioning System

Grass/Shrub Land cover class representing areas covered by grass and also areas consisting of a mixture of scattered bushes.

LCC Land Cover Classes

LUMC Land under Maize Cultivation

Swamp Land cover representing areas consisting of wetlands with surface or subsurface water

WGS-84 World Geodetic System 1984

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Foundation lays groundwork by highlighting spatiotemporal usage of land and changing coverage as a worldwide phenomenon which has a variety of effects on various land cover types. These changes have a huge impact on land under maize cultivation, maize being 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 land under maize farming. 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 in Likuyani Sub County’s land under 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 (2019), 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, 2019).

Land alterations affect ecology, hydrology, agriculture, forestry, and the environment, according to FAO (2021). 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 maize 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, 2020).

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 (2018) 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 yearly, according to research by Onono *et al.* (2018). According to Mwangi et al., (2017), a detailed and up-to-date spatial data on LULCC in Likuyani Sub-County are lacking, hampering accurate analysis and effective response strategies. Existing studies often fail to capture the current extent and dynamics of LULCC. While the environmental impacts of LULCC are documented, there is a scarcity of research on the socioeconomic drivers behind these changes. Factors such as population growth, economic pressures, land subdivision and policy decisions need to be analyzed to develop effective interventions.

Furthermore, Rosegrant's, et al. (2018) research, 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 schemes 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 of usage of land and coverage in Likuyani Sub County 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 Kakamega County Integrated Development Plan (CIDP) of 2018. Subsequently, the Kenyan government repossessed a significant portion of this land for large-scale seed production, the promotion of settlement 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 2020. As observed by Lewis (2018), this shift coincided with a consistent reduction in the land area dedicated to maize cultivation, including in regions like Likuyani sub-county, as documented by ongoing land use changes. Despite efforts to be self-reliant in maize production, the declining trend in land allocated for maize cultivation continues to decline, prompting Kenya to expend substantial foreign exchange on maize imports annually. 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, have contributed to influx of people from far and neighboring counties into the area.

Mwangi et al. (2017) highlighted the challenges of evaluating the impact of land use change on soil erosion in Kenya using remote sensing and GIS due to inadequate spatial data. Existing studies often focus on either biophysical or socioeconomic aspects of LULCC, overlooking the need for integrated approaches. Combining remote sensing, GIS, and field surveys with socioeconomic analyses is crucial for providing a holistic understanding of the drivers and impacts of LULCC on land under maize cultivation. Integrated approaches are essential for developing effective land management strategies that account for both environmental and socioeconomic factors as buttressed by Ndegwa et al. (2019). The current study aims to utilize medium-resolution satellite imagery and advanced remote sensing techniques to provide more accurate and detailed spatial data on LULCC in Likuyani Sub-County, allowing for a comprehensive analysis of its impact on maize cultivation. Reports by Kang'ethe (2019) and (Kiplimo, and Ngeno, 2019) 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. 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, (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 as farmers change their choice of what to cultivate.

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 staple food source, maize output, is impacted by spatiotemporal land use change.

1.3 Research Objectives

The overall objective of this study was to investigate the impact of Spatiotemporal Land Use and Land Cover Change on Land under Maize Cultivation in Likuyani Sub-County, Kakamega County Kenya.

1.4 Specific objectives

The specific objectives of the study were:

i. To determine LULCC that occurred in Likuyani Sub County from 1997 to2017,

ii. To evaluate SLULCC affecting different land cover classes in respect to land under maize cultivation in the Likuyani sub-county from 1997 to 2017,

iii. To assess the determinants influencing LULCC in the maize cultivating areas of Likuyani Sub County from 1997 to 2017

1.5 Hypotheses

The study was guided by the following hypothesis;

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

ii) Spatiotemporal LULCC has no significant effect on different land cover classes in respect to land under maize cultivation in Likuyani Sub County from 1997 to 2017.

iii) There is no significant determinants influencing LULCC on land under maize cultivation in Likuyani Sub County from 1997 to 2017.

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 utilization 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. This study will also significantly contribute to the existing body of knowledge regarding the dynamics of land use and land cover changes and their impacts on agricultural practices, specifically land under maize cultivation and also provide gapes for further research. As maize is a staple crop in Kenya, understanding how changes in land use and cover affect maize cultivation is crucial for developing sustainable agricultural practices and policies.

1.7 Scope of the study

The study covered a period of 20 years, from 1997 to 2017. This extensive time frame allowed for a comprehensive analysis of the dynamics and trends in land use and land cover change, particularly focusing on land under maize cultivation. The period from 1997 to 2017 was selected due to the availability of clear and consistent Landsat and Sentinel 2A satellite images. These satellite images provide high-resolution data that is crucial for accurately monitoring and analyzing land use and land cover changes over time. The availability of these images ensured that the data is reliable and was used to draw valid conclusions.

Focus was with regards to dynamics and causes of spatiotemporal coverage and usage of land under maize cultivation in Likuyani sub-county in Kakamega County Kenya between 1997 and 2017 at five year interval. Due to availability of clear and consistent Landsat and sentinel 2A satellite images were readily available during this period. It was possible to verify the land cover type by Google earth within the study 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 domestic 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 chapter present literature review on the impact of Spatiotemporal Land Use and Land Cover Change on Land under Maize Cultivation in Likuyani Sub-County, Kakamega County Kenya. Specifically, it addresses; changes in land use and cover, Land Change trends, factors influencing spatiotemporal changes in usage of land and coverage, effects of changes in land cover and land use within the study period on areas used for maize cultivation, detection in usage and coverage change of land and conceptual Framework.

2.2 Land use Land cover Change

LULCC, is a variety of changes brought about by humans that take place on Earth's surface. According to (Yetnayet, et,. al. 2017), 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. 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.

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 (Kabube, et al,. 2020). Alterations in usage of land and coverage are intricately connected to 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 (Kabube *et al.*, 2020). 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, Renny, (2018). 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.

The sophisticated process of "land-use changes" involves the transformation of land cover, a process referred to as land conversion (Noe,et al,. 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 (Kiplimo and Ngeno, 2019). 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. 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 and Geist, 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 cultivation. 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). Effective planning of land use and sustainable management practices for ensuring food security necessitates a comprehensive understanding of spatiotemporal impacts on land under maize cultivation (Renny, 2018). Land use change holds substantial influence over agricultural practices.

2.3 Impact of SLULCC on land under maize cultivation

Spatiotemporal land-use land cover changes significantly influences land under maize cultivation. This shift reflects a global trend where human history is marked by intensive exploitation leading to substantial alterations in usage of land and coverage, Kebaso's (2017). 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. 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. (Krah, K., 2023).

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, (Maitima *et al.*, 2019). 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.

Different types of land use and land cover changes (LULCC) are influenced by the complex interactions between environmental, economic, and sociocultural factors Lambin and Geist, 2019). 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).

2.4: Spatiotemporal LULCC affecting different land cover classes

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 (Dedehouanou, I. (2024). 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-Kitale 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 Lambin and Geist, (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, Lambin and Geist, (2019). 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. 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*,. (2019) 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 (DeMeo *et al.*, 2016). 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 and Geist. (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.

2.5: Causes of LULCC

2.5.1 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 and Giliba, 2017; Norrington & Thornton, 2017). Furthermore, the situation in underdeveloped countries is made worse by the lack of awareness about these changes and the appropriate mitigation and adaptation efforts. As per African Agricultural Status Report (AGRA, 2019), global temperatures are experiencing an upward trend, with a 0.58 degree Celsius increase by 2025.

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 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. Some results of drought are Crop fields damage and livestock loss, with dire consequences including starvation. Rosegrant (2018) 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.

2.5.2 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 land under maize cultivation, 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 land purchase and settlement by people from outside the Sub County who are attracted by fertile land, Wanyama (2017). 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 Barru (2018). 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 believe in owning land as a way of normal life. Large property holdings in Likuyani Sub-County, spanning from 15 to 100 acres, have drawn people 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. 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, 2016). 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 Allen and Burns (2019) in developing countries and Kioko and Okello (2022) within the Amboseli ecosystem link rural population growth to changes in land use.

This trend aligns with findings by Mbau, et al., (2018) 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, (2022). Baaru (2018) and Mbau, et al., (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 as a result of population increase in the area (Ayuyo and Sweta, 2016).

This shift in land use in Sub Saharan Africa was a response to the growing population's food demands, resulting in increased food production (Pellikka *et al.*, 2019). As reported by FAO (2021), 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, 2021).

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, lseading to a decline in land under maize cultivation, (GoK, 2020). 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 and Geist, (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.*, 2019). Effective natural resource management methods and the favorable acceptance of management practices depend on the integration of human perception on these interventions.

2.5.3 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 Wanyama (2017). 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 cultivation 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 Wanyama (2017). 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, Allen and Barnes (2019). 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 Niroula (2016). Studies conducted elsewhere have also highlighted the impact of agricultural expansion on forestland.

2.5.4 Market values and business opportunities

A variety of social-economic factors influence several dynamic land use patterns, which alter biodiversity (Maina, 2018). The 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, (Maina, 2018).

Crops with high potential earnings will be grown by farmers. Establishment of sugarcane processing plants in Kakamega County (West Kenya Sugar, Butali Sugar and Naitiri Sugar Factories) could potentially endanger maize cultivation land. Compared to maize, sugar cane is a more profitable cash crop for farmers per acre. Maize market price swings more frequently and is impacted by imports and a bumper harvest, the sugarcane market is far more consistent and predictable Kathumo (2017). Given the circumstances, more farmers would probably choose to plant sugar cane because the crop yields more sugar than maize does.

2.6 Detecting spatiotemporal land use land cover changes

Technique in detecting variations status of land cover by monitoring same area of land at various temporal 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. Some of these methods are: Image classification, Image differencing, Normalized difference vegetation index (NDVI). 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 is referred to as remote sensing. This is accomplished by detecting, logging, and processing electromagnetic energy that is reflected or transmitted, then using the data for analysis and application (Fors, 2017).

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, (Ahadov, 2023).

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, 2018). G.I.S improves combination of data of various sorts and from many sources.

This study employed 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 represents Landsat 4, 5, and 7 bands, their wavelength and areas used for land mapping.

Table 2.1: Landsat 4, 5 and 7 bands, wavelength and application areas

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 represents Landsat 8 bands, wavelength of the band and in areas where particular bands area applied.

Table 2.2: Landsat 8 sensors indicating bands, wavelength and application

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 represent Sentinel 2A band, their central wavelength, resolution and band description.

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)

2.6.1: Image Classification

The goal of change detection techniques is to pinpoint changes in LULCC 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). Image classification was 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 and Geist, 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, et al, 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 and Geist, 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, and Geist, 2017).

Maximum likelihood classification algorithm chosen due its widespread use and suitability for land use mapping, as supported by various research studies (Aykut and Necdet, 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.

2.6.2: 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).

2.7 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, (Aykut and Necdet, 2019). 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 (Kathumo, 2017). These components form the core structure of the study's framework, outlining the interdependence and influence of various factors on land use transformations.

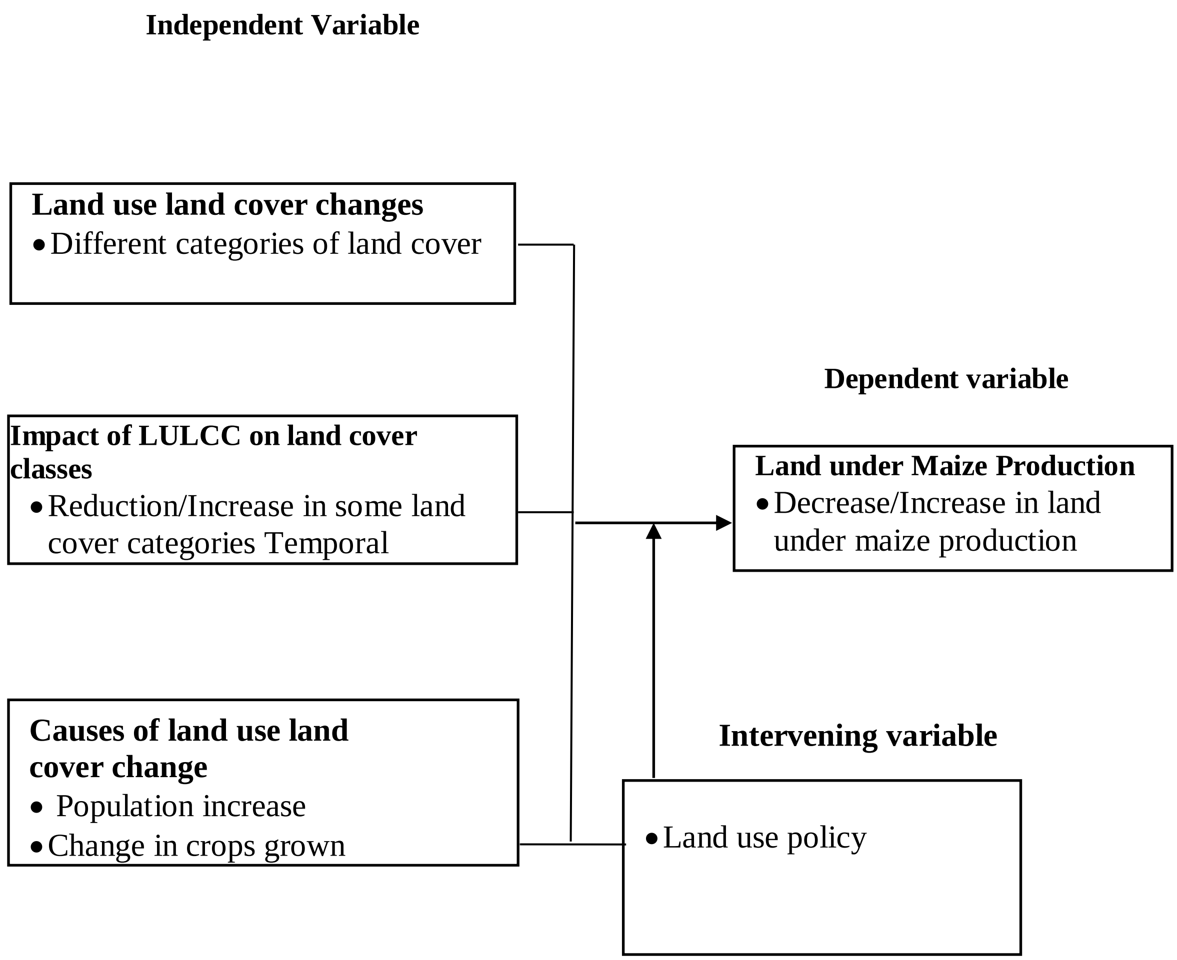

Figure 2.1: Conceptual Framework

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 study on the impact of spatiotemporal land use and land cover change on land under maize cultivation is focused on Likuyani Sub-County in Kakamega County, Kenya. This area is approximately situated at a latitude of 0.6167 degrees North and a longitude of 34.9500 degrees East, with its geographical boundaries roughly extending from 0.7000 degrees North, 34.8500 degrees East in the northwest to 0.5333 degrees North, 35.0500 degrees East in the southeast.

The research domain The Likuyani sub-county, one of Kakamega County's Sub Counties spans around 309 square kilometers. Situated between 1300 and 1800 meters above sea level is the Sub-County. Introduction of County units in 2013 saw the creation of the sub county from the former Lugari constituency. 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. Land in Likuyani sub-county was subdivided according to schemes ranging from 15 acres to 100 acres. It is divided into five wards: Likuyani, Kongoni, Sango, Nzoia, and Siniko. It is located in the far north Estern of Kakamega County, bordering Tongaren sub County of Trans Nzoia County to the North, Kiminini Sub County of Trans Nzoia County to the north, Soy and Turbo sub counties of Uasin Gishu County to the east and South, and Lugari Sub County to the West. The Northern and Western sub counties are separated from one another by the River Nzoia, whereas Eldoret-Kitale and Eldoret-Turbo highways almost form the boundary with the Eastern and southern sub counties. Likuyani Sub-County was chosen for this study due to its significant agricultural potential and reliance on maize cultivation, a critical staple and cash crop in the region. The area's agricultural practices and land use patterns provide a compelling case for examining the impacts of spatiotemporal land use and land cover changes. Given the region's dependence on rain-fed agriculture and the presence of both commercial and subsistence farming, understanding the dynamics of land use change is crucial for informing sustainable agricultural practices and policy-making (Aykut and Necdet, 2019).

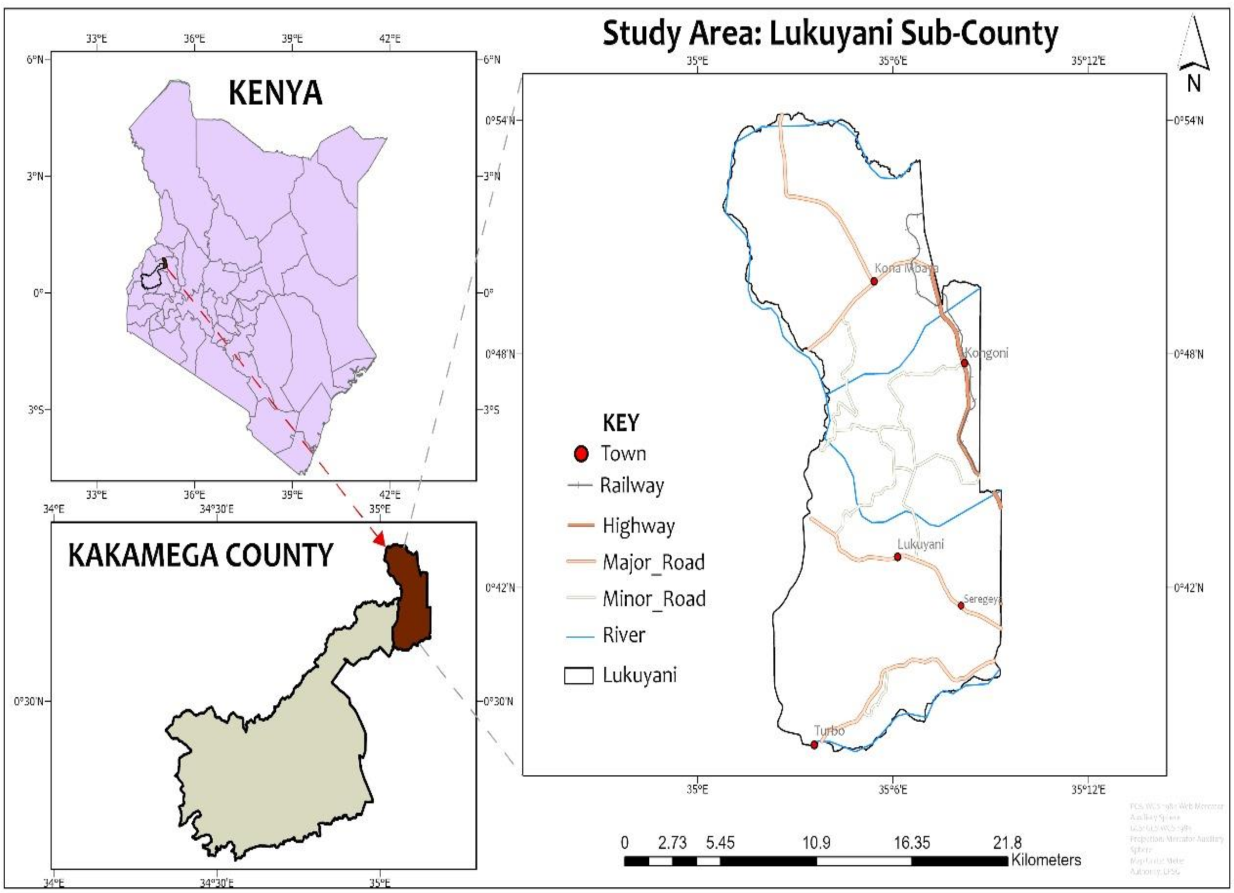

Figure 3.1: Map of the study area

Source: Topographic maps from SOK

Figure 3.1 represents map of the study area.

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 and Nzoia Forests.

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 (KFS). 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, (Udry, 2019). 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)

Table 3.1: Represents comparison in potential for agricultural production among the Sub counties in Kakamega County.

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, (Lucas, 2020). The land sizes at inception of the schemes in 1963 were allocated as in Table 3.2. Table 3.2 represents the settlements schemes of Likuyani sub county, number of land parcels and their sizes in acres,

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 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, 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.

3.3 Data Collection tools and sources

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. Factors 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 season to avoid seasonal and phonological differences.

iii) Differences in vegetation greenness.

Table 3.3 represents 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 5, 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: Researcher (2021)

3.4 Data preprocessing

The process involved converting the hard copies of Topographic maps and RIMs into suitable data formats through scanning. Afterward, these datasets underwent geo-referencing using ArcGIS 10.3, 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 software through linear equalizing stretch techniques.

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

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 cultivation as indicated on figure 3.2.

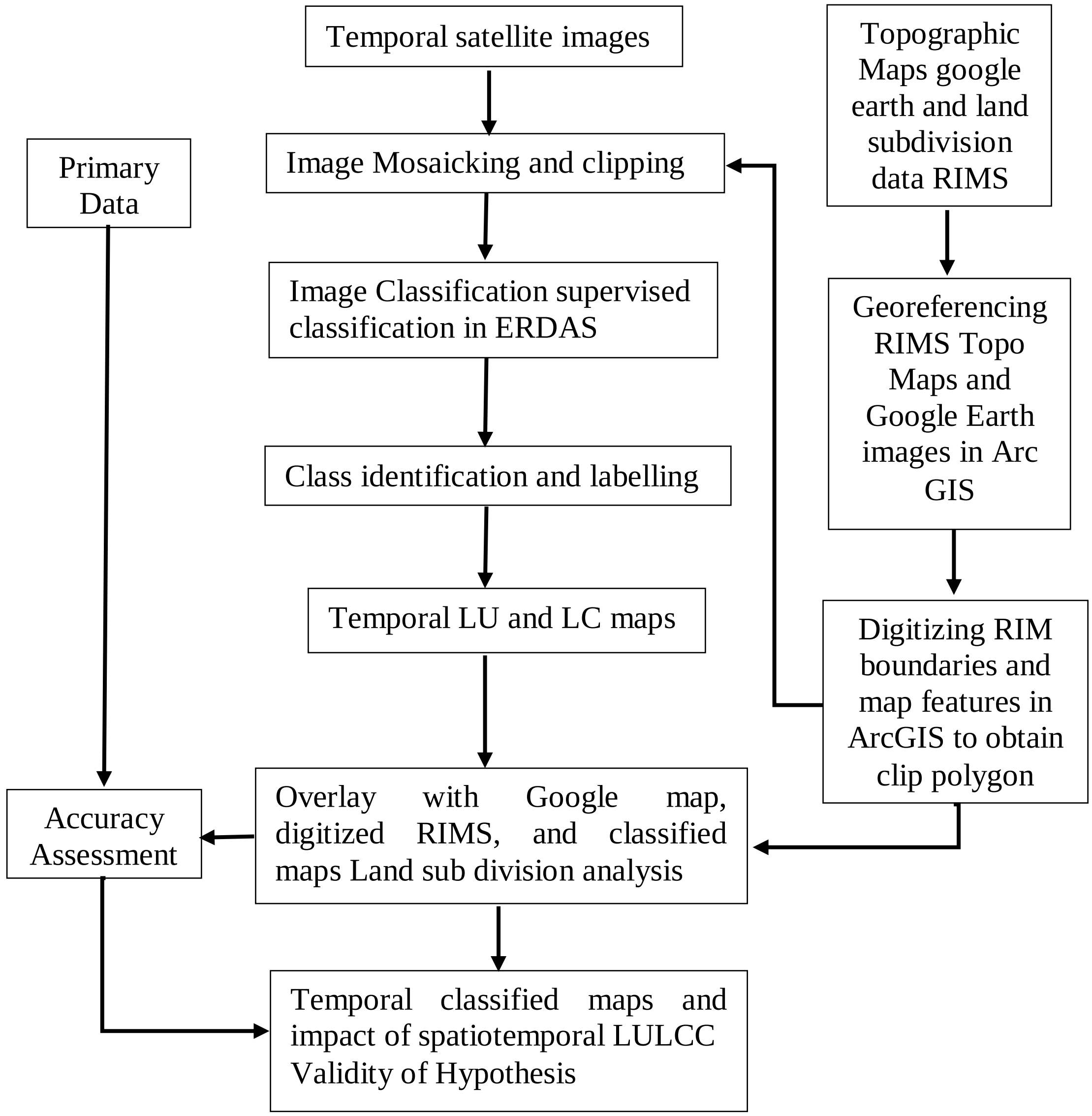

Figure 3.2: Flow diagram for data processing

Source: Researcher, 2021

Figure 3.2 outlines steps taken by the researcher to process the data in ArcGIS, SPSS and ERDAS IMAGINE software to achieve the desired results.

3.5 Research Design

De Vaus (2018) 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, 2019). In essence, it is the systematic execution of a research technique within a study, facilitating assessment by readers and encouraging replication (Sandra, 2020). 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, 2018). The research employed a descriptive, longitudinal survey and correlation methodology, utilizing both primary and secondary data sources to comprehensively analyze spatiotemporal land use and land cover changes in Likuyani Sub-County. Primary data included field observations to directly ascertain ground cover types, GPS field verification surveys to confirm image classification accuracy, and questionnaires administered to local respondents to gather qualitative insights on land use practices and socio-economic factors influencing agriculture.

Secondary data comprised the Agriculture and Food Authority Year Book of Sugar Statistics 2020 for agricultural data, Land Adjudications Office Records for historical land ownership information, topographic and registry index maps for geographical and administrative details, satellite images for remote sensing analysis, and population data from the Kakamega County Bureau of Statistics to understand demographic impacts on land use. This mixed-method approach ensured a holistic understanding of land use dynamics, integrating accurate, up-to-date observations with historical and demographic data to support sustainable agricultural practices and policy-making in the region (Sandra, 2020). 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 represents a summary of details adopted in the research. It highlights objective, measurable indicator, research design adopted for the particular objective and expected output.

Table 3.4: Summary research design and expected output as per each objectives

Objective	Approach	Measurable Indicator	Research Design	Output
i)To Determine LULCC that occurred in Likuyani Sub County from 1997 to 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 from 1997 to 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 assess the determinants influencing LULCC in the maize cultivation areas of Likuyani Sub County 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.

Source: Researcher, 2021

3.6 Target population

The study targets 1,123 respondents who have direct control over land ownership in the original land subdivision parcels within these settlement schemes of Sango, Sergoit, Soy, and Nzoia. This focus ensures that the research captures perspectives and insights from individuals who are directly impacted by land tenure policies and practices (Okoth, 2018). Moreover, by concentrating on settlement schemes where land parcel owners are included, the study not only enhances community participation but also facilitates a deeper understanding of local dynamics and stakeholder perspectives regarding land governance (Khan, 2020). The target population for the study is provided in Table 3.5

Table 3.5: Study target population

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

Source: Land adjudication Kakamega office (2021)

Table 3.5 represents the selected settlement schemes and number of land parcels that guided in selecting number of respondents. These number of land parcels were considered as households.

3.7 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. For this reason, purposive sampling technique was adopted. For land cover analysis, the whole of Likuyani Sub county was considered for comparison with the changes within the settlement schemes since image data was available.

3.7.1 Sampling techniques

The selection of respondents based on households (Table 3.5) 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 labeling 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.

3.7.2 Sample size

The number of land parcels allotted to farmers at the start of the settlement schemes, from the Survey of Kenya land settlement scheme data, was used to compute the sample size. Each land parcel represents one respondent. 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;

$$s = \frac{x^2 \mathrm{Np}(1-\mathrm{p})}{p^2(\mathrm{N}-1) + x^2 p(1-p)} \qquad (1)$$

Where:

S is the desired sample size

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 (2019), 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) which is 25.5% of the target population. To get sample distribution for each settlement scheme, the same formula was applied (n) being the number of land parcels representing households. For Sango, n = 540 and applying the formula, the sample size is 225 respondents. Same was applied to the rest of the settlement schemes giving the results in Table 3.6.

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: Researcher (2021)

Table 3.6 represents selected settlement schemes, sample size per settlement scheme and area of each settlement scheme. The distribution of the target population across Sango, Sergoit, Soy, and Nzoia settlement schemes in Likuyani sub-county, Kakamega County, totaling 1,123 respondents, was determined using the Krejcie and Morgan (2015) formula. This formula is designed to ensure a representative sample size from each subgroup based on their relative proportions within the overall population. Initially, the total target population for each settlement scheme Sango (540), Sergoit (190), Soy (156), and Nzoia (237) was identified. Applying the formula involved calculating a proportionate sample size for each subgroup to ensure statistical validity and representation. As a result, a specific number of respondents were selected from each scheme 225 from Sango, 13 from Sergoit, 7 from Soy, and 41 from Nzoia—culminating in a total sample of 286 respondents. This systematic approach using the Krejcie and Morgan formula guarantees that the study captures diverse perspectives on land ownership and management across different settlement schemes in Likuyani sub-county, enhancing the reliability and relevance of the research findings (Krejcie & Morgan, 2015).

3.8 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 Thermatic Mapper for 1997, Landsat 7 Enhanced Thermatic Mapper Plus for 2002, 2007 and 2012 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 RCMRM and USGS Portal USGS Glo-Vis (https://glovis.usgs.gov/) websites. 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 for providing information on the average acreage of sugarcane 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 for data processing and presentation.

3.8.1 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, 2019). The researcher examined the land ownership papers to ascertain the effects of property subdivision on the area in Likuyani Sub County, Kakamega, Kenya, that is used for maize cultivation.

3.8.2 Clipping Study Area Boundaries

The base map and the study area's borders were provided by the topographic maps. The data was first saved in an ArcMap geodatabase. The two hard copies of the Topographic maps were scanned, and the soft copies were archived in the geo-database from which the boundary map of the study area was digitized and produced. After being imported into ArcMap, the soft copies underwent geo-referencing. Geo-referencing is the process of bring the data to the same geographic location. It was achieved by manipulating the coordinates at the Topographic map corners in Arc-map. After geo-referencing, 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 represents the geo-referenced Topographic map of Soy before mosaicking.

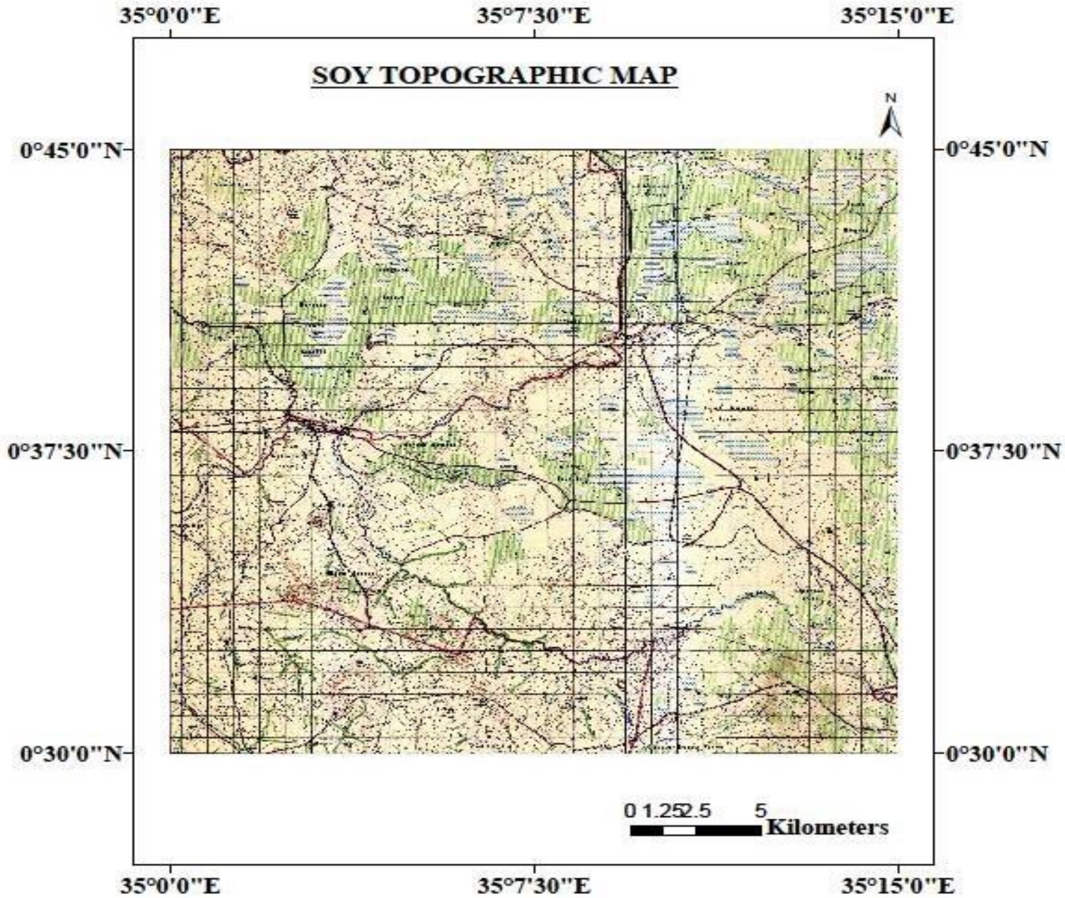

Figure 3.3: Topographic map of Soi before mosaicking.

Source: Survey of Kenya Kakamega office

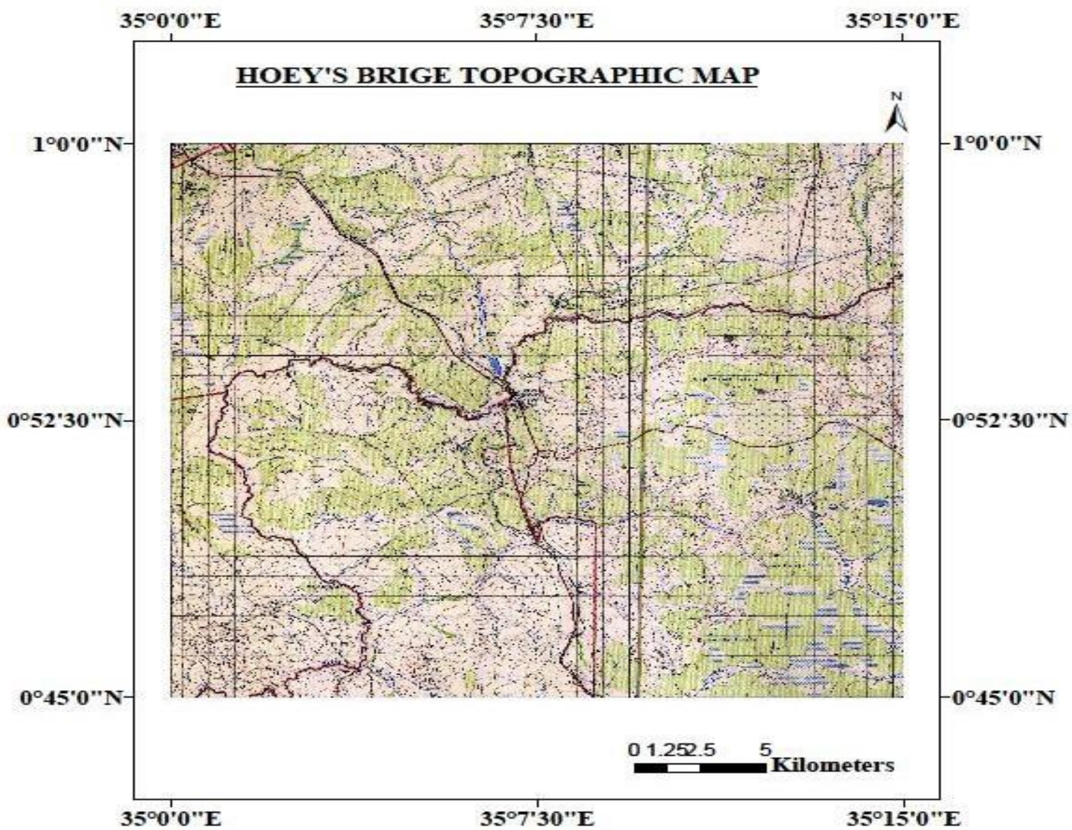

Figure 3.4: HOI'S BRIDGE 89-1 Topographic map before geo-referencing and mosaicking
Source: Survey of Kenya Kakamega office

Figure 3.4 represents the map geo-referenced Topographic map of Hoi's Bridge before mosaicking. The Topographic maps four corner coordinates were used to accomplish geo-referencing. The illustration in Figure 3.5 shows this. The digital version of the Likuyani Sub County shape-file feature class was created using geo-referenced 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 images, leaving only the study region to deal with.

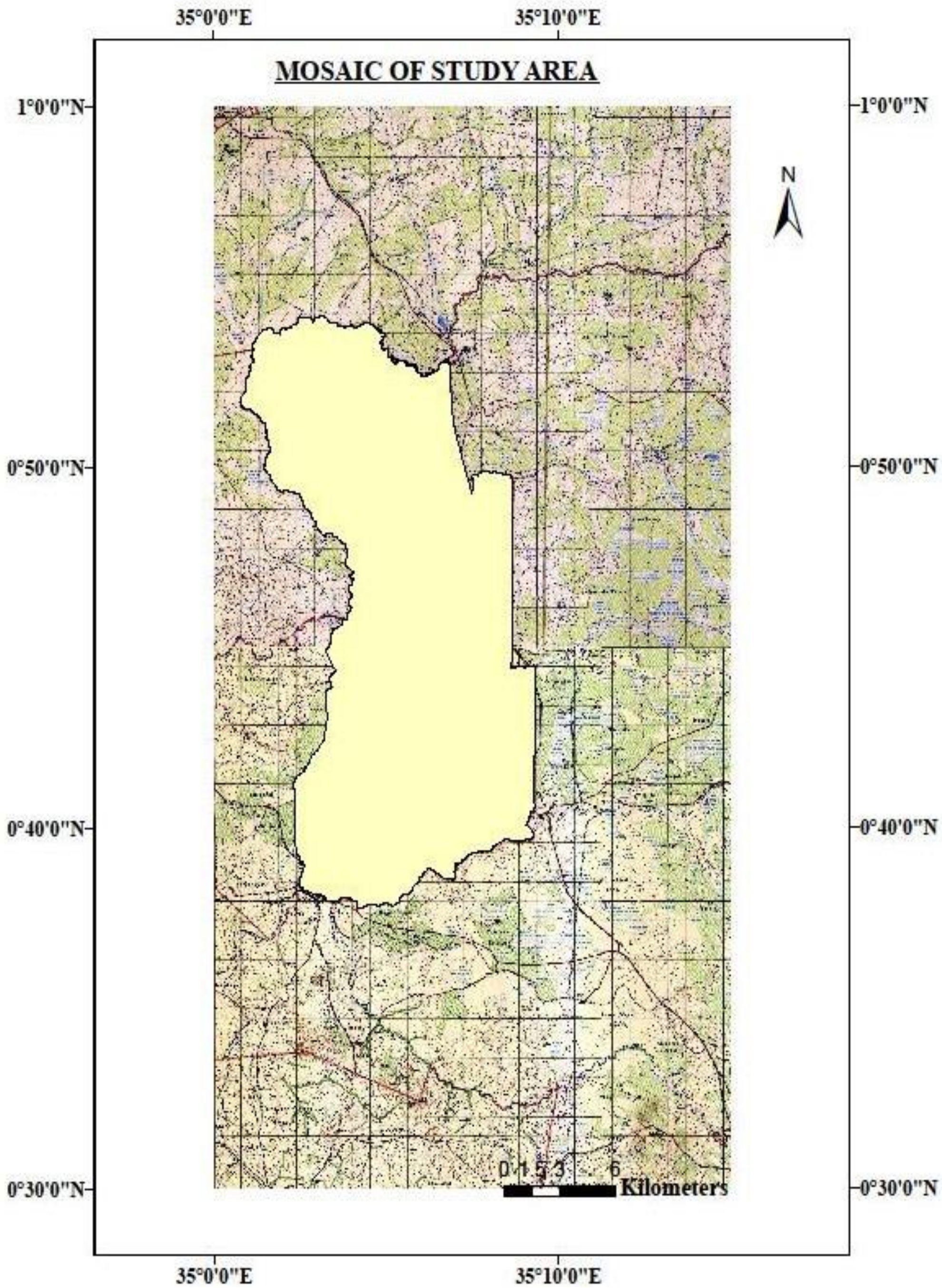

Figure 3.5: Mosaicked geo-referenced Topographic maps with Likuyani Sub County shape-file

Source: Survey of Kenya Kakamega office:

Figure 3.5 represents a mosaic of two topographic maps of Soy and Hoi's Bridge with a digitized map of the study area. This served as a base map from which the study area shape-file was extracted from through clipping process.

3.8.3 Interview Schedule

The researcher conducted interviews with local assistant area chiefs to obtain information on locating respondents who had lived in the study area for the relevant period, forest officials on forest cover change, and Ministry of Land officials on viable land area sizes for maize production. 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 (2019), 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.

3.8.4 Secondary Data Employed

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 5, Landsat 7 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) Sugar cane production data

3.8.5 Software

The data processing involved the use of several software tools, including ArcGIS 10.3, 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 10.3 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 geo-referenced 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 5	30m	1997	TM
Landsat 7	30m	2002	ETM+
Landsat 7	30m	2007	ETM+
Landsat 7	30m	2012	ETM+
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		

Source: Researcher (2021)

3.8.6 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 and

Sentinel2A were 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 not charged any fee to acquire.

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

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

ii) 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 5 (1997 Landsat TM imagery), Landsat 7, (2007 and 2012 Landsat ETM+ imagery and Sentinel 2A (2017) selected for this study. These images were between the months of late December and early March the same dry season in the study area. This is a dry spell season where it was possible to detect ploughed land as bareland and the unploughed land as farmland. These combined categories form the land under maize cultivation in Likuyani Sub County.

Table 3.8: Satellite image bands used in LULC detection

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

Source: Landsat 5, 7 and Sentinel 2A images.

Table 3.8 represents satellite sensor, date the image was acquired, the bands compiled for each image and its spatial resolution.

3.8.7 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.

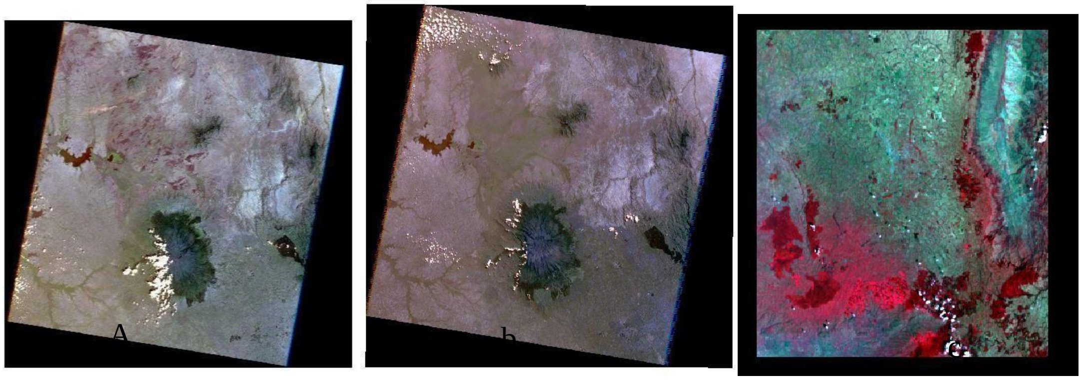

Figure 3.6: Composite 1997 Landsat 5. Composite 2007 Landsat 7 and Composite 2017 Sentinel 2A unages

Source; RCMRM and USGS Portal USGS Glo-Vis (https://glovis.usgs.gov/) website

Figure 3.6: Represents the composite images of Landsat 5, Landsat 7 and Sentinel 2A as they appear in EARDASS IMAGINE software after band compositing. From these images, the study area was clipped for analysis.

3.8.8 Layer Stacking and Compositing

The acquired photos had already undergone geo-referencing and radiometric error corrections. 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 required for the study. A composite image was created by layer stacking Landsat 5 Thematic Mapper (TM) bands 1, 2, 3, 4, and 5 for the year 1997. The same method was used using Landsat 7 Enhanced Thematic Mapper plus (ETM+) 8, Landsat Operational Land Imager (OLI), and Thermatic 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.

3.8.9 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 shape-file was used to clip the area of interest from all the composited pictures. The cropped photos that depict the research region are represented by Figure 3.7.

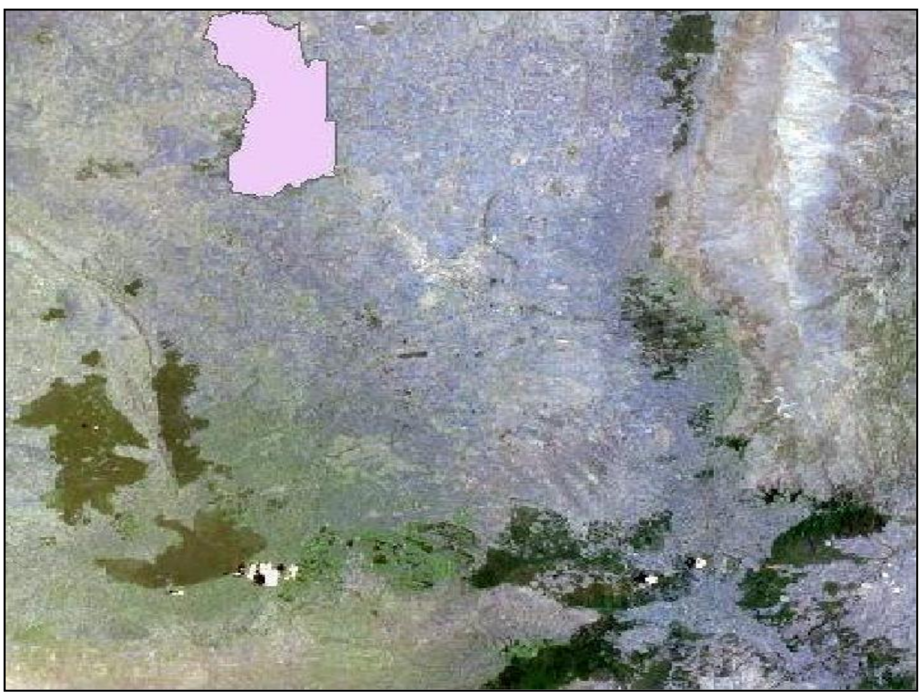

Figure 3.7: Study area overlaid on 2017 Sentinel 2A Image before clipping
Source: USGS Portal Glo-Vis (https://glovis.usgs.gov/) websites

Figure 3.7: Represents a composite image from 2017 Sentinel 2A with an overlay of the study area. The study area was clipped with the resulting images of the study area

represented by figures 3.8 and 3.9

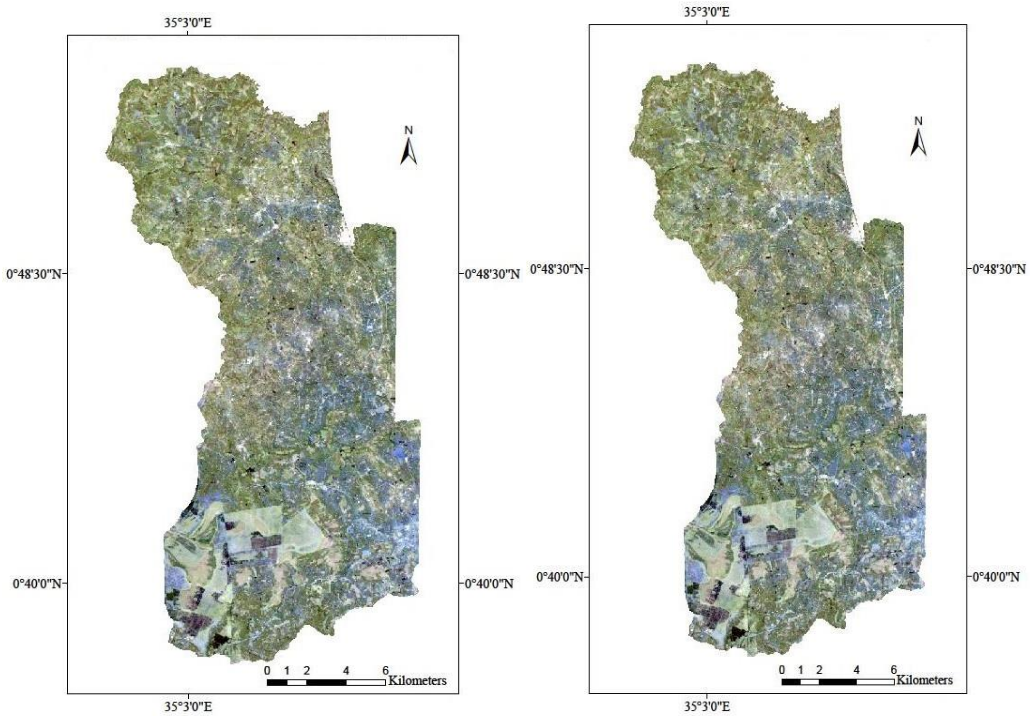

Figure 3.8: Clipped 1997 and 2002 Likuyani images

Source: Landsat 5 Likuyani image

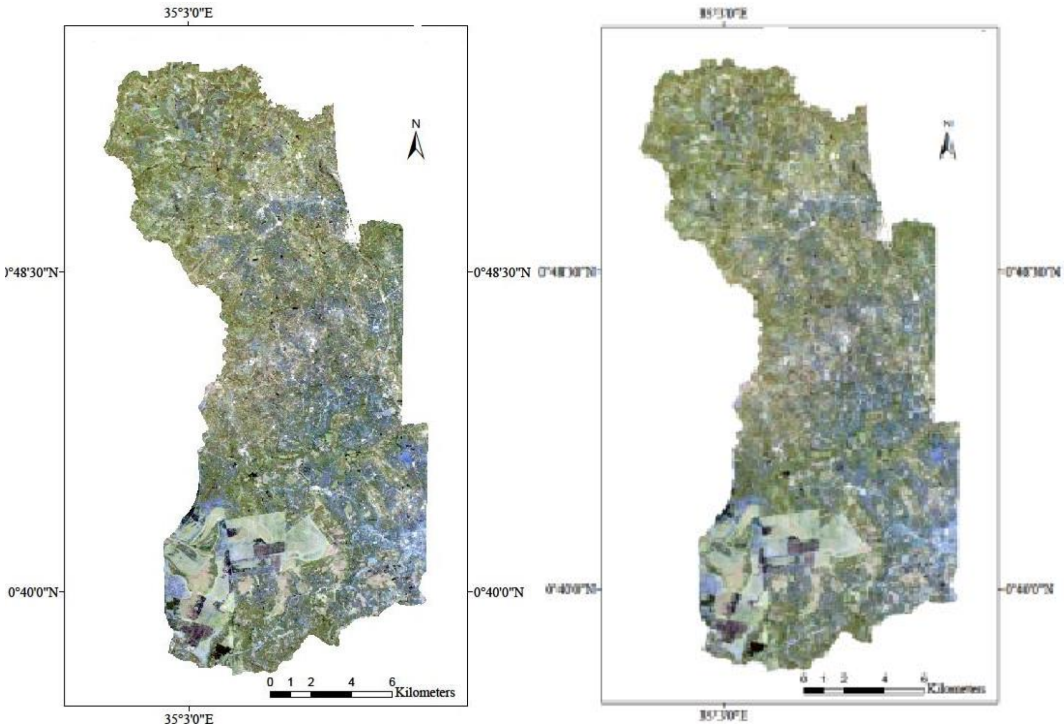

Figure 3.9: Clipped 2007 and 2012 Likuyani Landsat 7 Images

Source Landsat 7 Likuyani 2007 and 2012 Images

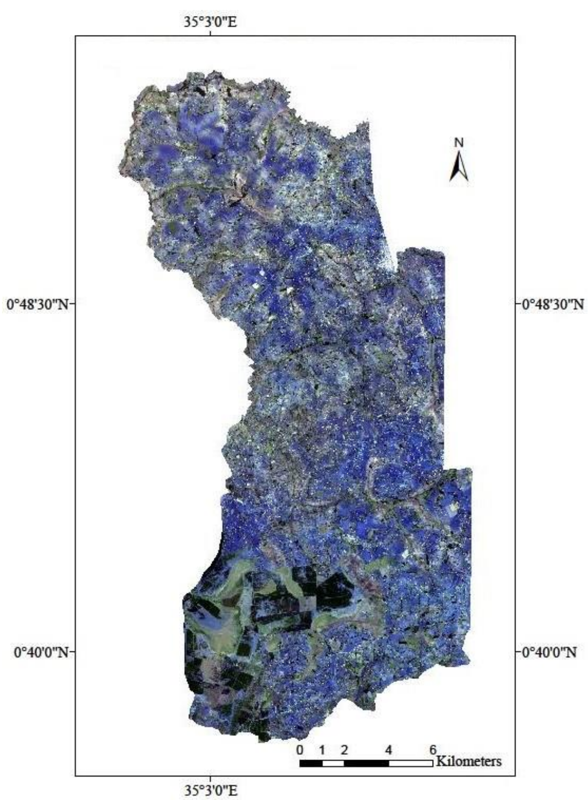

Figure 3.10: Clipped 2017 Sentinel 2A image

Source: USGS Portal "USGS Glo-Vis (https://glovis.usgs.gov/) websites"

Figure 3.8 a and 38 b: Represents the clipped images of the study area from the composite images of Landsat 5, 7 and Sentinel 2A sensors for the years 1997, 2002, 2007, 2012 and 2017.

3.8.10 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. Pixels containing a mixture of land cover classes that cannot be allocated to one group are referred to as mixed pixels. These and other classes that were not selected for classification were selected by the software and grouped as unclassified for each image. These values of unclassified pixels are constant for each year for a classified image hence did not have an impact on the outcome. Depending on the needs and specifications of the researcher as well as the desired results, a variety of image categorization techniques are employed. As explained 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.

3.8.11 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 5 bands 1, 2, 3, 4, 5, and 7 were layered, stacked, and composited to form the 1997 image. Landsat 7 bands1, 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), band 5 was included for false color enhancement which provided enhanced contrast for visual identification and interpretation of features in RGB and false color composite. False color 4 3 2 rendition, vegetation appears in shades of red, buildings are cyan blue and soils vary from dark to light brawn. Band combination of 4 5 and 1, vegetation appear in red, brawn, orange and yellow depending on their health and density. Soils appear as green and brown while buildings are white, cyan and grey. 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 8, 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, and band 8 NIR which constitutes a true and false color (RGB) composite. Band 8 infrared is composited with other bands to create false images. 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 8, 4, and 2 yielded a false color image that was utilized to differentiate buildings from other categories. In this band combination vegetation appears red while build up areas appear grey in color. Since Sentinel 2A has a high spatial resolution than Landsat, the percentage of classification has a higher accuracy.

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.

3.8.12 Extracting Signatures

The signature file contains essential information about the distinct spectral responses of each category of interest (Stacy, *el al*, 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 (2016). In Likuyani land cover, six classes were identified as the most prevalent that could easily be extracted. 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.

Source: Researcher (2021)

Using the maximum likelihood technique, supervised classification was carried out on Landsat 5, Landsat 7, 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 3.8, 3.9, and 3.10 show the results of the picture classification. After that, these outputs were entered into ArcGIS and Choropleth maps were created for each year; refer to figures 3.1, 3.13, and 3.14. For each year image capture, accuracy assessment was analyzed using error matrix from which percentage land cover changes were extracted.

3.8.13 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 measure 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.

3.8.14 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 geo-referenced 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 geo-database 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. Through comparison between digitized and the original allocation, the extent of land subdivision in the area was determined, as well as the smallest subdivision land parcel that is incapable of supporting sustainable maize production. It was feasible to calculate the number of divided land pieces that are too small for sustainable maize cultivation for any sustainable economic purpose. This calculation was attained through application of SQL in ArcGIS on the digitized settlement scheme maps.

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.

3.9 Hypothesis testing.

To test validity of the Hypothesis, data from respondents and error matrix was coded and analyzed in SPSS software through regression analysis. This served to determine validity of the hypothesis.

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 (2019).

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, 2019). 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 cultivation	4.6619718	.370	.027	.066[a]
Impact on land under maize cultivation	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 (2006) 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 Commission for Science, Technology and Innovation (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 spatiotemporal impact of land use land cover changes on land under maize production in the four settlement schemes within Likuyani Sub County. 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 (2015). In alignment with

Kothari (2019) and Mugenda and Mugenda (2015), 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 (Land under Maize Cultivation)

Independent variables which include;

X1 is spatiotemporal land use land cover changes, **X2** is impact of land use land cover change and, **X3** is Impact of land use land cover change.

In the model, **β0** represents the constant term while the coefficients **β1**, **β2**, and **β3**, were used to measure the sensitivity of the dependent variable (**Y**) to unit change in the predictor variables **X1**, **X2**, and **X3**.

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

Where **β0** = a constant

β0, β1, β2, and **β3** are the regression coefficients

Є = the stochastic term

M Intervening variable.

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 land use land cover changes 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 land use changes on land dedicated to maize cultivation. 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 cultivation in Likuyani Sub County.

4.2 To Determine LULCC that occurred in Likuyani Sub County from 1997 to 2017

4.2.1 LULC classes in Likuyani Sub county 1997

Landsat and Sentinel 2A sensors have coarse resolution that cannot be used to extract maize as a crop land cover. For this study, the months of December to early March were chosen because it is possible within this period to map ploughed land (Bareland) and Farmland (un-ploughed land) categories. This two classes combined form the land under maize cultivation.

The examination of the 1997 Landsat 5 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 90.93%. This data was extracted from the error matrix (confusion matrix) after accuracy assessment of the classified image Landsat 5 of 1997.

Table 4.1: Error matrix 1997 image accuracy analysis

LAND COVER	FOREST	GRASS/ SHRUB	BARE LAND	BUILDINGS	SWAMP	FARM LAND	TOTAL REFERENCE POINTS
Forest	189	22	0	0	3	0	214
Grass/Shrub	27	207	0	3	7	19	263
Bareland	0	0	370	39	0	12	421
Buildings	13	12	22	58	5	0	110
Swamp	0	19	0	9	57	35	120
Farmland	0	28	36	3	7	319	393
Total Classified Points	229	288	428	112	79	385	1521
Total Correct Referenced Points							
Total True Referenced Points							1383
Percentage overall accuracy							90.93%
						USER ACCURACY	**PRODUCER ACCURACY**
Forest						88.32	82.53
Grass/Shrub						78.71	71.85
Bareland						87.89	86.45
Buildings						52.73	51.79
Swamp						47.50	72.15
Farmland						81.17	82.86

Source: Classified Landsat 5 image

Table 4.1 represents the confusion matrix, from which percentage of land cover classes and kappa coefficient was computed from. Kappa coefficient is the accuracy measure, which evaluates how well the classification was performed. Kappa coefficient is calculated by the formula

$$K = \frac{nx - \Sigma(U_1 \; x \; P_1) + (U_2 \; x \; P_2) + \cdots (U_n \; x \; P_n)}{n^2 - \Sigma(U_1 \; x \; P_1) + (U_2 \; x \; P_2) + \cdots (U_n \; x \; P_n)} \qquad (3)$$

Where k is the kappa coefficient

n is the total sum of reference points

X is the sum of correctly classified pixels (In the diagonal)

U is the sum of reference point for every class in row

P is the sum of classified points for every class in the column.

Figures extracted from Table 4.1 and computed through application of formula 2 gave a kappa coefficient of K = 0.8856

Classification accuracy was computed by dividing:

$$\frac{\text{Total Correct Referenced Points} \quad 1383}{\text{Total True Referenced Points} \quad 1521}$$

$$k=\frac{(1521x1383)-\sum(214x229)+(263+288)+(421x428)+(112x110)+(79x120)+(393x385)}{1616^2-\sum(214x229)+(263+288)+(421x428)+(112x110)+(79x120)+(393x385)}$$

$$K=\frac{1625500}{1835398}=0.8856$$

K= 0.8856 which is 88.56% and the classification accuracy of 90.93% was achieved. Based on these results, the accuracy and kappa coefficient values have good criteria thus the results are reliable for the study. The land cover categories and their respective extents were extracted from the error matrix 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%. The land under maize cultivation was the combined percentage for Bareland and Farmland which was 49.81%.

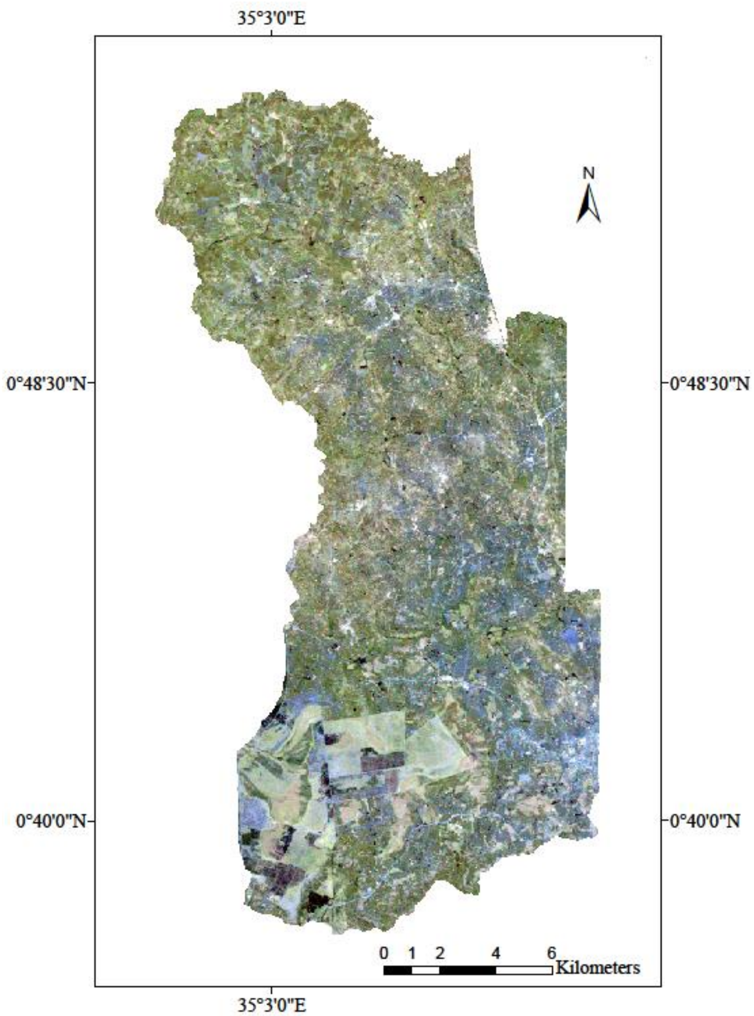

Figure 4.1: Classified Land use land cover Map of Likuyani Sub County 1997
Source: Regional center for Mapping and Resource Management

Figure 4.1 represents the classified map of Likuyani Sub County in the year 1997. The land cover classes in this this map are represented by colors in the legend.

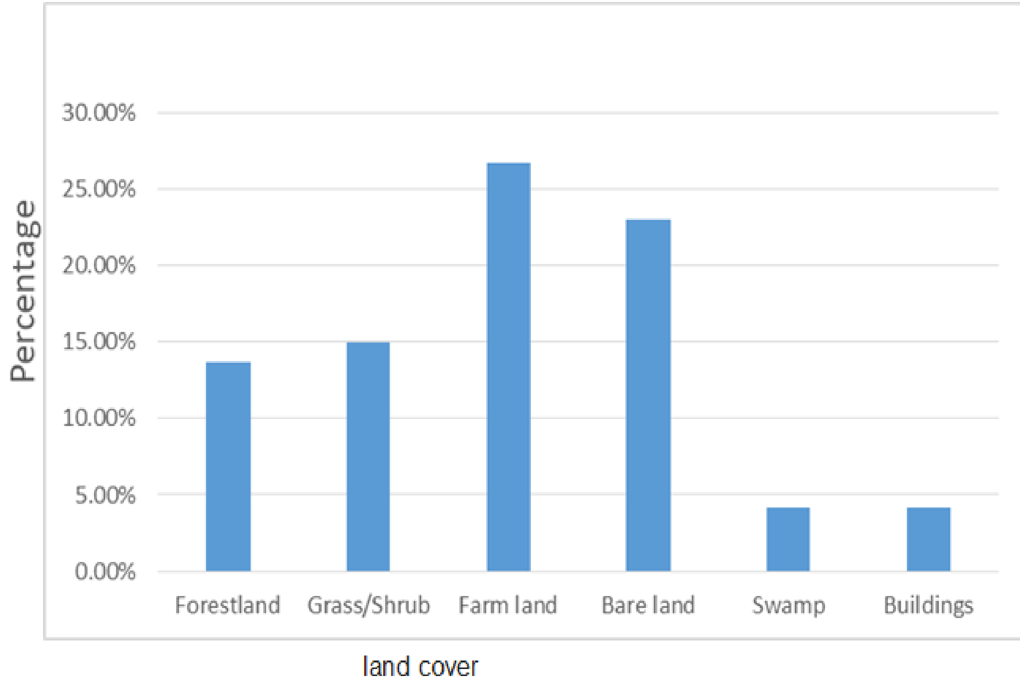

Figure 4.2: LULC classes in percentage cover for the study area in 1997

Source: Error Matrix 1997 image classification

Figure 4.2 is a bar chart representation of percentage land cover classes in Likuyani Sub County in the year 1997 from Landsat 5 image classification.

To analyze land cover within the Likuyani Sub County's settlement schemes, four settlement schemes were analyzed and the results were as depicted in Figure 4.3. Figures 4.3 represent land covers in Sergoi settlement scheme in the year 1997. Land cover classes are represented in the legend. Black represents land cover that was not classified because it does not fall in any of the six classes selected for classification.

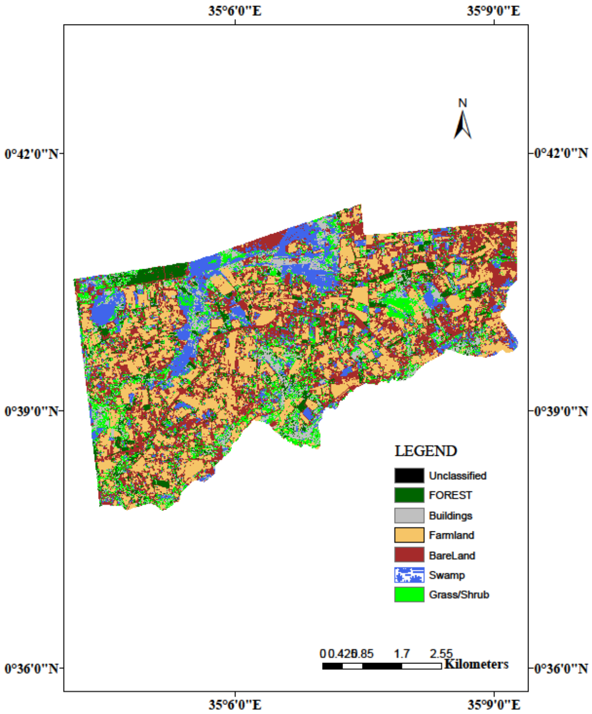

Figure 4.3 Sergoit classified maps in 1997

Source: Likuyani Landsat image of 1997

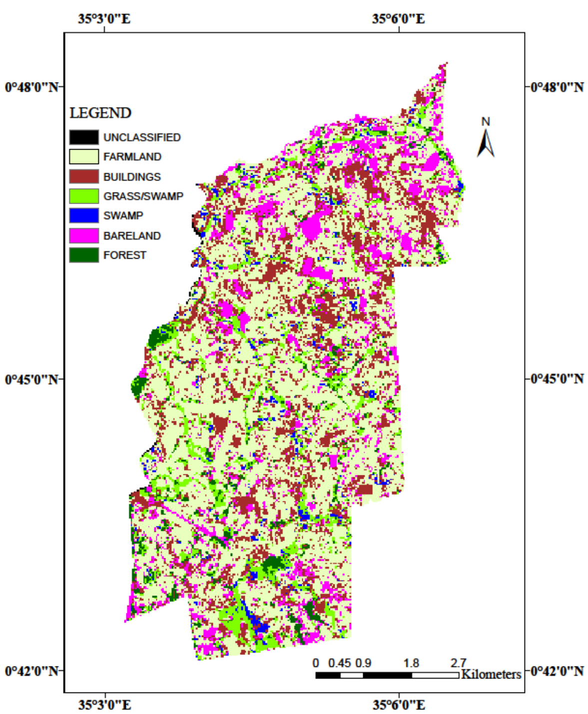

Figure 4.4: Sango classified map 1997

Source: Likuyani Landsat image of 1997

Figure 4.4 represent the classified map of Sango settlement scheme in the year 1997.

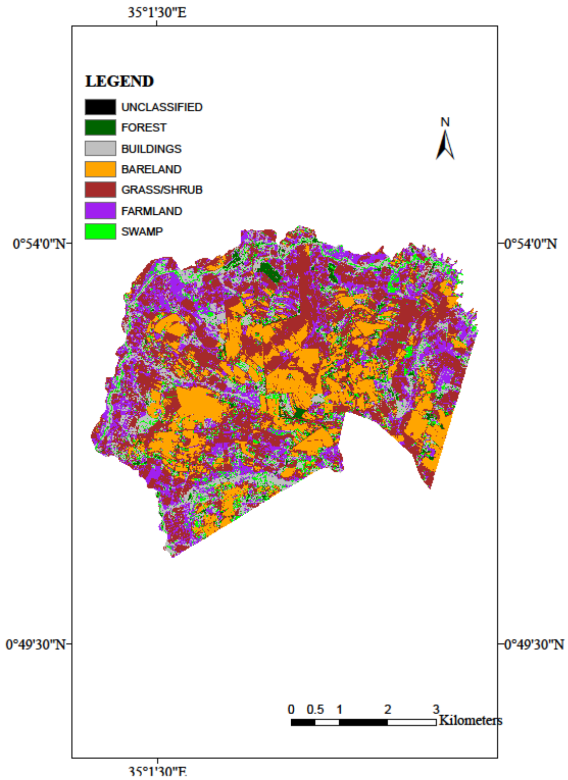

Figure 4.5: Nzoia classified map 1997

Source: Likuyani Landsat image of 1997

Figure 4.5 represents the classified map of Nzoia settlement scheme in 1997. Bareland color is dominant indicating most of the land had been ploughed at the time of image acquisition.

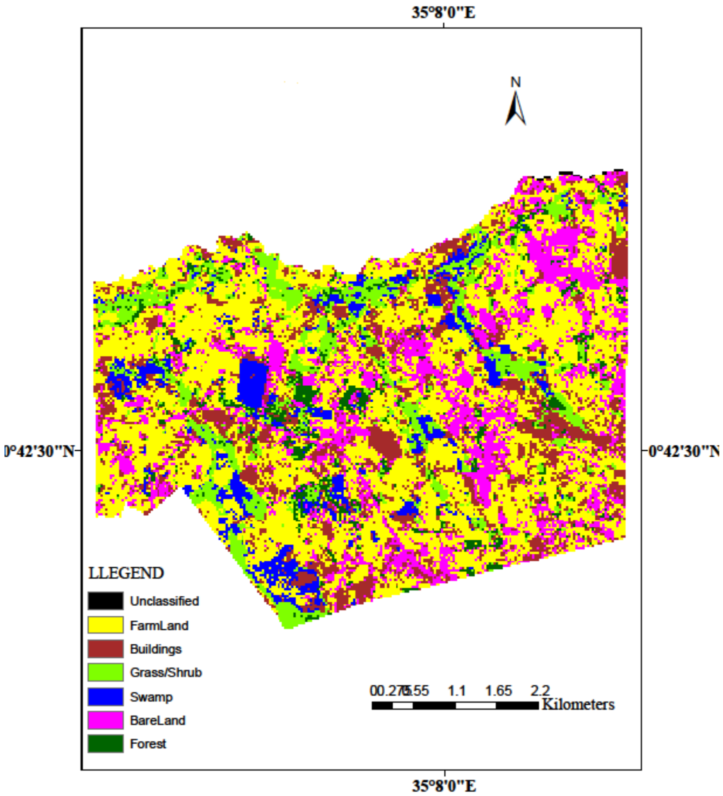

Figure 4.6 Classified map of Soy in 1997

Source: Likuyani Landsat image 1997

Figure 4.6 represents classified map of Soy settlement scheme in 1997. The color representing Farmland is dominant indicating most of the agricultural land had not been ploughed when the image was acquired.

Land cover results extracted from the error matrix are summarized in Table 4.2. Land under maize cultivation is the sum of Farmland and Bareland. Land cover under maize cultivation extracted from the classified map are also presented in Table 4.2.

Table 4.2: Land use land cover classes in the four Settlement Schemes in 1997
Source: error matrix 1997

	Farmland	Bareland	Forest	Swamp	Buildings	Grass/Shrubs	LUMC
SANGO	26.77	19.23	12.44	5.23	3.23	31.87	46
SERGOIT	19.87	20.23	11.89	4.94	3.89	28.11	40.1
SOY	31.81	18.44	14.44	6.77	4.12	21.95	50.25
NZOIA	20.82	25.07	8.03	7.19	3.48	27.82	45.89

Table 4.2 represents land cover classes in the four settlement schemes in percentage cover in 1997. During the image acquisition period in 1997, the percentage of farmland varied across the settlement schemes: Sango accounted for 26.77%, Sergoit 19.87%, Soy 31.81%, and Nzoia 20.82%. Bare land cover was notable, constituting 19.23% in Sango, 22.23% in Sergoit, 18.44% in Soy, and 25.07% 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. During the image capture, Soy showed the highest farmland area, followed by Sango. Sergoit and Nzoia displayed relatively similar extents of farmland areas. Moreover, Nzoia had the largest portion under building cover, followed by Soy, Sergoit and Sango. Conversely, Nzoia and Soy exhibited the most significant coverage of swamp compared to Sango, which had the smallest swamp area.

4.2.2 LULC classes in Likuyani Sub county 2002

Likuyani sub County categorized map for the year 2002 is represented by Figure 4.7. The land cover values are represented by the bar chart in Figure 4.8 which entails the land cover results for each category of land cover as indicted in. Field visits aided in ground verification of land cover types.

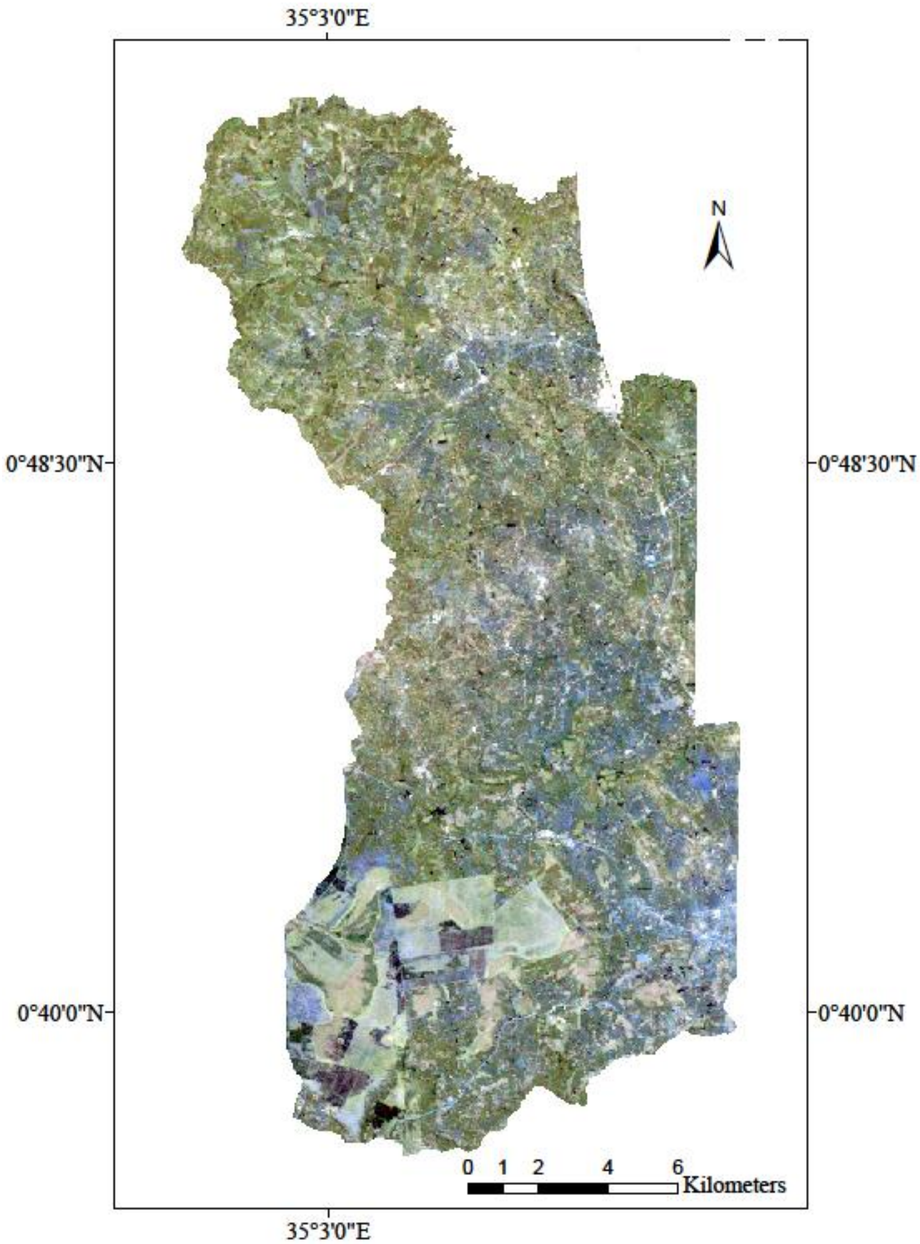

Figure 4.7: Classified map of the Likuyani Sub County for the year 2002

Source: Regional center for Mapping and Resource Management

Table 4.3: Error Matrix from 2002 Landsat 7 Image

LAND COVER	FOREST	GRASS/ SHRUB	BARE LAND	BUILDINGS	SWAMP	FARMLAND	TOTAL REFERENCE POINTS
Forest	251	24	0	0	21	7	303
Grass/Shrub	23	285	0	9	15	23	355
Bareland	3	7	479	27	1	7	524
Buildings	3	7	7	165	3	7	192
Swamp	3	7	0	3	77	13	103
Farmland	5	15	7	3	7	535	572
Total Classified Points	288	345	493	207	124	592	2197
Total Referenced Points							2197
Total True Referenced Points							2049
Percentage overall accuracy							93.26%
						USER ACCURACY	**PRODUCER ACCURACY**
Forest						82.84	87.15
Grass/Shrub						80.28	82.61
Bareland						91.41	97.16
Buildings						79.71	85.94
Swamp						74.76	62.10
Farmland						93.53	90.37

Source: Classified Landsat 7, 2002 image

Table 4.3 represent the error matrix extracted from classified Landsat 5 image covering Likuyani Sub County. Data extracted and computed from error matrix for 2002 image classification gave a land cover in percentage at a classification accuracy of 93.26%. Kappa value calculated from the error matrix by applying formula 2 to the extracted values gave a value of k = 84.70%. Based on classification accuracy of 93.26% and Kappa coefficient of k = 84.70%, the results were reliable for the study.

Information extracted from the error matrix analysis of the Landsat 7 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 Bareland, primarily due to ongoing ploughing activities in the region. Farmland, 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 6.54% and 3.45% of the total land cover, respectively

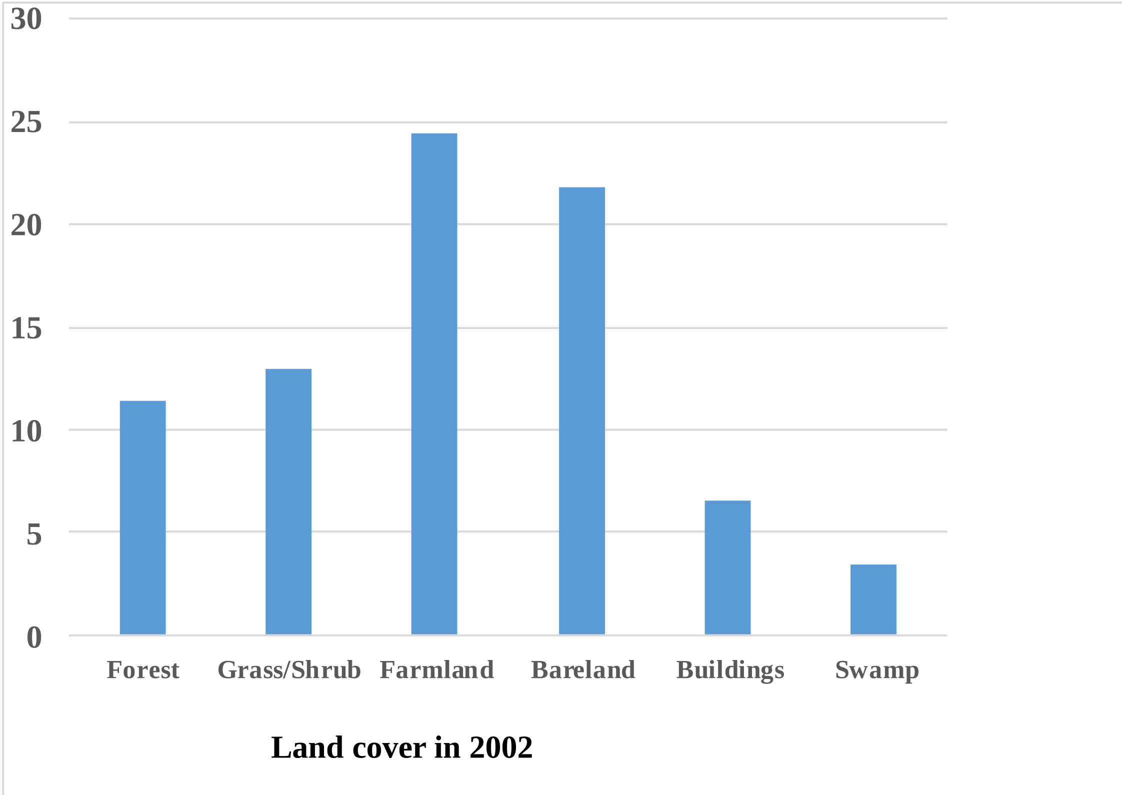

Figure 4.8: Likuyani Land cover in the year 2002
Source: Error matrix 2002 image classification

Figure 4.8 represents the land cover classes in percentage which were extracted from the error matrix of the classified Likuyani Landsat 5 image for the year 2002

4.2.4 LULC Classes in the four Settlement schemes in the year 2002

Land cover classes of the four settlement schemes were extracted from the classified Lokuyani 2002 image and their land cover during the year 2002 analyzed. This was to narrow down on the changes at a large scale at the settlement scheme level. Figure 4.9 represents the classified map of Sango settlement scheme for the year 2002.

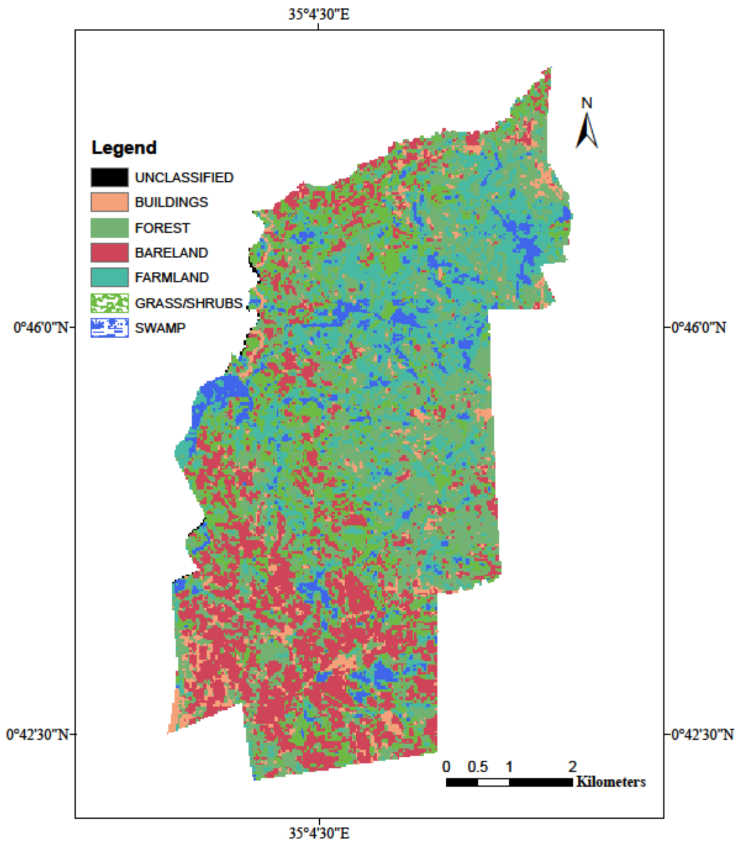

Figure 4.9: Sango Settlement 2002 classified map

Source: Landsat 7 2002 Image

In Sango settlement scheme, land cover was as followers: Farmland covered 23.5%, Bareland 23.21%, Forest cover was 10.11%, Swamp 3.01% Buildings occupied 4.33% and Grass/Shrub category accounted for 24.51%. Total cover for land under maize cultivation is the sum of farmland cover and Bareland cover which is 46.71%. Compared to the year 1997, there was an increase in LUMC of 0.71% in Sango settlement scheme.

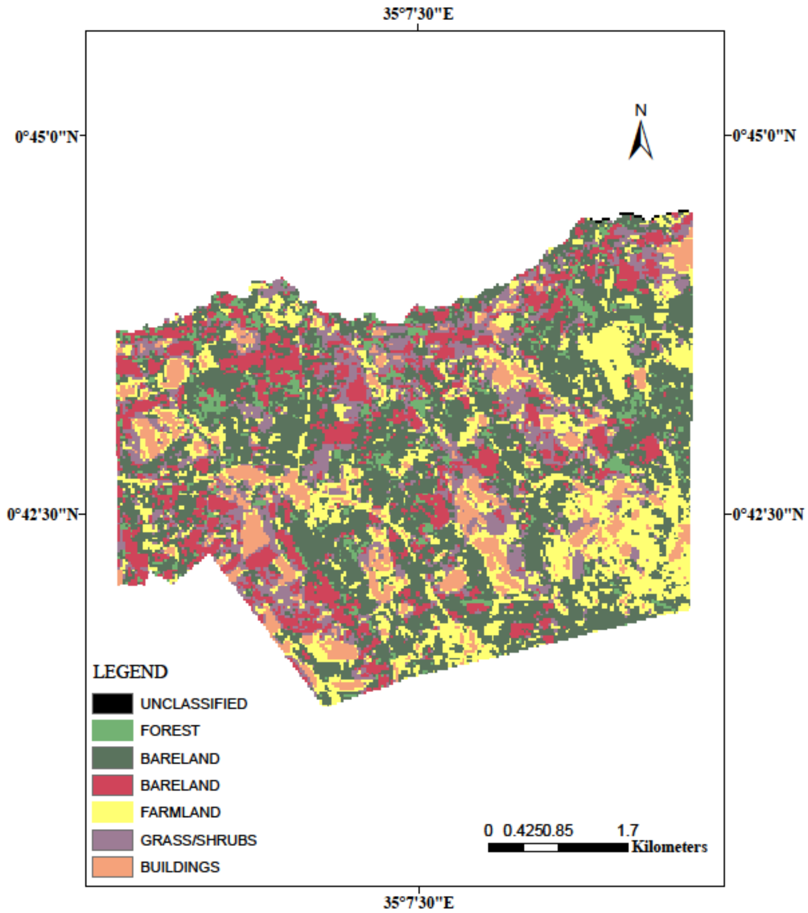

Figure 4.10: Soy Settlement scheme 2002 classified map

Source: Landsat 7 2002 image

Figure 4.10 is a classified map representing land cover classes for soy settlement scheme in the year 2002. During this period, Farmland cover was 28.11%, Bareland 19.03% Forest 11.80%, Swamp 4.45%, Buildings 5.78% and Grass/Shrub cover occupied 20.21%. In 1997 LUMC was summed at 50.25%, five years after in 2002, LUMC was 47.10%. In Soy settlement scheme, there was a reduction of 3.11%in LUMC.

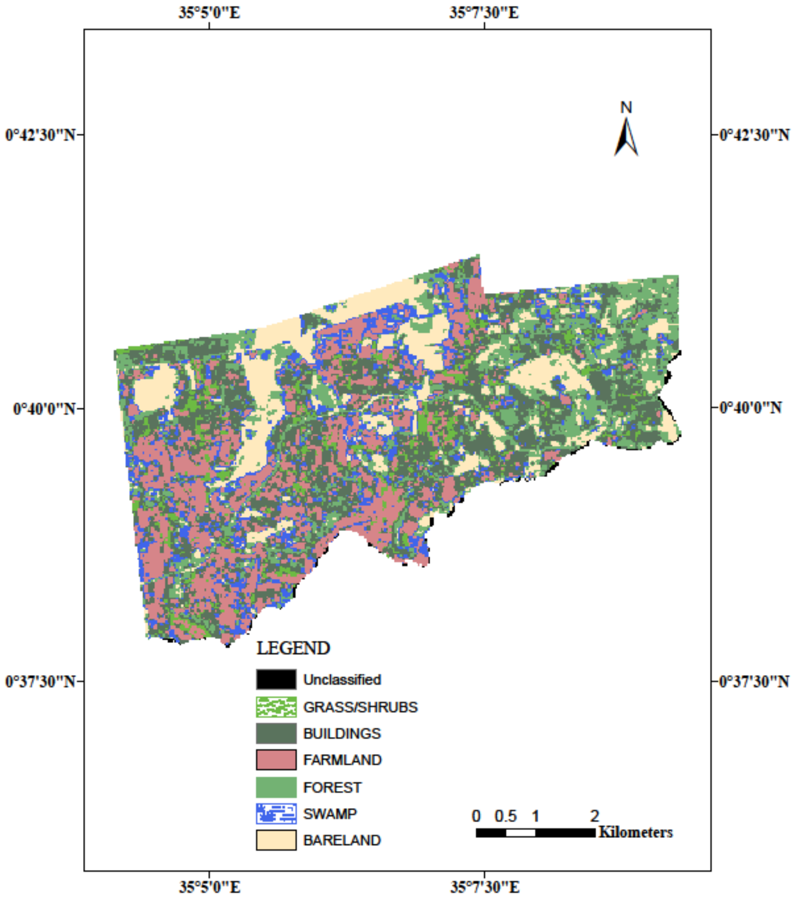

Figure 4.11: Sergoit classified image for the year 2002.

Source: Landsat 7, 2002 image.

Figure 4.11 represents the classified map of Sergoit settlement scheme in 2002

Land cover mapped for Sergoit settlement scheme in the year 2002, Farmland cover was 16.81%, Bareland covered 23.44%, Forest covered 9.11%, Swamp occupied 4.01% and Grass/shrub cover was 25.63%. LUMC was computed at 40.25%. In 1997, LUMC cover in Sergoit was 40.10% in 2002. This was an increase of 0.15%. Buildings land cover increased from 3.89% in 1997 to 5.11% in 2002. This increase in Buildings land cover can be attributed to increase in population that lead to more land being converted from Grass/shrub category to LUMC. Grass/Shrub decreased form 28.11% in 1997 to 25.63 in 2002. A reduction of 2.48%. This explains the increase in Bulidings over and LUMC.

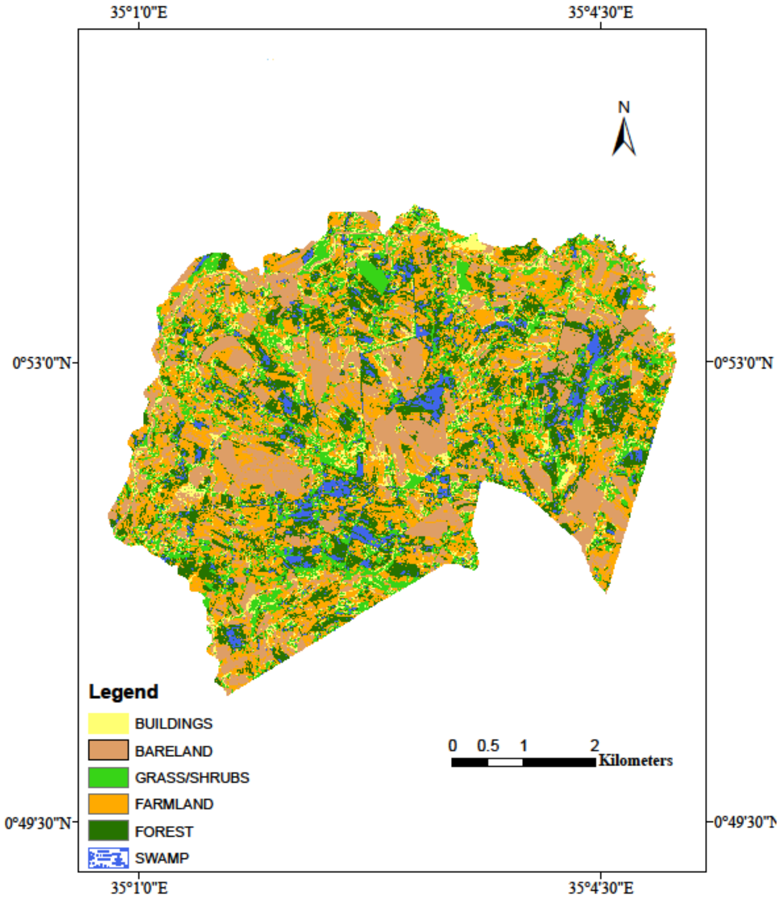

Figure 4.12: Nzoia classified image for the year 2002

Source**:** Landsat 7 2002 Image.

Figure 4.12 represents land cover classes for Nzoia settlement scheme in the year 2002. Farmland occupied 18.77%, Bareland cover was 32.89%, Forest cover was 6.55%, Swamp was mapped at 4.05% and Grass/Shrub covered 17.77%. Computed LUMC gave a result of 51.66%. This was an increase of 5.77% from 1997. Buildings cover increased from 3.48% to 4.23% during the same time span while Grass/Shrub reduced by 10.71%. This increase in LUMC and decrease in Grass/Shrub can be attributed to the Grass/Shrub being converted to LUMC as population increased.

Figure 4.13 represents a summary of image classification results for Sango, Soy, Sergoit, and Nzoia settlement schemes in a bar chart.

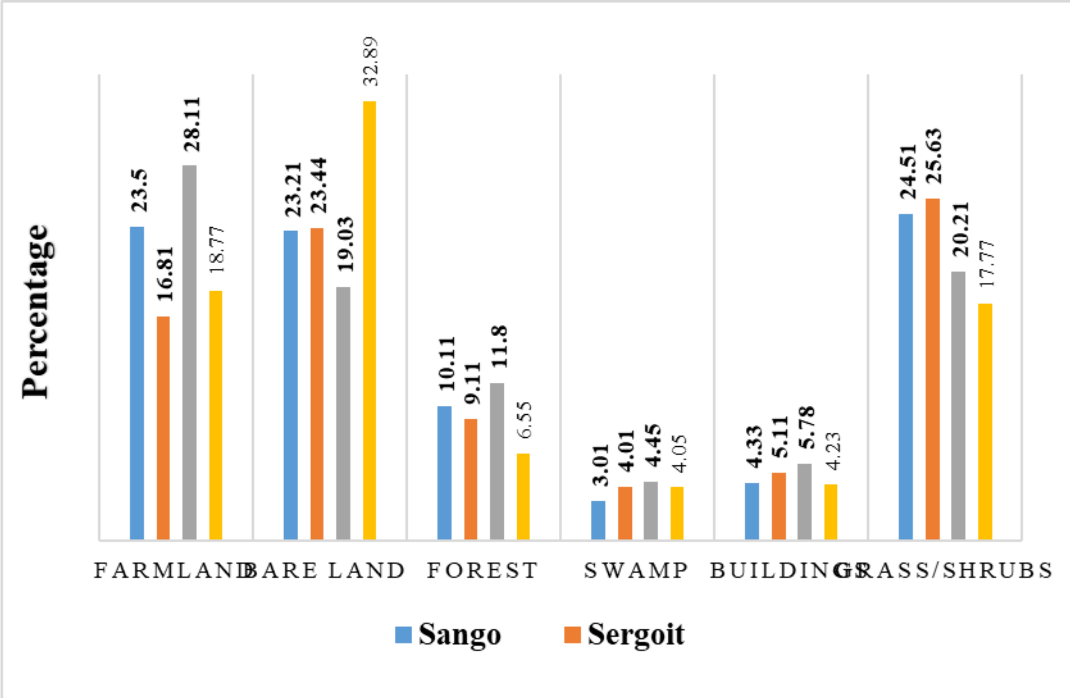

Figure 4.13: Land cover categories for Sango, Sergoit, Soy and Nzoia in 2002

Source**:** Error matrix 2002 image classification

4.2.5 LULC classes in Likuyani Sub County in 2007

Data extracted from the confusion matrix in accuracy assessment process for the year 2007gave the results as explained below.

Table 4.4: Confusion matrix for Likuyani Landsat 7 image 2007

LAND COVER	FOREST	GRASS/ SHRUB	BARE LAND	BUILDINGS	SWAMP	FARM LAND	TOTAL REFERENCE POINTS
Forest	211	24	0	0	0	0	235
Grass/Shrub	52	177	0	9	15	26	279
Bareland	3	0	377	71	1	2	454
Buildings	3	7	67	193	11	3	284
Swamp	0	19	0	5	66	23	113
Farmland	7	12	17	3	12	235	286
Total Classified Points	276	239	461	281	105	289	1651

Total Correct Referenced Points		1259
Total True Referenced Points		1651
Percentage overall accuracy		76.26%
	USER ACCURACY	**PRODUCER ACCURACY**
Forest	89.79	76.45
Grass/Shrub	63.44	74.06
Bareland	83.04	81.78
Buildings	67.96	68.68
Swamp	58.41	62.86
Farmland	82.17	81.31

Source: 2007 Classified Landsat 7 image

Table 4.4 represents the error matrix from the classified image of Likuyani Sub County from Landsat 7 image for the year 2007. Classification accuracy of the 2007 Landsat 7 image was 76.26% with a kappa coefficient of 72.13%. Based on this accuracy and kappa coefficient values, the results were reliable for the study. 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%, Bareland constituted 20.83%, and buildings comprised 7.69% of the total classified cover. Figure 4.14 represents the bar chart for the six land cover classes in Likuyani Sub County for the year 2007 in percentage cover.

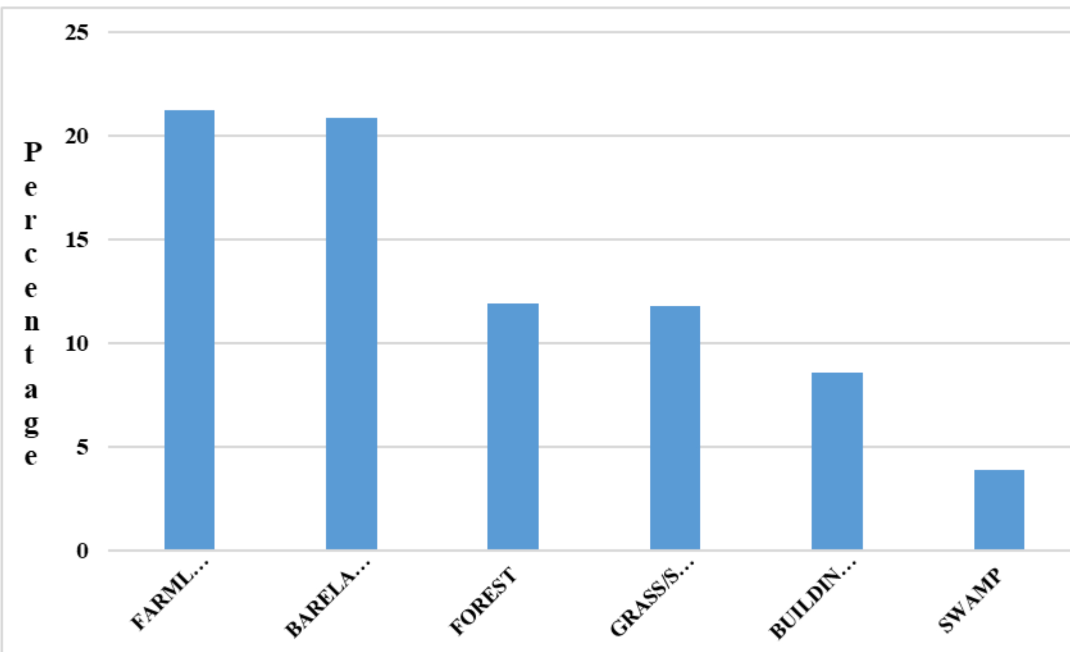

Figure 4.14: LCC classes in Likuyani sub county in the year 2007
Source: Error matrix 2007 Landsat 7 image classification

Figure 4.15 represents the classified map of Likuyani Sub County in the 2007. LUMC for the year 2007 for Likuyani Sub County was 42.05. This being the sum of Bareland and Farmland.

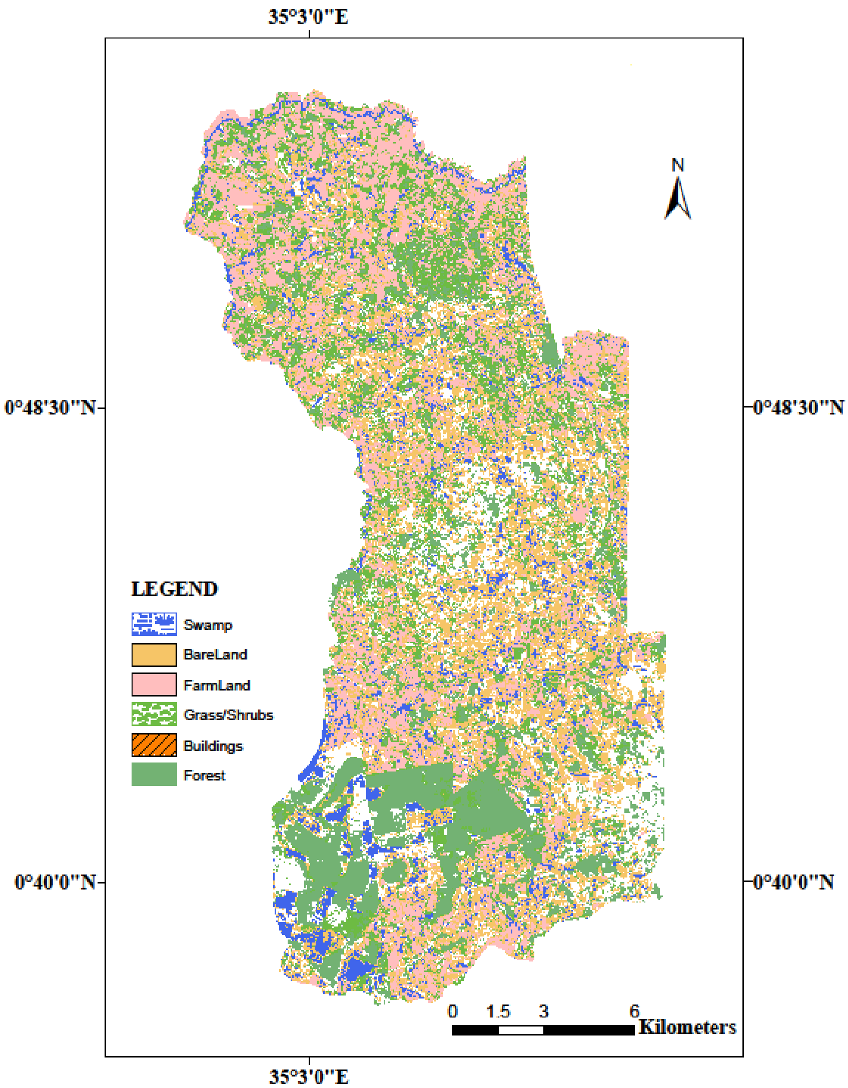

Figure 4.15: Classified map of Likuyani in 2007

Source: Regional center for Mapping and Resource Management

4.2.6 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 changes (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.

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. Bareland 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 4.16. Each bar represent land cover for the four settlement schemes in a corresponding color.

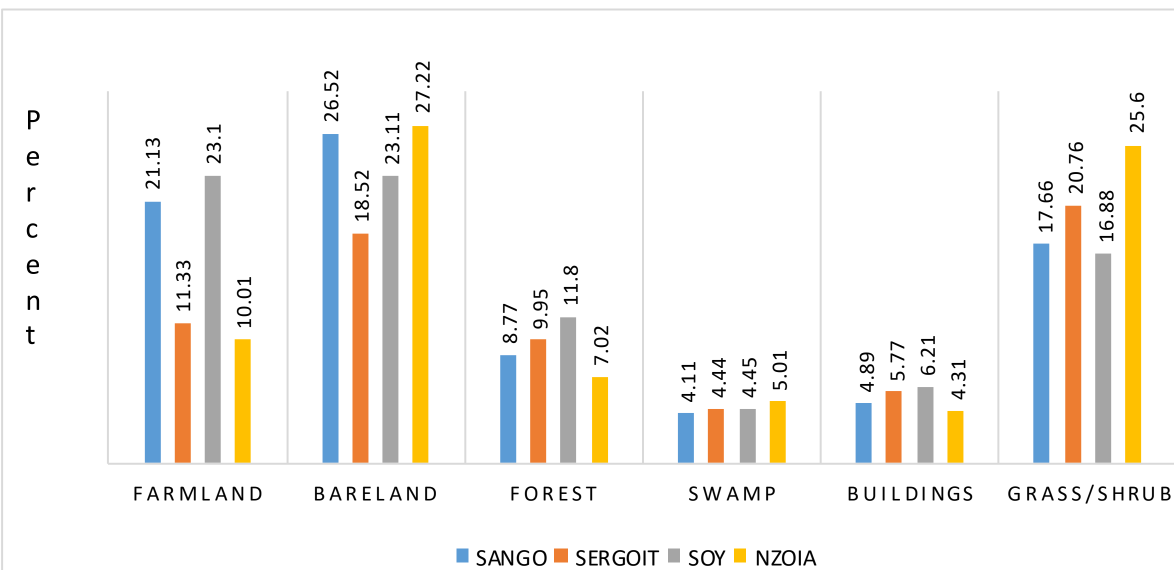

Figure 4.16: Land cover in the settlement Schemes in 2007

Source**:** Error matrix from 2007 Landsat 7 image classification

Figure 4.16 represents a bar chart for land cover classes in the Sango, Sergoit, Soy, and Nzoia settlements.

Classified land cover maps of Sango, Sergoit, Nzoia and Soy, settlement maps from which the land cover data was obtained from. Figure 4.17, 4.18, 4.19 and 4.20 represent classified maps of Sergoit, Sango, Nzoia and Soy settlement schemes in the year 2007 respectively.

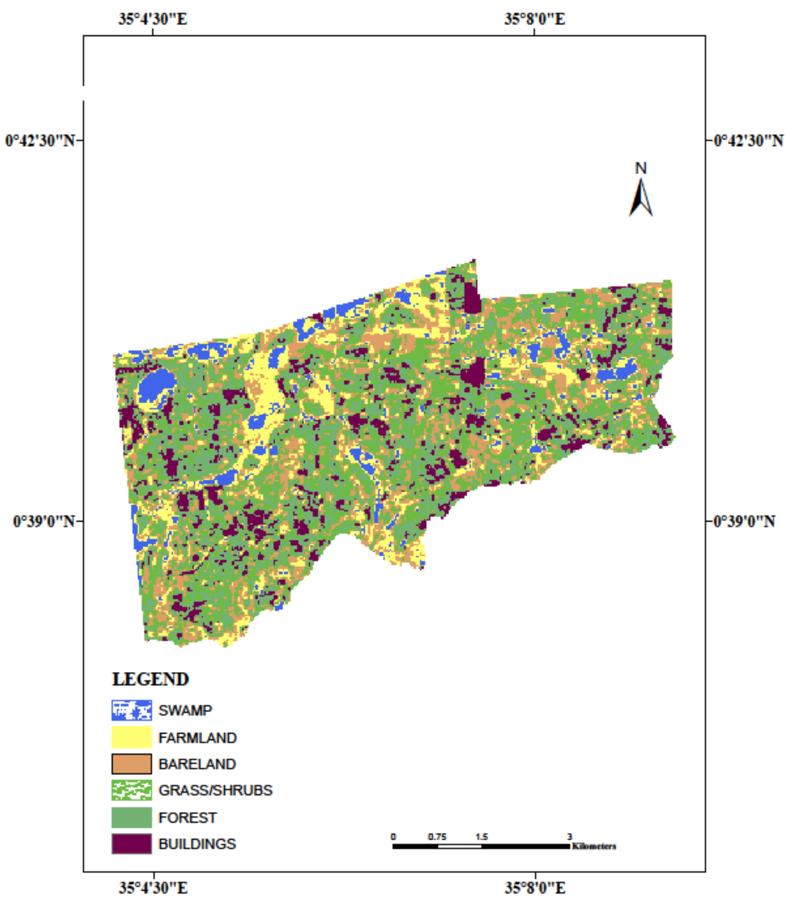

Figure 4.17: Classified Sergoit map 2007

Source: Landsat 7, 2007 image

Figure 4.17: represents the map of Sergoit settlement scheme in the year 2007

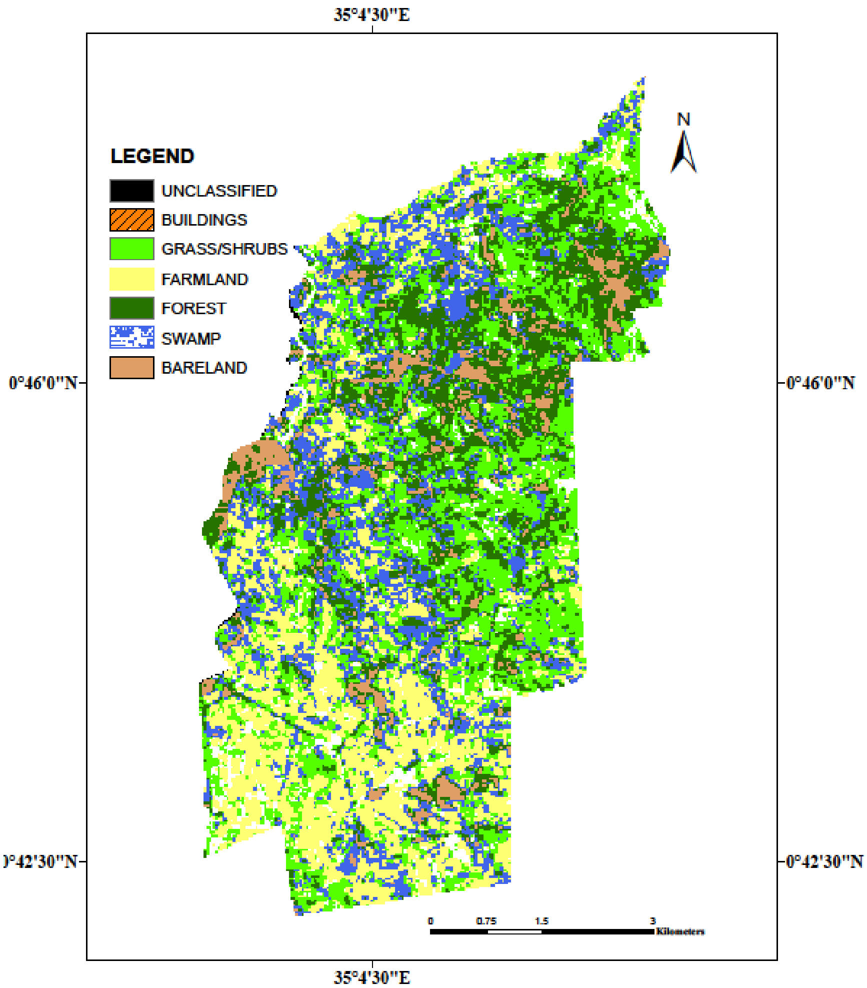

Figure 4.18: Sango scheme 2007 classified map

Source: Landsat 7, 2007 image

Figure 4.18: represents the classified map of Sango settlement scheme in 2007.

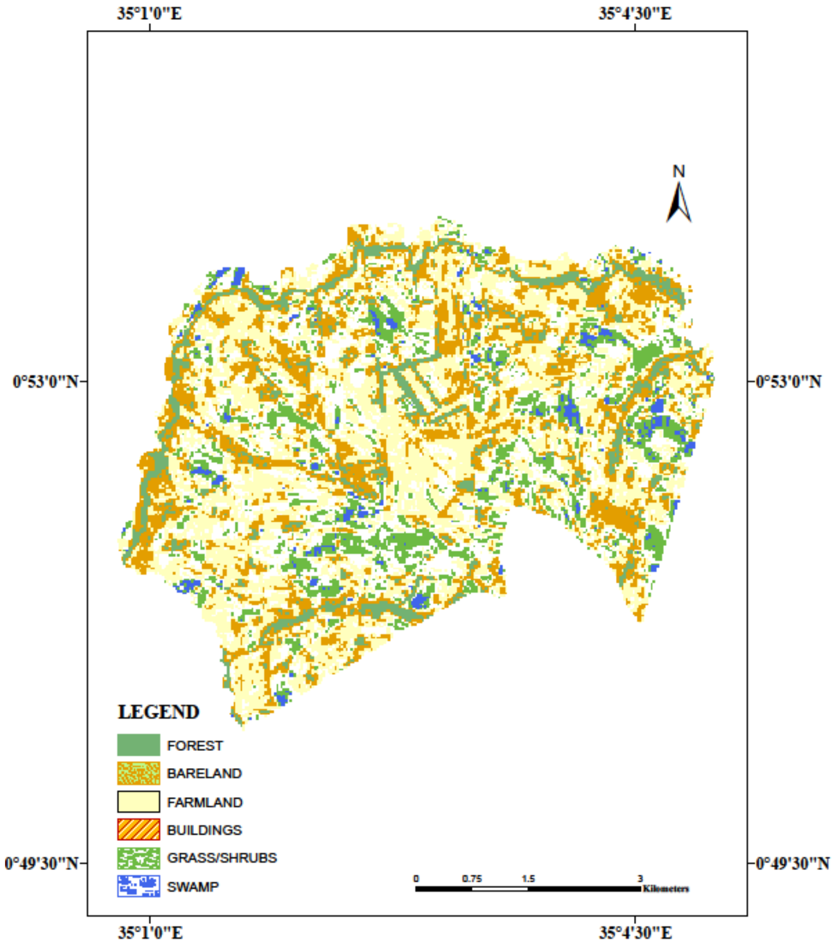

Figure 4.19: Classified land cover map of Nzoia settlement scheme in 2007

Source**:** Landsat 7 of Likuyani image 2007

`Figure 4.19: represents the classified map of Nzoia settlement scheme in 2007

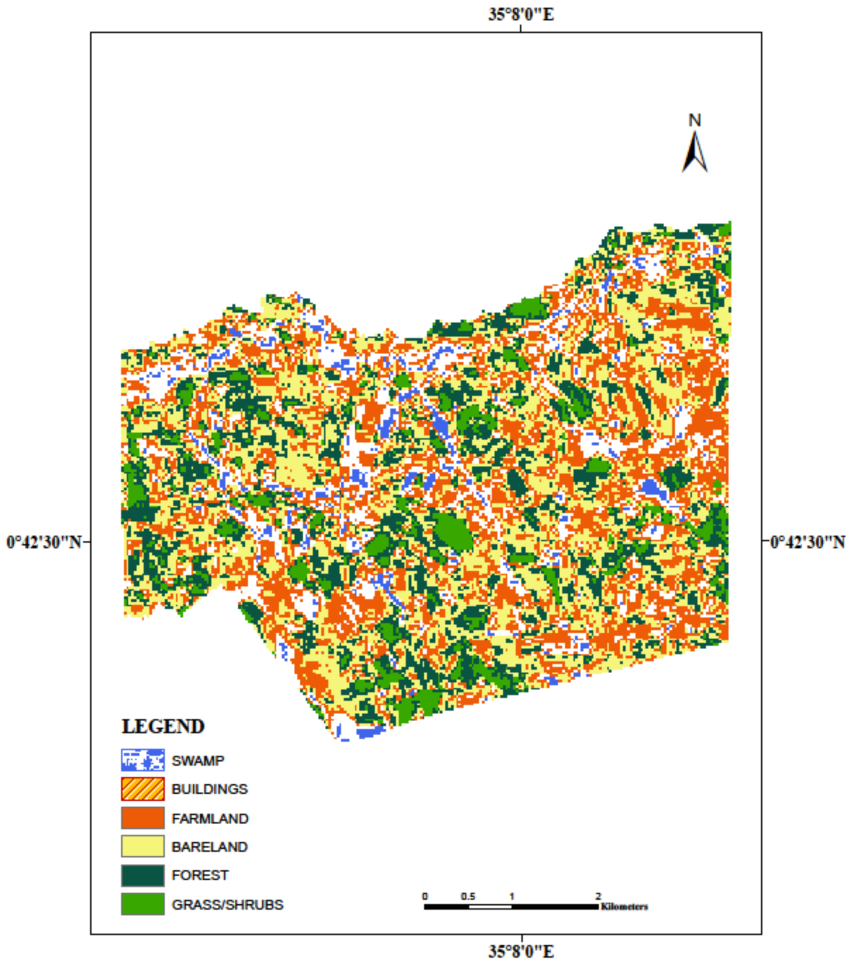

Figure 4.20: Classified land cover map of Soy settlement scheme in 2007

Source: Landsat 7 of Likuyani image 2007

Figure 4.20: represents the classified map of Soy settlement scheme in 2007

4.2.7 Land cover classes in Likuyani Sub County in 2012

The Landsat 7 image of Likuyani Sub County was classified and an error matrix for the image extracted and presented in Table 4.5

Table 4.5: Error matrix for Likuyani Landsat 7 image
Table 4.7: Error matrix 2012

LAND COVER	FOREST	GRASS/ SHRUB	BARE LAND	BUILDINGS	SWAMP	FARMLAND	TOTAL REFERENCE POINTS
Forest	190	3	4	0	5	0	202
Grass/Shrub	11	156	9	0	9	13	198
Bareland	0	0	226	3	0	0	229
Buildings	1	1	2	137	3	0	144
Swamp	3	7	1	1	62	3	77
Farmland	7	5	0	0	11	325	348
Total Classified Points	212	172	242	141	90	341	1198
Total Correct Referenced Points							
Total True Referenced Points							1608
Percentage overall accuracy							74.50%
					USER ACCURACY		**PRODUCER ACCURACY**
Forest					94.06		89.62
Grass/Shrub					78.79		90.70
Bareland					98.69		93.39
Buildings					95.14		97.16
Swamp					80.52		68.89
Farmland					93.39		95.31

Source: 2012 image accuracy assessment error matrix extract

A classification accuracy of 74.5% and Kappa coefficient of 70.20% were acquired. From the error matrix, values for varies land cover classes were obtained and are presented in table 4.6. Forest cover captured at 11.88%, Grass/Shrubs at 9.77%, Buildings was 8.53%, Swamp 3.87%, Farmland 20.22% and bare land covered 14.33%.

Table 4.6: 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: Error matrix from 2012 image classification

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 4.85% during the period from 1997 to 2012. This correlates with population growth and escalating land subdivision activities recorded in the Sub County. When land is subdivided, the new owners setup residence which results in reduction of the cultivation area.

Figure 4.21 represents classified map of Likuyani Sub County in the year 2012. The deference in percentage land cover for a particular land cover class, shows extend by which this particular land cover has changed from 1997 to 2012. Using this trend analysis, it was possible to calculate by what percent land under maize cultivation was being affected by changes in other land covers classes.

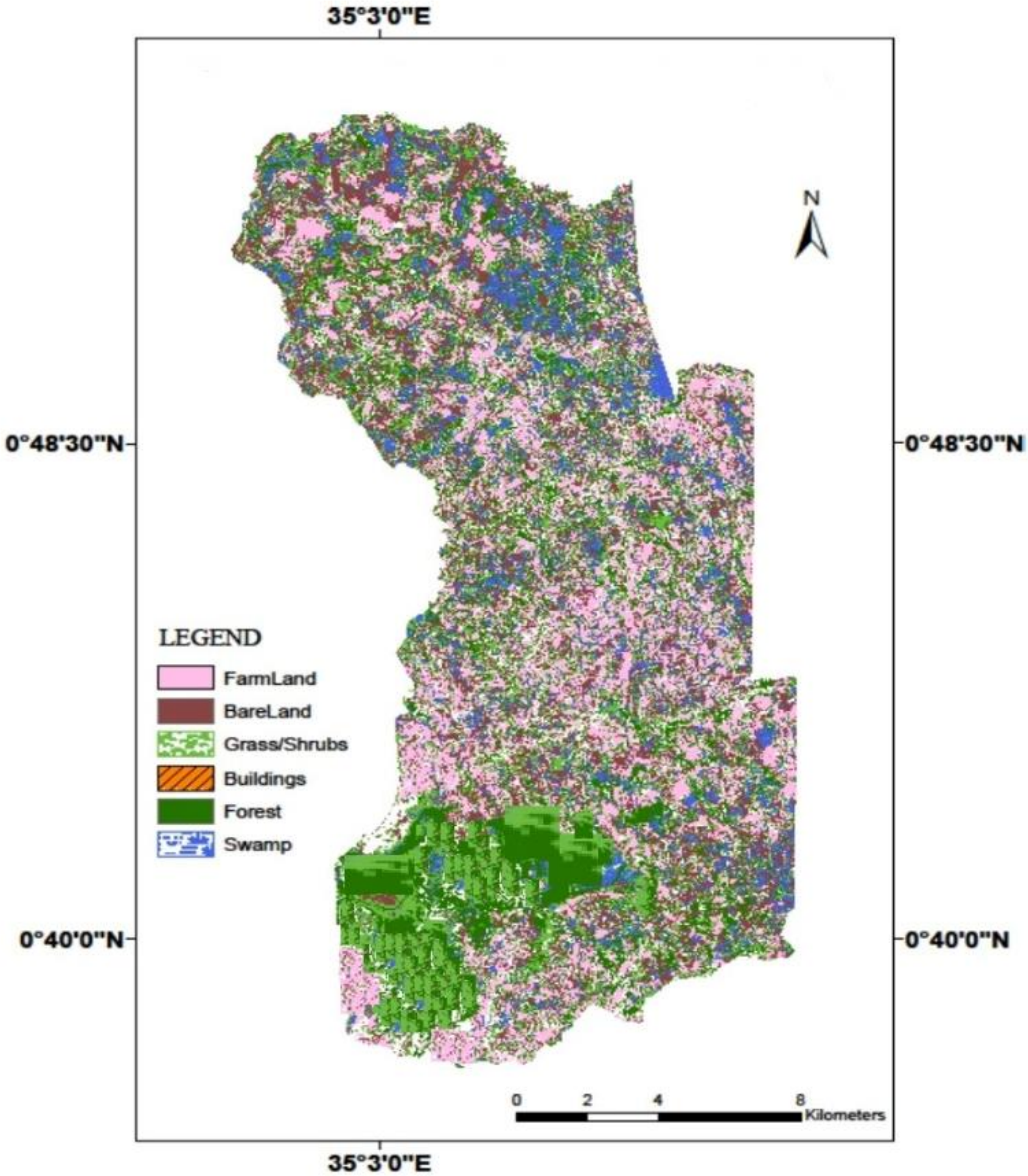

Figure 4.21: Likuyani land cover classes in 2012

Source: 2012 Landsat 7 Likuyani image

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

To analyze how land cover change was occurring inside the Likuyani Sub County in the year 2012, images of the four settlement schemes were clipped from the Likuyani 2021

Landsat 7 image. Land cover results for the four schemes are represented in Figure 4.22 represent percentage of land cover area in the Sango, Sergoit, Soy and Nzoia settlement scheme in the year 2012. X axis is land cover type and Y axis is percentage.

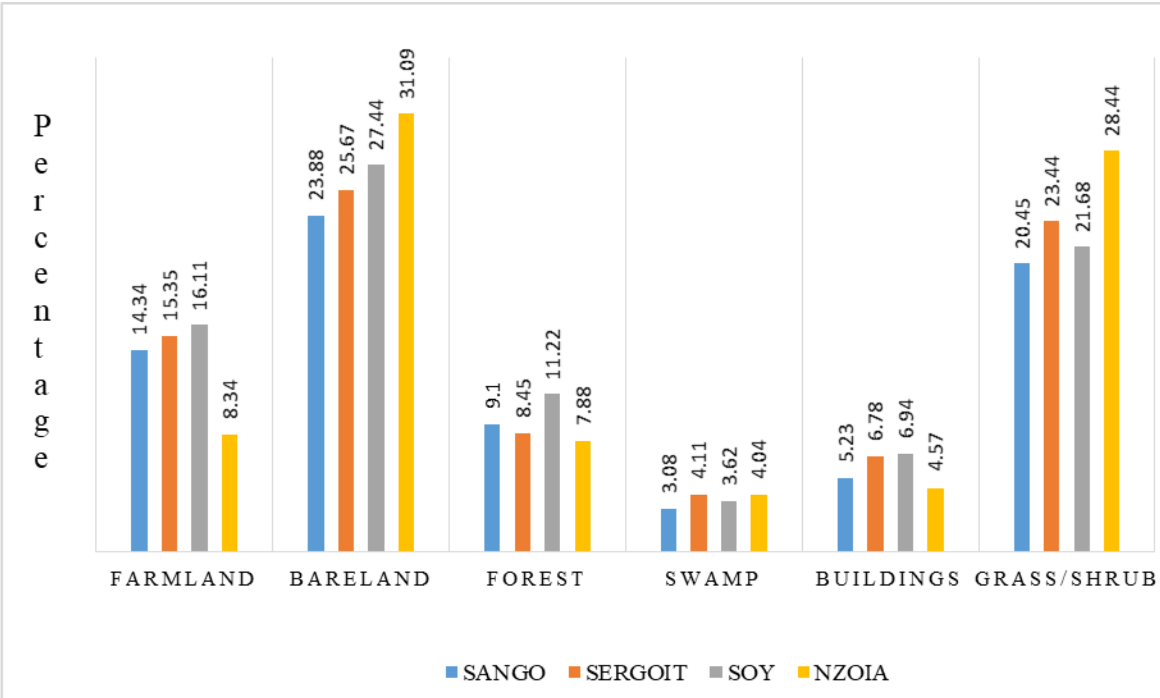

Figure 4.22: Land cover for Sango, Sergoit, Soy and Nzoia settlement schemes.
Source: Error matrix 2012

In Nzoia, Farmland cover was 8.34% while Bareland covered 31.09%. Forest cover was recorded at 7.88%, Swamp was 4.01%, Buildings covered 4.57% and Grass/shrub category was 28.44%. Grass/shrub cover rose exponentially from 25.6% in 2007 to 28.44 in 2012. GPS ground truths revealed some areas classified as Grass/shrub were sugarcane fields. Some farmers had shifted to Sugarcane farming. Figure 4.17, represent the classified map of Nzoia settlement scheme in the year 2012. Figure 4.18, represents classified map of

Sergoit settlement scheme from Landsat 7 image of the year 2012.

Figure 4.23 represents classified map of Nzoia settlement scheme in the year 2012.

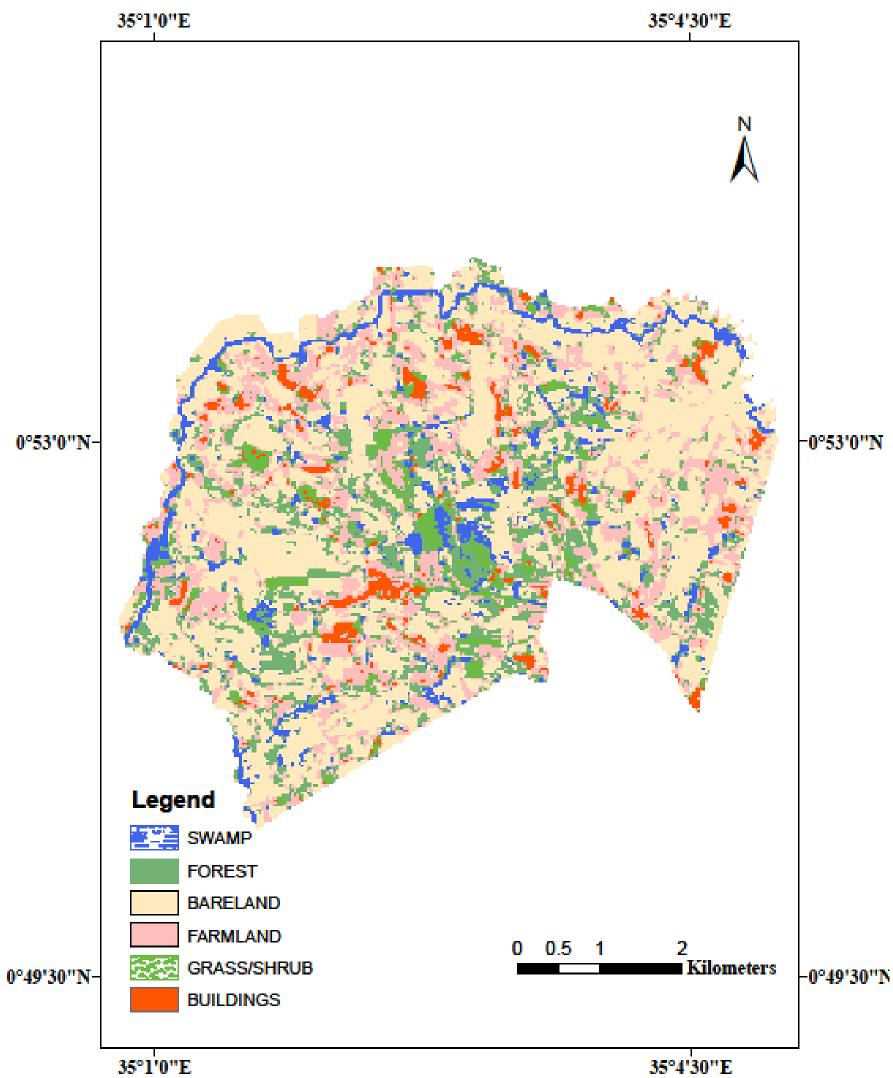

Figure 4.23: Nzoia Scheme 2012

Source: Landsat 7 of Likuyani image 2012

Figure 4.23 represents classified map of Nzoia settlement scheme in the year 2012.

Bareland category is most prominent indicating most of the land had been ploughed at the time of image acquisition.

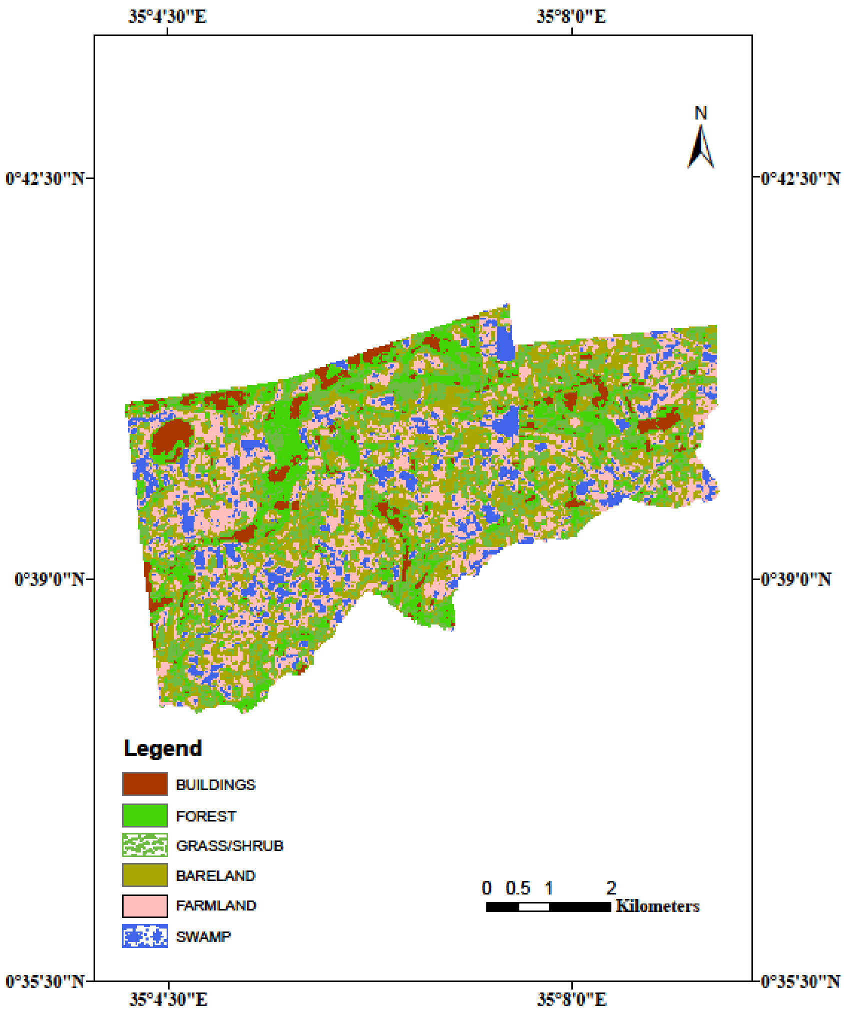

Figure 4.24: Sergoit scheme 2012

Source: Landsat 7 Likuyani image of 2012

Figure 4.24 represents the classified map of Sergoit settlement Scheme in 2012. Farmland cover was 15.35%, Bareland was recorded at 25.67% while Forest cover was 8.45%. Swamp, Buildings and Grass/shrub accounted for 4.11%, 6.78% and 23.44% respectively. LUMC (sum of Farmland and Bareland) was 41.02%. Correlation between Buildings and LUMC had a negative relationship in that, Buildings land cover continued to increase over time while LUMC reduced. The parcel of land subdivided for either sale or family member, a section is used for settlement thus the increase in Buildings and reduction in LUMC.

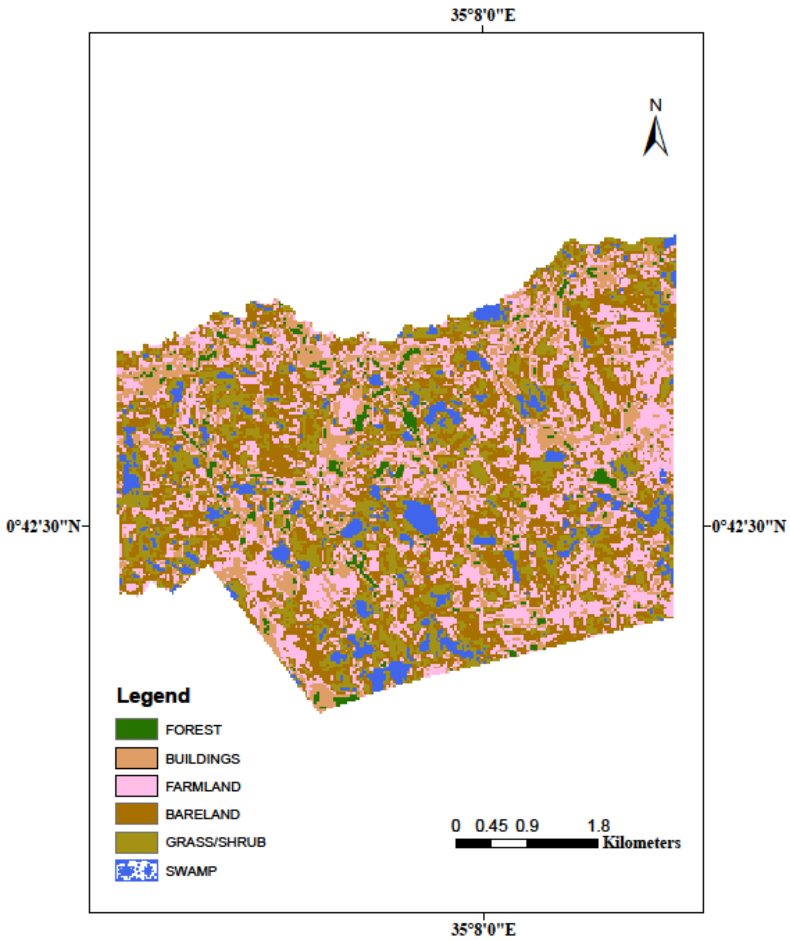

Figure 4.25: Classified Soy map 2012s
Source: Landsat 7 of Likuyani 2012 image

Figure 4.25: represents Landsat 7 classified map of Soy settlement scheme in the year 2012. Land cover classes were as follows; Farmland was recorded at 16.11%, Bareland 27.44%, Forest 11.22%, Buildings 6.94%, Swamp cover was 3.62% and Grass/shrubs 21.68%. In Soy, LUMC reduced from 46.21% in 2007 to 43.55% in 2012.

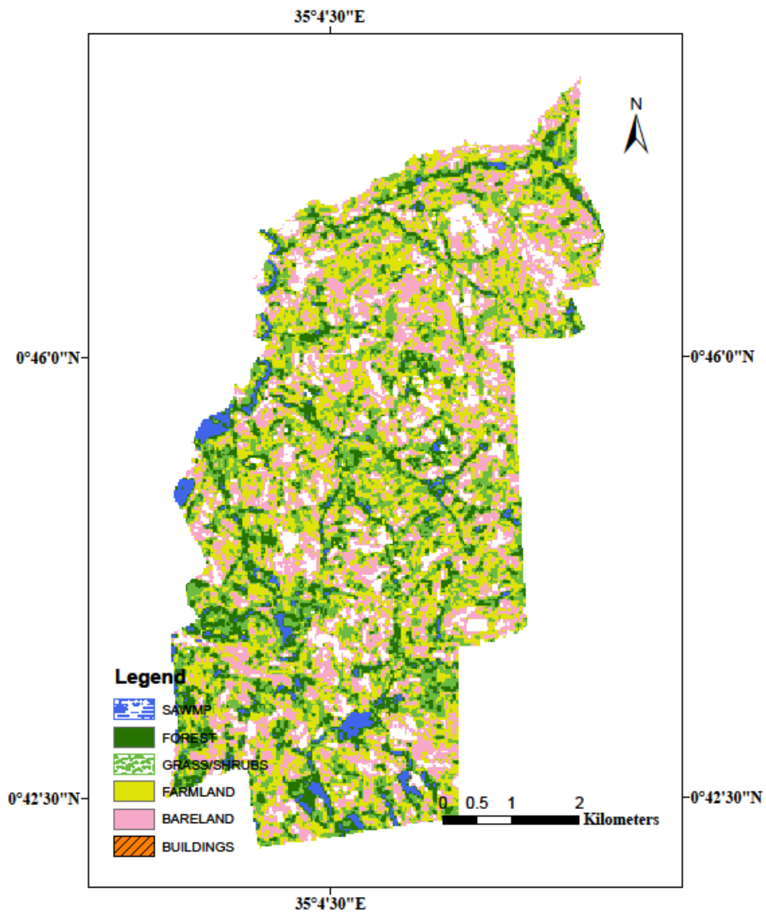

Figure 4.26: Classified Sango settlement scheme 2012

Source: Landsat 7 Likuyani 2012 image

Figure 4.26 represents land cover classes in Sango settlement scheme in 2012. Farmland covered 14.34%, Bareland 23.88%, Forest cover was 6.10%, Swamp recorded 3.08%, Buildings covered 5.23% and Grass/shrub was 20.45%. LUMC reduced from 47.65% in 2007 to 38.22% in 2012. Some portions of LUMC was converted to sugarcane farms. This explains the increase in the Grass/shrub category as sugarcane fields were mapped as Grass/shrub. Part of this class also converted to Buildings land cover as population increased. In all the four settlement schemes, Grass/shrubs and Buildings cover recorded a constant increase.

4.2.9 LULC in Likuyani Sub County in 2017

Data for land cover classes for the year 2017 were extracted from the accuracy assessment of the error matrix presented in Table 4.7. The overall accuracy of 80.51% and kappa coefficient of 76.24% shows the classification values had good criteria.

Table 4.7: Error matrix 2017

LAND COVER	FOREST	GRASS/ SHRUB	BARE LAND	BUILDINGS	SWAMP	FARMLAND	TOTAL REFERENCE POINTS
Forest	23	3	0	0	1	0	29
Grass/Shrub	1	26	0	0	3	6	27
Bareland	0	0	32	0	0	0	36
Buildings	1	1	2	15	3	0	48
Swamp	0	5	1	3	9	3	27
Farmland	0	5	0	0	0	29	28
Total Classified Points	27	31	39	44	22	32	195
Total Correct Referenced Points							195
Total True Referenced Points							157
Percentage overall accuracy							80.51%
						USER ACCURACY	**PRODUCER ACCURACY**
Forest						86.21	92.59
Grass/Shrub						62.96	54.84
Bareland						100.00	92.31
Buildings						85.41	93.18
Swamp						55.56	68.18
Farmland						82.14	71.88

Source: 2017 image accuracy assessment error matrix extract

Land cover percentage cover is summarized in Table 4.8. Forest covered 14.64%, Grass/Shrub 16.56%, Buildings covered 9.55%, Swamp, 4.46%, Farmland and Bareland occupied 18.47% and 20.38% respectively.

Table 4.8: Percentage land cover for classes in 2017

Land cover	Percentage cover
Forest	14.64

Grass/Shrub	16.56
Buildings	9.55
Swamp	4.46
Farmland	18.47
Bareland	20.38
LUMC	38.47

Source: 2017 error matrix

Table 4.8 represents a summary of percentage land cover classes in Likuyani Sub County in 2017.

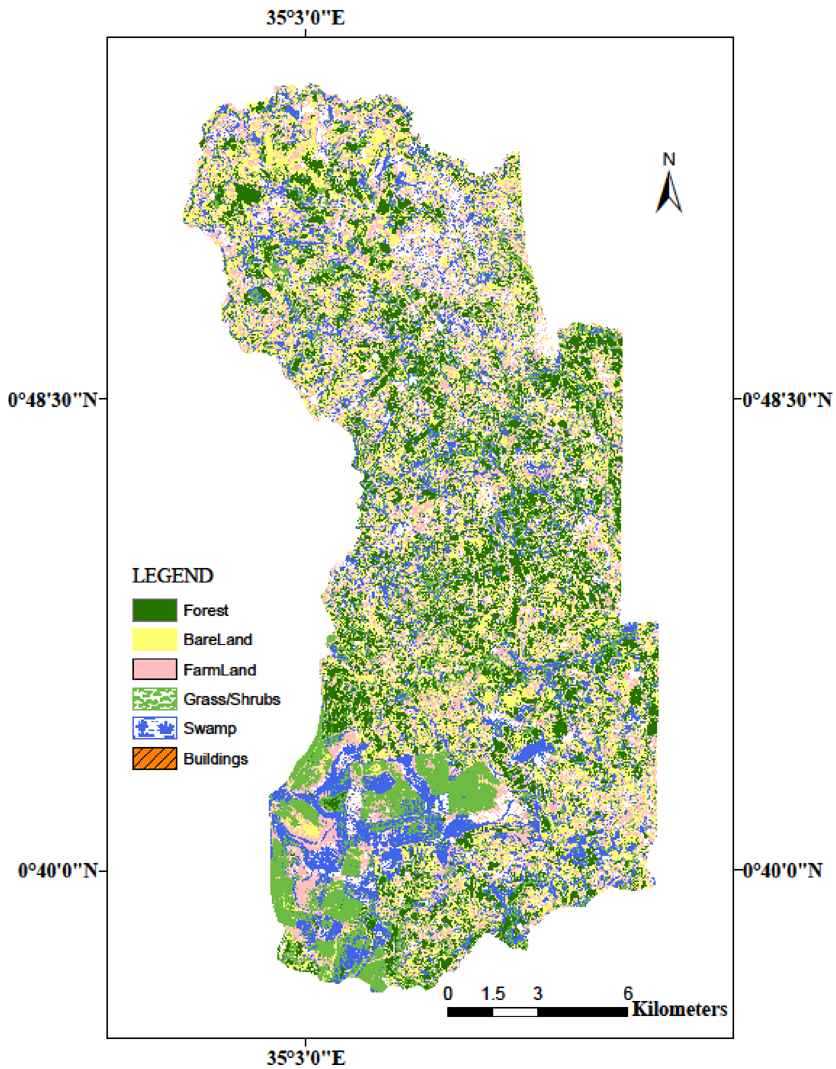

Figure 4.27: Likuyani classified map for the year 2017

Source: USGS Portal "USGS Glo-Vis (https://glovis.usgs.gov/) websites"

Figure 4.27 represents classified map of Likuyani Sub County in 2017. The analysis was to compare land cover trends with what was happening within the settlement schemes.

4.2.10: LC Classes in the selected settlement schemes in 2017

Land cover classes in Soy, Sergoit Sango and Nzoia settlement schemes in 2017 are represented in Figure 4.28. Examination of land cover alterations in the chosen four settlement schemes indicated a considerable upsurge in Buildings land cover class across all schemes from 1997 to 2017, albeit more restrained in Nzoia compared to the remaining three. The growing population necessitated additional housing, leading to increased land subdivision, impacting Farmland and Bareland classes. 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 cover classes is presented in Figure 4.22.

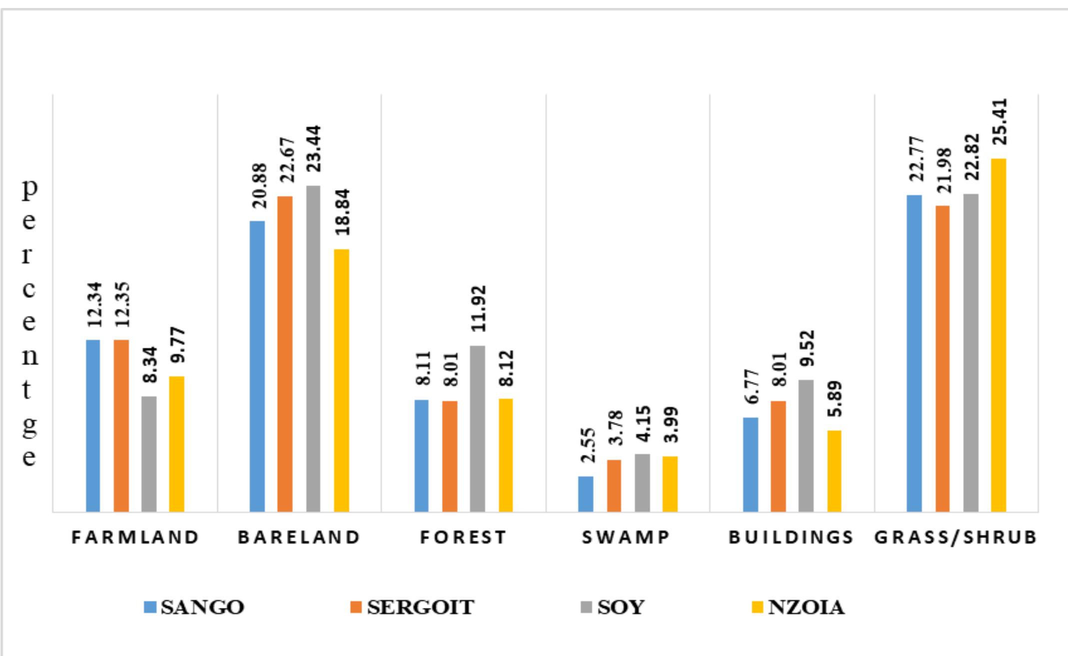

Figure 4.28: LULC in Sango, Sergoit, Soy and Nzoia Settlement schemes in 2017

Source: Error matrix 2017 image classification. Figure 4.28 is a bar-chart representation of land cover classes in the four settlement schemes in 2017 in percentage cover. In Sango, Farmland covered 12.34%, Bareland 20.88%, Forest 8.11%, Swamp 2.55% Buildings 6.77% and Grass/shrub 20.77%. LUMC was summed at 33.22%. Grass/shrubs cover increased by 2.32% from represented in Figure 4.23. 2012 to 2017 indicating continues shift from maize to sugarcane farming.

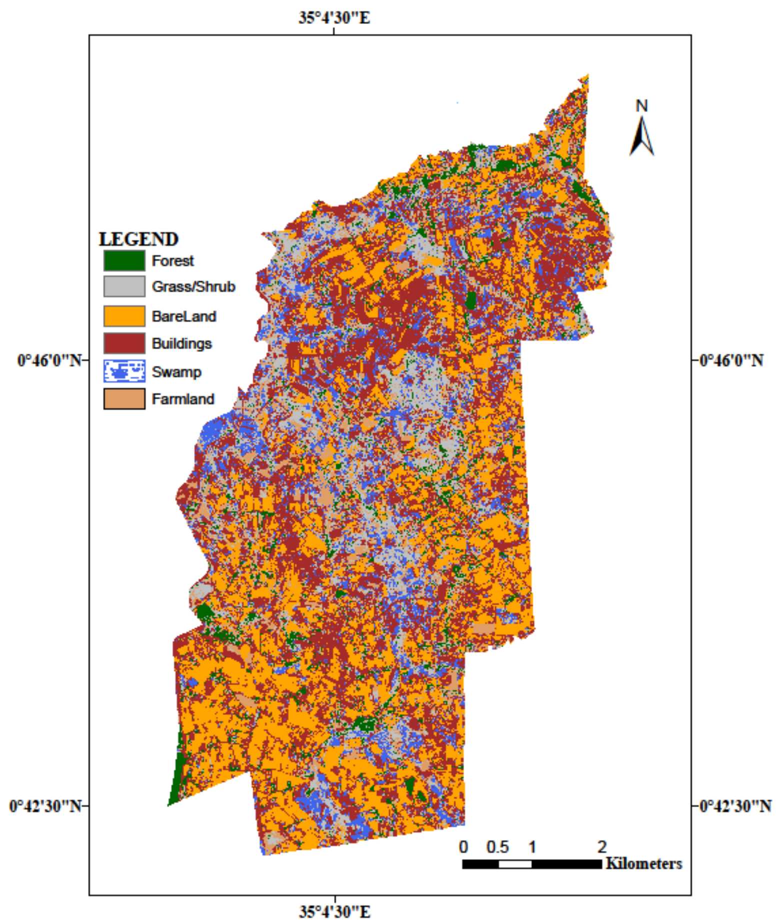

Figure 4.29: Sango Settlement scheme land cover in 2017

Source: Sentinel 2A Likuyani image

Figure 4.29 represents land cover in Sango settlement scheme in 2017. There is an observed major change in land under maize cultivation from 1997 to 2017. Grass/shrub and Buildings land cover being most affected.

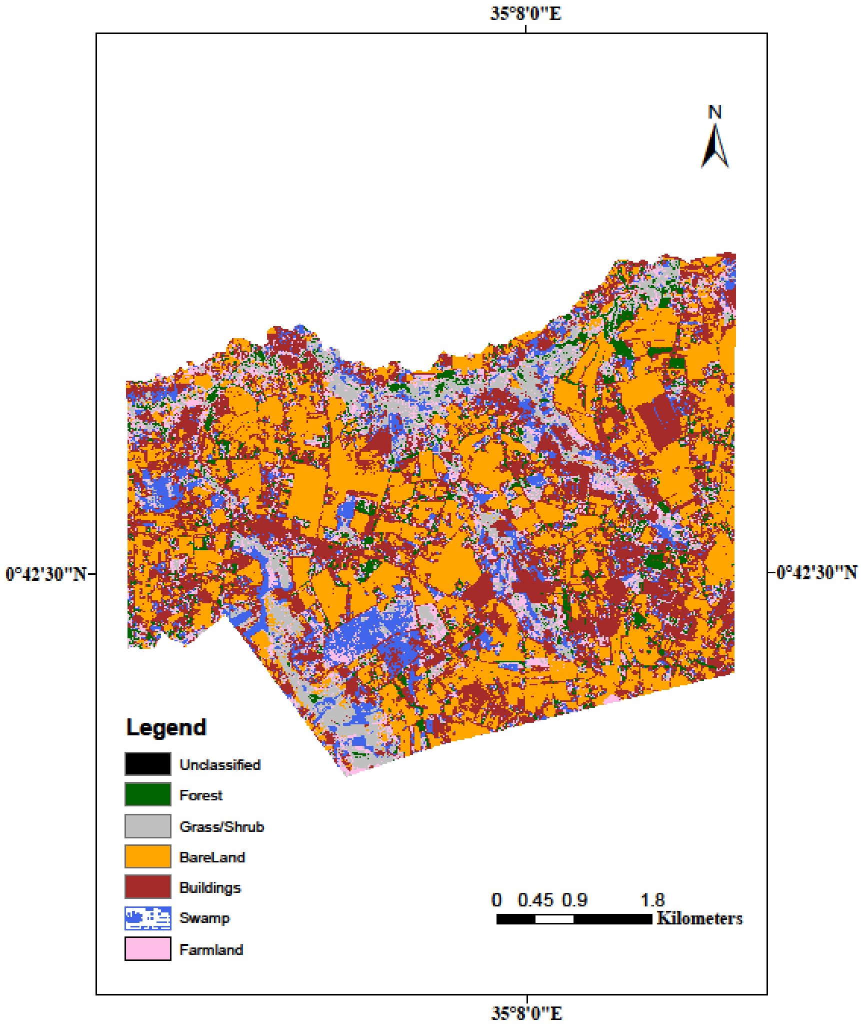

Figure 4.30: A Soy settlement scheme in 2017

Source: Sentinel 2A Likuyani image 2017

Figure 4.30 represents Soy settlement scheme classified map. Farmland cover was 8.34%, Bareland cover was 23.44%, Forest covered 4.15%, Buildings was mapped at 9.52%, Swamp covered 4.15% and Grass/shrub accounted for 22.82%. Buildings land cover was more pronounced in Soy settlement scheme raising from 6.94% in 2012 to 9.52% in 2017, an increase of 2.58%.

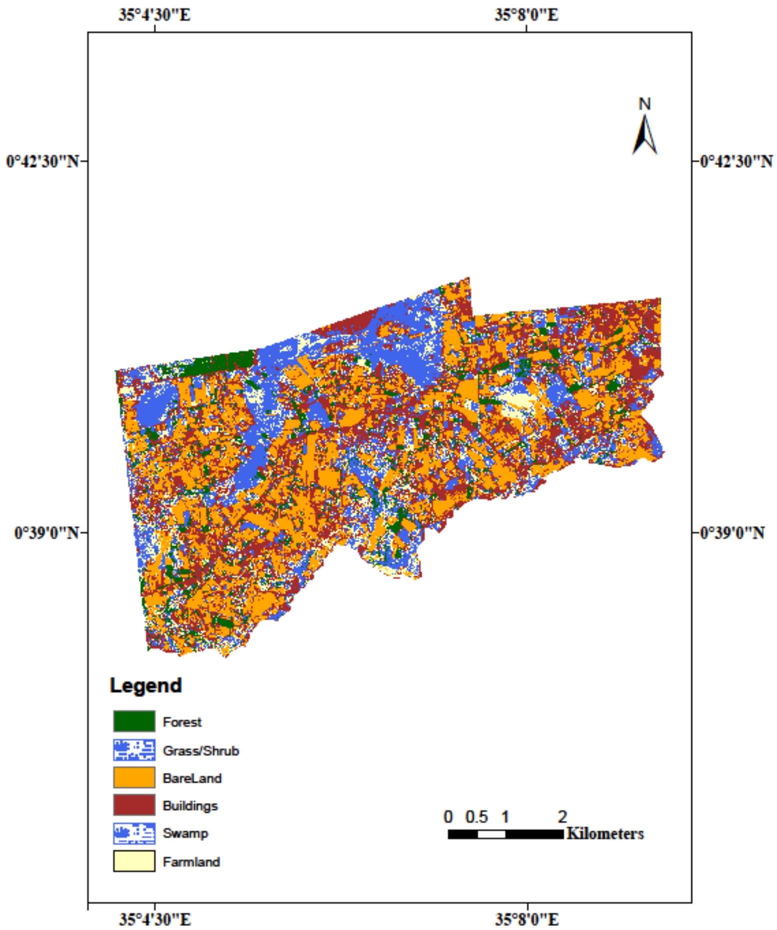

Figure 4.31: Sergoit Settlement scheme classified map 2017

Source: Sentinel 2A Likuyani image 2017

Figure 4.31, represents classified map of Sergoit settlement scheme in 2017. Land cover for Farmland was 12.35%, Bareland cover attributed for 22.67%, Forest cover was 8.01%, Buildings cover was 8.01%, Swamp cover was 3.78% and Grass/shrubs accounted for 21.98%.

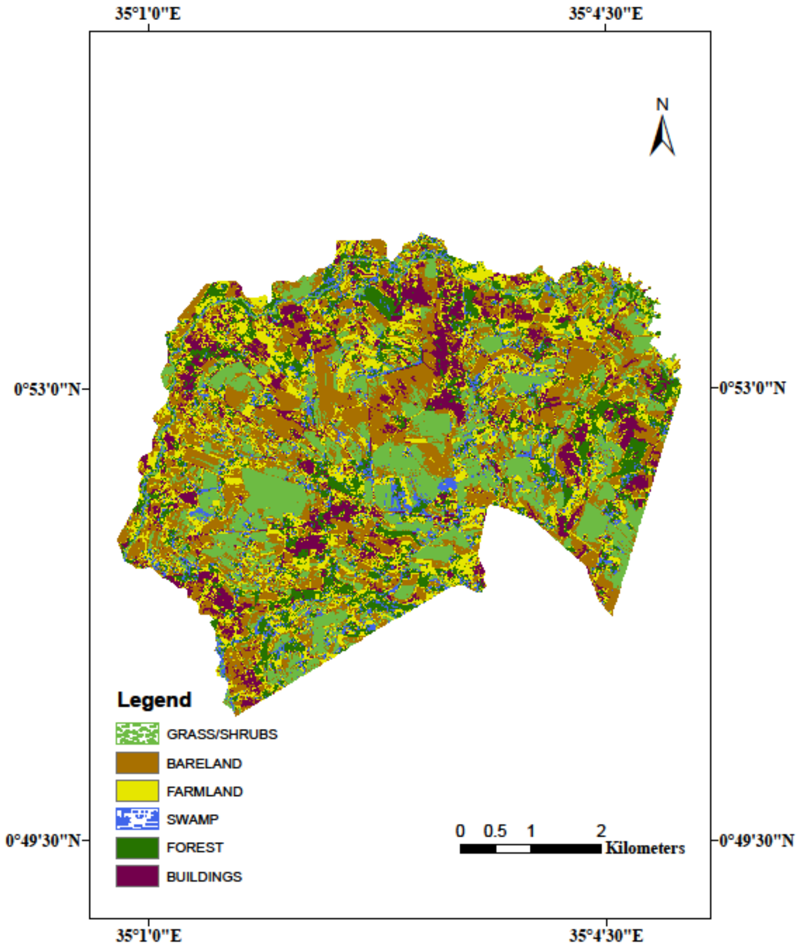

Figure 4.32: Nzoia settlement scheme classified map 2017

Source: Sentinel 2A Likuyani image 2017

Figure 4.32 represents the classified map of Nzoia settlement scheme in the year 2017. Farmland cover in Nzoia was 9.77%, Bareland covered 18.84%, Forest cover was 8.12%, Swamp covered 3.99%, Buildings land cover was 5.89% and

Grass/shrub was mapped at 25.41%.

4.2.11 Analysis of validity of hypothesis one

Land use land cover change from 1997 to 2017 was analyzed. To comprehend significant change if any, respondents were asked to indicate what land use changes were most prevalent in the area. Respondents representing 100% of the study population had witnessed LULCC in the study area. Response to land cover classes that LUMC changed to are captured in Table 4.9.

Table 4.9: Land use change

Response	No of Respondents	Percentage
Forest	21	7
Sugarcane	51	17
Buildings	214	75

Source: Researcher (2021)

Table 4.9 represents the number of respondents that indicate various land cover that has occurred in Likuyani Sub County from 1997 to 2017. Table 4.9 show that (21)7% of the respondents say they have observed land change from LUMC to tree plantation (planted Blue gum trees). (51)17% say they have observed land change from LUMC to sugarcane. Majority (214)75% of the respondents agree that Buildings has changed most of the land cover from LUMC to Buildings. This statistical outcome from the questionnaire and error matrix was analyzed in SPSS software to test hypothesis one. This results correlates with image analysis results and were used to test hypothesis one. The results imply there were significant land use change over the 20 year temporal span. The outcomes indicated in Table 4.9 provides an R-square value of 75%, suggesting that approximately 75% of the variance in the dependent variable (Land under maize cultivation) 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 cultivation. 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 4.10: 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)

Table 4.10 represent the tabulation for determination of spatiotemporal LULC in Likuyani Sub County.

Consequently, the outcome 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."

4.3 Evaluate SLULCC affecting different LCCS in respect to LUMC from 1997 to 2017

The primary objective of the study was to evaluate the impact of land use and land cover changes on different land cover classes by analyzing the percentage variations in each land cover category. From 1997 to 2017, an observable exchange occurred between areas classified as Farmland and Bare land. Ploughed Farmland was recognized as bare land, while un-ploughed land was identified as Farmland. These two classifications collectively constitute the land allocated for maize cultivation, 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 cultivation.

4.3.1 SLULCCs on LCCs between the years 1997 and 2002

Data from the 2002 categorized image of Likuyani sub County (Figure 4.5) 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 4.11. Table 4.11 represents land cover data for the years 1997 and 2002 and the percentage change for each classified class.

Table 4.11: Likuyani land cover change between the years 1997 and 2002

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					1.39	
Decrease	1.04	3.97	2.35	4.23		0.69

Source: Error matrix of 1997 and 2002

Data in Table 4.11, indicate there was a reduction in Forest and grass/Shrub cover by 1.04% and 3.97% respectively. Additionally, Bareland reduced by 4.23%, Farm/Land showed a reduction of 2.35%. Buildings cover increased by 1.39% while swamp cover reduced by 0.69%. Land under maize cultivation reduced by 6.58% within this period.

4.3.2 LULCCs on LCCs between the years 1997 and 2007

Impact of LULCCs on different land cover classes in respect to LUMC between the years 1997 and 2007 were analyzed. Land cover for the year 1997, 2002 and 2007 are presented in Table 4.11.

Table 4.12: Likuyani land cover classes for years 1997, 2002 and 2007

Year	Forest	Grass/Shrubs	Farmland	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
2007	10.87	10.72	21.22	20.83	7.69	4.00

Source: Error matrix of 1997, 2002 and 2007

Table 4.12 represents Likuyani Sub County land cover classes in percentage for the years 1997, 2002 and 2007. During this time span, Forest, Grass/shrub, Farmland and Bareland experienced decreased cover, Buildings cover had a constant increase while Swamp fluctuated. Increase in Buildings cover was as a result of increased population that led to more structures and conversion of forest and Grass/shrubs. Between 1997 and 2002, mature trees were harvested for timber (Records from KFS office). LUMC reduced by 6.58% from 1997 to 2002 and by 4.18 between 2002 and 2007. Buildings land cover had the highest negative impact on the other land cover classes while Swamp did not have any significant impact. The changes in LULC are summarized in Table 4.13.

Table 4.13: Percentage LCC between 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: Error matrix 1997 to 2007 image classification

Table 4.13 represents land cover changes that occurred in Likyuyani Sub County form 1997 to 2007 in percentage cover.

4.3.3 LULCCs on LCC between the years 1997 and 2012

Changes in land cover classes between the years 1977 and 2012 were analyzed, land cover extent is represented in Table 4.13. Forest cover was recorded to have increased from 2007 to 2012. GPS ground truething points confirmed planted blue gum trees on what was formerly cultivation land and Grass/shrub land cover. This coupled with ever increasing population impacted cultivation land and Grass/shrub land cover categories. Land under maize cultivation shows a contnues decline.

Table 4.14: Likuyani land cover classes for years 1997, 2002, 2007 and 2012

Year	Forest	Grass/Shrubs	Farmland	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
2007	10.87	10.72	21.22	20.83	7.69	4.00

2012	11.88	9.77	20.22	14.33	8.53	3.87

Source: Error matrix of 1997, 2002 and 2007

Table 4.14 represents percentage land cover in Likuyani Sub County in the years 1997, 2002, 2007 and 2012.

4.3.4 LULCCs on LCC between the years 1997 and 2017

Grass/shrub land cover experienced a pronounced increase from 1997 to 2017. From ground observation and GPS ground confirmation points, it was confirmed that some farmers had ventured into sugarcane farming. With the course spatial resolution of Landsat at 30 meters and Sentinel at 10 Meters, sugarcane was classified as Grass/shrub. This explains the upsurge in the Grass/shrub category. All the same Grass/shrub cover impacted LUMC negatively. Structures were coming up in LUMC due to land subdivision and population growth. Impact on LUMC was negative. The impact was measured by percentage increase or reduction. Spatiotemporal land use land cover change saw land under maize cultivation decline by a total of 13.96% from 1997 to 2017. Main land cover classes affecting LUMC were Buildings, planted Forest on cultivation land and introduction of sugarcane farming.

Data extracted from the error matrices, depicted in the bar chart presented in Figure 4.33, indicates that the Buildings category had the most substantial influence on land designated for maize cultivation. Figure 4.33 represents land cover classes for the years 1997, 2002, 2007, 2012 and 2017 in Likuyani Sub County.

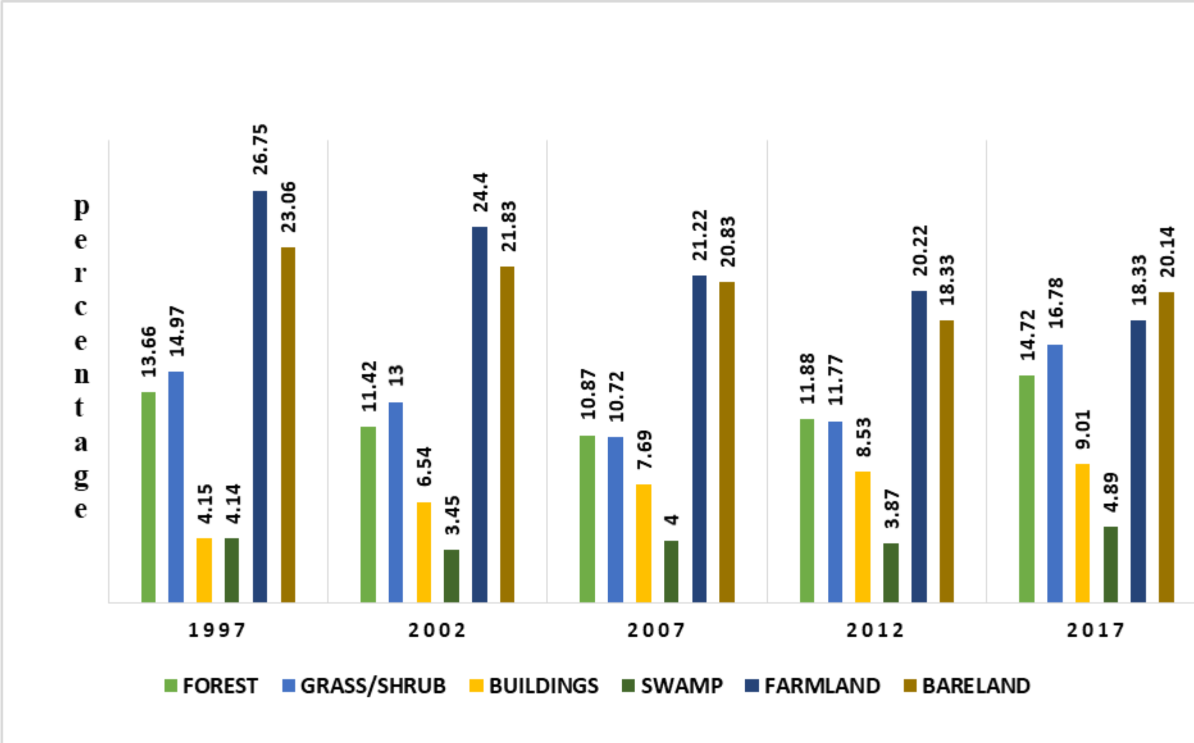

Figure: 4.33: Land cover in Likuyani from 1997 to 2017 at five year interval Source: Error matrixes for 1997, 2002, 2007, 2012 and 2017

Data from Figure 4.33 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, 125,137 in 2009 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. By 2017, the area under buildings increased in percentage cover to 9.01%, indicating the most substantial negative impact on land designated for maize cultivation. 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. Interestingly, the rise in forest cover was observed in areas previously categorized as Grass/Shrub and Farmland due to the continuous expansion of eucalyptus gum tree farming practices. During this period, Farmland decreased to 18.33%, while bare land decreased to 20.14%.

When considering the overall changes in Farmland and Bareland from 1997, there was a noticeable reduction in these two classes, which primarily represent areas utilized for maize cultivation. Moreover, the land cover under swamp increased by 0.75%, attributed to increased rainfall experienced in the preceding year (as observed in the field). Table 4.15 represents the land percentage land cover of each class for the years 1997, 2002, 2007, 2012, and 2017.

Table 4.15: Percentage land cover from 1997 to 2017

	FOREST	**GRASS/SHR**	**BUILDING**	**SWA**	**FARMLAN**	**BARELAN**
1997	13.66	14.97	4.15	4.14	26.75	23.06
2002	11.42	13	6.54	3.45	24.4	21.83
2007	10.87	10.72	7.69	4	21.22	20.83
2012	11.88	11.77	8.53	3.87	20.22	18.33
2017	14.72	16.78	9.01	4.89	18.33	20.14

Source: Error matrices for 1997, 2002, 2007, 2012 and 2017

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.

4.3.5 LULCCs on LCC In the settlement schemes from 1997 to 2002

Land cover change in the four settlement schemes: Sang, Soy, Sergoit and Nzoia for the years 1977 and 2002 are represented in Table 4.16.

Table 4.16: LCC from 1997 to 2002 in the settlement schemes

	Forest	Grass/Shrubs	Buildings	LUMC	Swamp
Sango	-2.33	-7.36	+1.10	+0.7	-2.22
Sergoit	-2.78	-2.48	+0.17	-7.46	-0.93
Soy	-2.64	-0.74	+1.66	-3.11	-2.23
Nzoia	-4.48	-10.05	0	+5.77	-3.14

Source: Researcher 2021

Table 4.16 represents land cover in percentage change in the four settlements schemes from 1997 to 2002. In Table 4.15, Land under maize cultivation (LUMC) is the sum of Bareland and Farmland. Changes in land cover are difference in percentage land cover. In Sango, there was an increase of 0.7% in LUMC. The rest of the classes reduced apart from Buildings which increased by 1.10%. This suggests there encroachment on Forest cover, Grass/shrub and Swamp as land was converted to farmland. Soy and Sergoit experienced a reduction in all land cover classes apart from Buildings that continued to increase. In Nzoia, there was significant raise in LUMC. All the other classes reduced, an indication that they were being converted to LUMC.

4.3.6 LULCCs from 1997 to 2007 in the four settlement schemes

In the Sango settlement scheme, 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 4.34 Represents forest cover changes between the years 1997 and 2007 in the four settlement schemes.

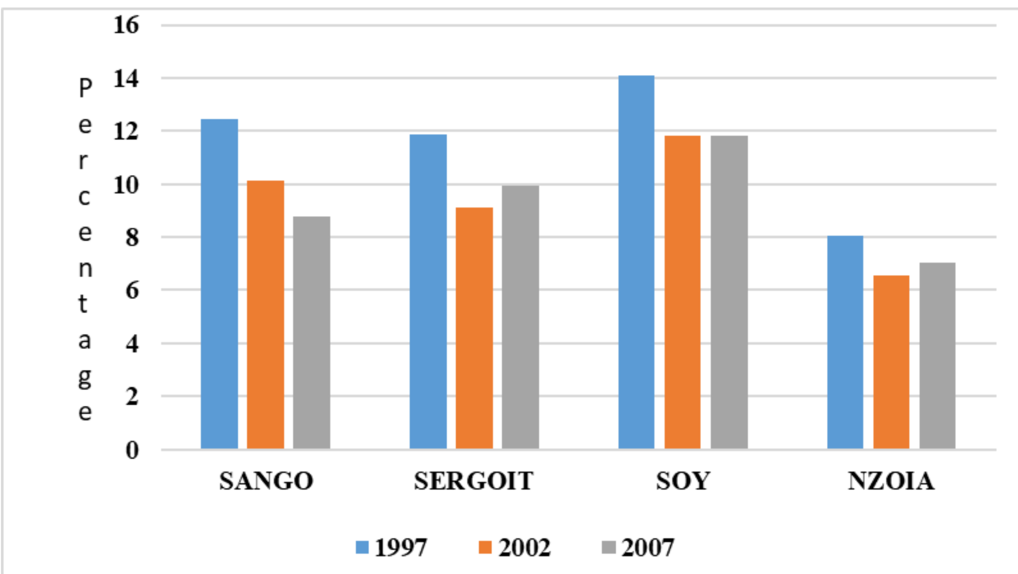

Figure 4.34: Forest cover from 1997 to 2007 in the four settlements.
Source: Error matrix 1997 to 2007 Landsat 5 and Landsat 7 image classification

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 AFA, (2020) revealed that the land was being converted to sugarcane cultivation. The software classified sugarcane as part of the Grass/Shrub category, explaining the increase in this land cover classification. Figure 4.29 represents Grass/shrub land cover changes in the four settlement schemes.

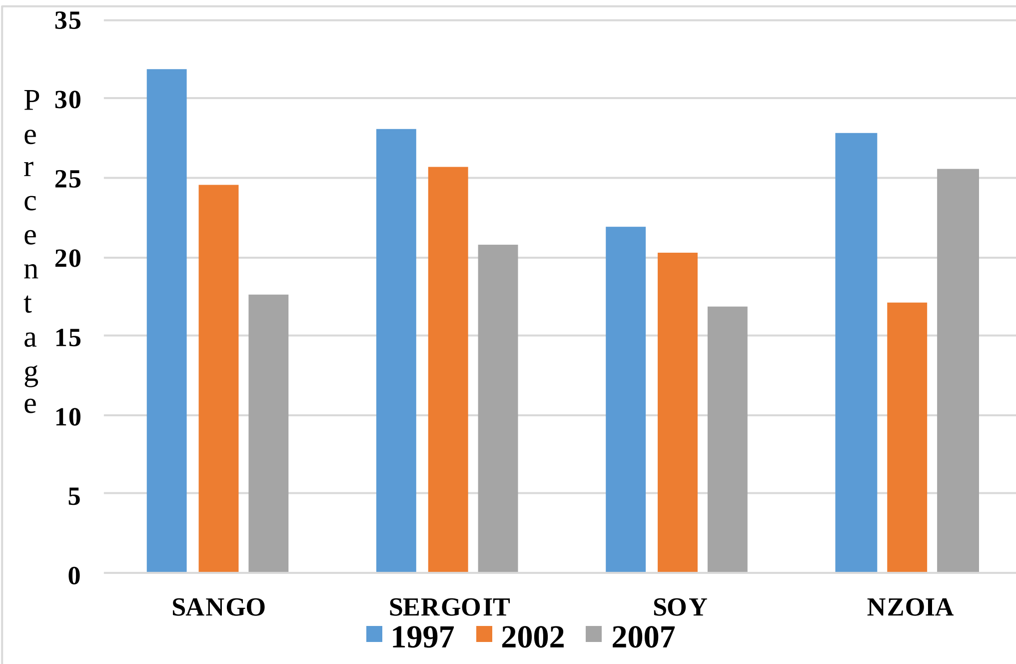

Figure 4.29: Grass/Shrub land cover changes between the years 1997 and 2007

Source: Error matrix 1997 to 2007 classification

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 4.36 represents details of the area under Buildings cover change for the period of fifteen years which begins from 1997 to 2007.

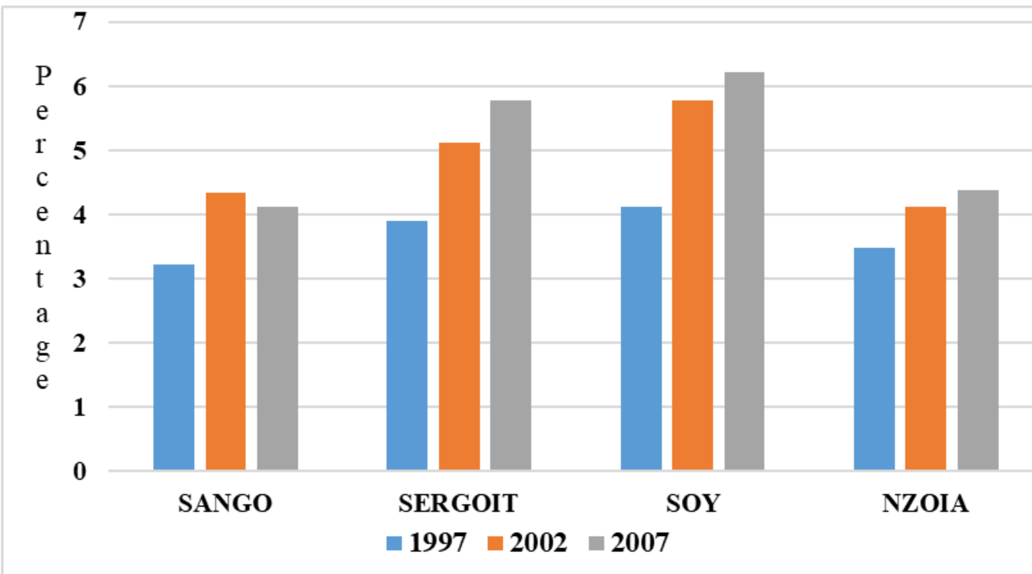

Figure 4.36: Building land cover from 1997 to 2007 in the four settlement schemes
Source: Error matrix 1997 to 2007 classification

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 ploughed farmland is represented by bareland. Un-ploughed, barren land will be designated as farmland at the same time.

There is a rise in bareland and a decrease in farmland in Sergoit. These two categories have decreased overall, which suggests that less land is being used for the cultivation of maize. Analysis of Sergoit Settlement, Soy, and Sango maps all exhibit the same situation.

4.3.7 LULCCs between 2007 and 2012 in the four settlement schemes

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 the causes for the noticeable increase in land cover in this category. All settlement schemes classification 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, LUMC decreased by 7.23% from 46% in 1997 to 38.22% in 2012. In Sergoit, LUMC increased by 1.01% from 40.01% in 1977 to 41.02% in 2012. There is a notable reduction in the Grass/Shrub category which is associated with sugarcane farming. Ground verification revealed sugarcane harvested fields were classified as Farmland thus giving raise to LUMC category. Notably, Soy experienced the highest loss in LUMC, dropping by 6.7% from 50.25% to 43.55%. This correlates with shape increase in Buildings which rose by 2.8% from 4.12% to 6.92% within the same period, an indicator of shape rise in population. Meanwhile, in Nzoia, LUMC decreased by 6.40% from 45.89% to 39.49% in the same period.

4.3.8: Land cover Changes in the four schemes between 1997 to 2017

In the four settlement schemes, land cover classes exhibited a fluctuating pattern from one settlement scheme to another. In all the four settlement schemes, Buildings land cover had an upward trend. Soy had the highest increase of 5.4% from 4.12% in 1997 to 9.42% in 2017. Its proximity to the highway (Eldoret-Kitale great North road) contributed to its attraction to land buyers who moved in to settle. Sergoit followed with an increase of

4.12% from 3.89% in 1997 to 8.01% in 2017. Sergoit's proximity to highway (Eldoret-Malaba road) also contributed to its growth in this land cove. Nzoia being further from ease of access from the major highways experienced the minimum growth from 4.11% in 1977 to 1.89% in 2017 being an increase of 1.78%.

Table 4.17: Buildings cover in percentage from 1977 to 2017

Year	Sango	Soy	Sergoit	Nzoia
1977	3.23	4.12	3.89	4.11
2002	4.33	5.78	5.11	4.23
2007	4.89	6.21	5.77	4.31
2012	5.23	6.94	6.78	4.57
2017	6.77	9.52	8.01	5.89

Source: Researcher 2021

Table 4.17 represents fluctuations in Buildings land cover in the four settlement schemes from 1997 to 2017. Buildings impacts LUMC negatively since construction takes place on the subdivided land on areas initially utilized for maize cultivation. Buildings goes in tandem with increase in population. Records from KBS indicated a rise in Likuyani's population from 91,210 in 1999 to 125,137 in 2019. This is directly associated with an escalation in settlement and a reduction in agricultural land.

Table 4.18: Response on farmers who had constructed on initial LUMC

Response	**Frequency**	**Percentage**
Yes	109	38.11
No	177	61.89

Source: Researcher 2021

Table 4.18 represents number of respondents on whether they had constructed on land that was initially used for maize cultivation. 109 of the respondents representing 38.11% agreed to have constructed on LUMC while 177% representing 61.89% had not. In this consideration, Buildings impacted LUMC negatively.

Table 4.19: Grass/shrub land cover in the four settlement schemes

Year	Sango	Soy	Sergoit	Nzoia
1977	31.87	21.95	28.11	27.82
2002	24.51	20.21	25.63	17.77
2007	17.66	16.88	20.76	25.60
2012	20.45	21.68	23.68	28.44
2017	22.77	22.82	21.98	25.41

Source: Researcher 2021

Table 4.19 represents Grass/Shrubs land cover fluctuations from 1977 to 2017 in the four settlement scheme. Grass/Shrub category fluctuated in all the schemes first reducing then but steadily increasing in Sango from 1977 through 2007, from 31.87% to 17.66% then increased to 20.45% in 2012 and to 22.77% in 2017. Soy had similar trends while Sergoit and Nzoia experienced a drop in the first five years. In 2012 Grass/shrub cover saw in increase from 20.76% to 23.68% in Sergoit and 25.60% to 28.44% in Nzoia. This was attributed to increase in sugarcane farming in the area. Field data analysis supports the increase in Grass/Shrub category as a result infiltration of sugarcane farming in the settlement schemes which was included in the Grass/shrub land cover. 286 respondents interviewed, 84 agreed they preferred to grow sugarcane representing 29.4% while 202 representing 70.6% did not agree had planted sugar cane.

Table 4.20: Response on those preferred to grow sugarcane

Response	Frequency	Percentage
Yes	84	29.4
No	202	70.6
Total	286	100

Source: Researcher 2021

Table 4.20 represents respondent's response on whether they preferred to grow sugarcane as opposed to growing maize. Since land is fixed in area, an increase in one land cover means a reduction in another land cover. In this case structures constructed on land for maize cultivation ultimately reduces this land. The main culprits in this case are Buildings and shift to sugarcane farming.

4.3.9 Trends in land cover changes

There are notable fluctuations in the land under maize cultivation over the years which have in turn affected maize production. Both farm land has been steadily reducing as shown in figure 4.26. This shows the interrelation between the two classes. Figure 4.26 is a graph showing the relationship between farmland and Bareland classes for the temporal study period.

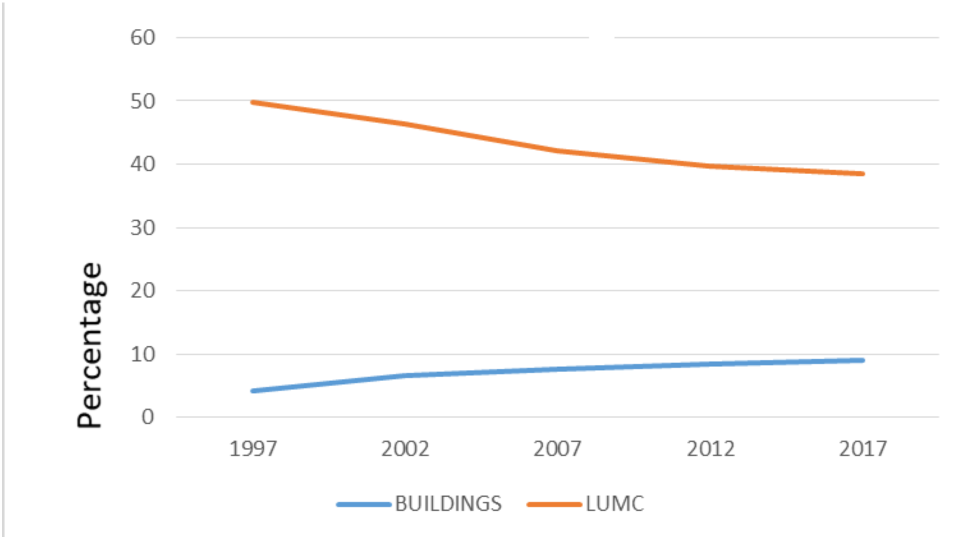

Figure 4.38: Comparison between LUMC and Buildings cover

Source: Field Data, 2021

Figure 4.38 represents the trends between Land under maize cultivation and buildings cover over the study temporal period. The two have an inverse interrelationship. There is a steady decline in LUMC and a steady increase in Buildings category.

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 as indicated in figure 4.26. Ground observations, data from AFA, and questionnaire results indicated the raise in Grass/Shrub class as a result of sugar cane being classified as Grass/Shrub. 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. The results indicate a future projection trend of 0.567% decline in land under maize.

4.3.10 Analyzing validity of Hypothesis two

The study sought to determine the validity of Hypothesis number two. Field data from respondent's questions on LULCC on land cover classes was coded and analyzed in SPSS software. The results are summarized in table 4.21**.**

Table 4.21 represents the tabulation of values for determination of coefficient of LULCC on other land cover classes.

Table 4.21: 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**:** Researcher 2021

Table 4.21 represents the tabulation of values for determining the significance of the Hypothesis two. Outcome illustrated in indicate an R-squared value of 55.9%, suggesting that approximately 55.9% of the variations in the dependent variable (Land under Maize cultivation) 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>0.05, which is 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."

4.4 Determinants influencing LULCC in maize cultivating areas from 1997 to 2017

4.4.1 Land Subdivision

The study aimed to assess determinants influencing LULCC in areas under maize cultivation in Likuyani Sub County from 1997 to 2017. This which included examining the extent of land subdivision within the area into parcels deemed unsuitable, (less than 50 square meters in size), for sustainable land under maize cultivation, market forces, socio economic influence and diversity in types of plants grown.

Utilizing digitized RIMs of the chosen four settlement schemes, valuable insights were obtained regarding the degree of land subdivision present in the region. Table 4.22 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 50 meters square per settlement scheme, and the percentage of subdivisions per settlement scheme.

Table 4.22: Settlement scheme distribution and allocation of land parcels

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: SOK Kakamega office

Table 4.22: represents number of Land parcels at inception, after subdivision, Number of parcels less than half an acre and percentage subdivision per settlement scheme. Data extracted from Table 4.22 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 50 square meters 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. The digitized land subdivision maps of the four settlement schemes offer a visual representation of the land subdivision patterns observed. Figure 4.32 entails land subdivisions from the initial 540 parcels to 1335 parcels in Sango scheme

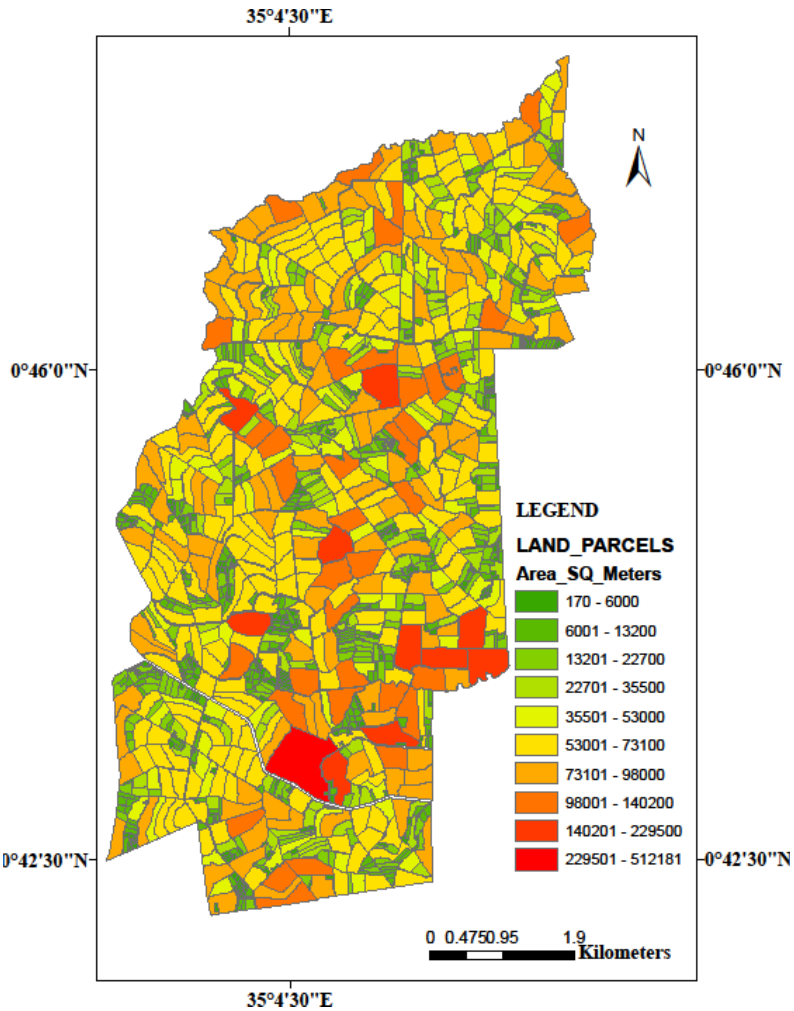

Figure 4.39: Sango settlement scheme Land subdivision map

Source: Researcher 2021

Figure 4.39 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 170 square 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. Figure 4.33 represents the map of Nzoia scheme after land subdivision from the initial 237 parcels to 412 parcels.

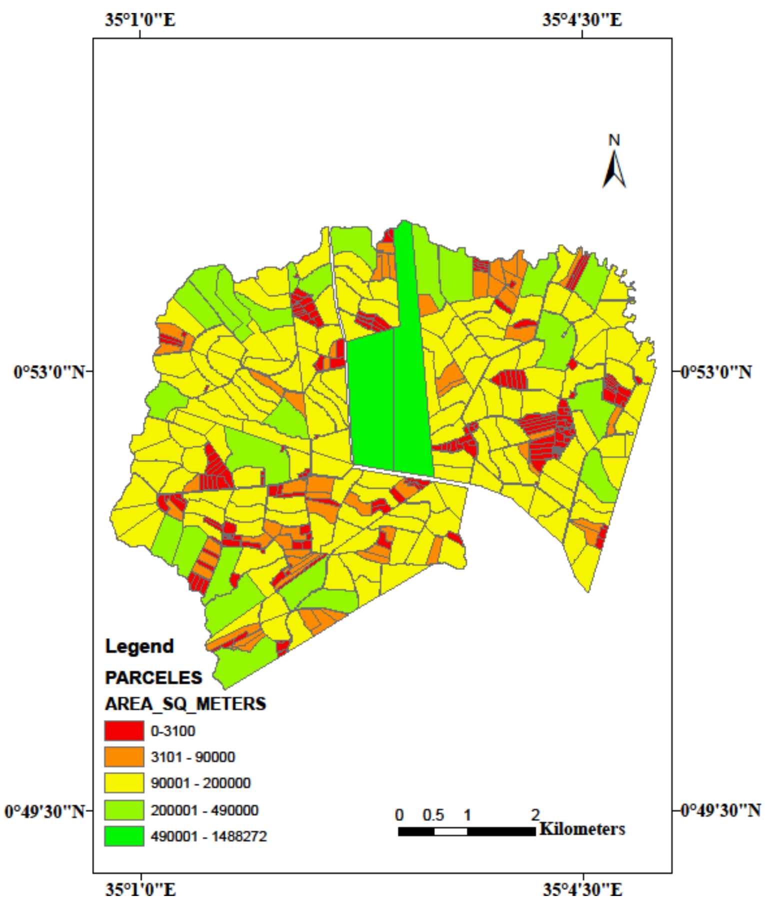

Figure 4.40: Nzoia settlement scheme land subdivision map

Source: Survey of Kenya RIM Maps 2021

Figure 4.40 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 less in number and those ranked in red as the smallest in area are mostly located along main roads.

Figure 4.34 represents the map of Sergoit settlement scheme after land subdivision from the initial 190 parcels to 926 parcels.

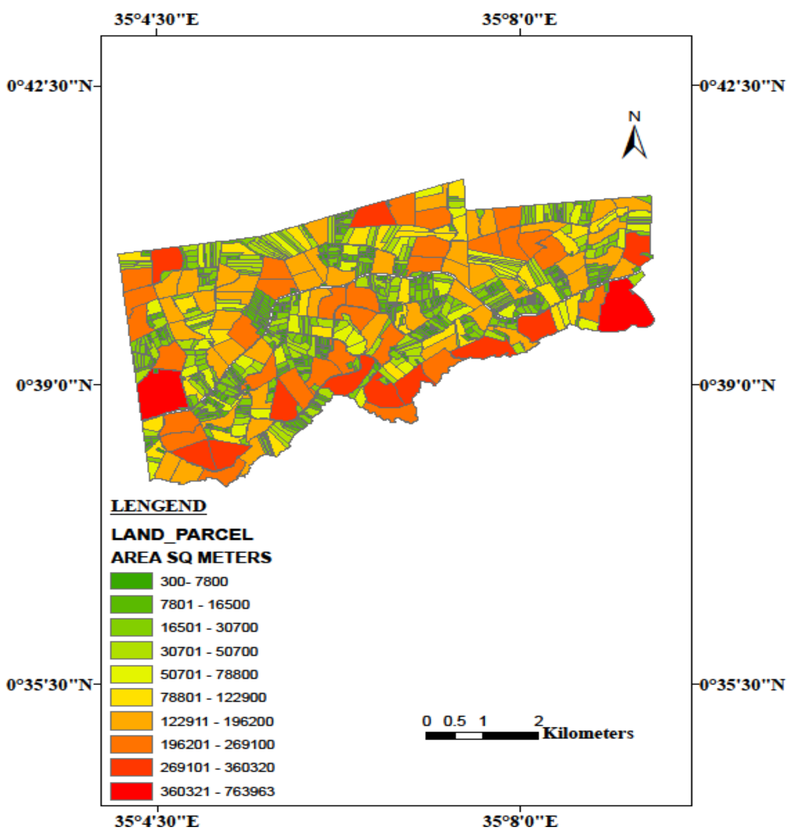

Figure 4.41: Sergoit Settlement Scheme Land subdivision map

Source: Survey of Kenya RIM Maps 2021

Figure 4.41 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 4.35 presents the map of Soy scheme after land subdivision from the initial 157 parcels to 821 parcels.

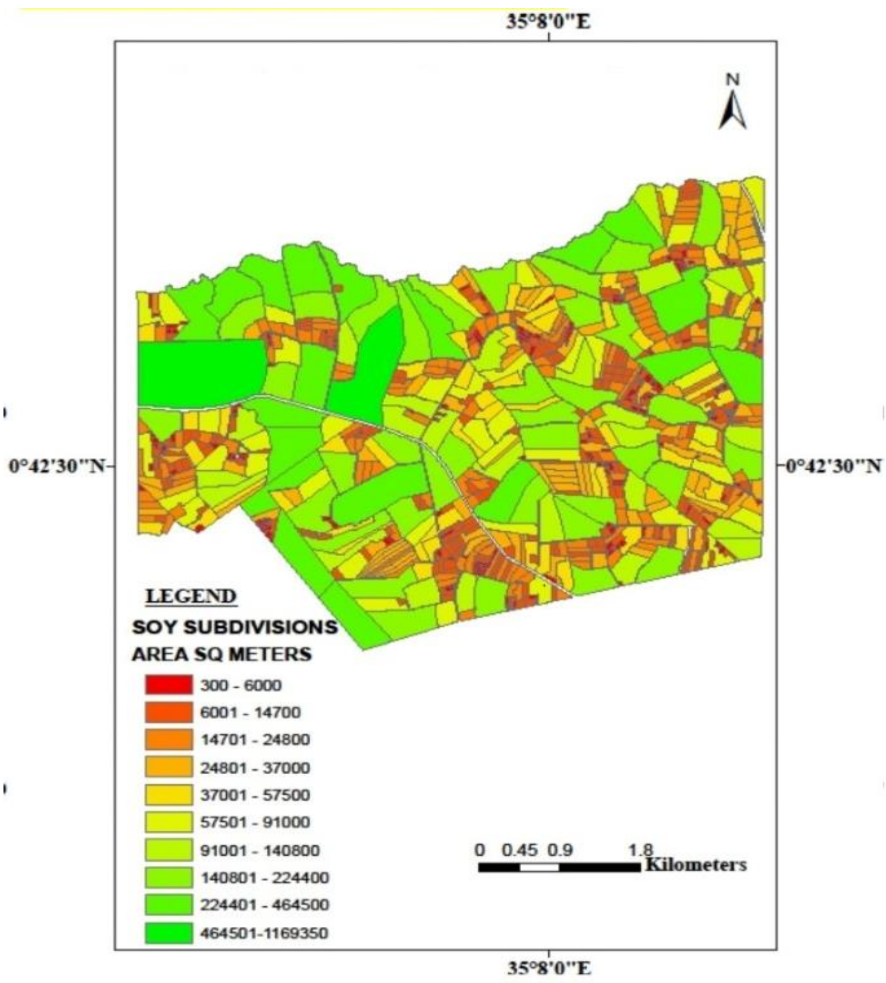

Figure 4.42: Soy Settlement Scheme land subdivision map
Source: Survey of Kenya RIM Maps 2021

Figure 4.42 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. 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 land under maize cultivation 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.

From the land subdivision map of Sango settlement scheme, it is 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 less than 50 square meters in size, rendering them unsustainable 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.

Table 4.23: Response on those who have subdivided their land

Response	**Frequency**	**Percentage**
Yes	271	94.8
No	15	5.2
Total	286	100

Source: Researcher 2021

Table 4.23 represents number and percentage of respondents on land subdivision. Land subdivision emerged as a significant driver of land use and land cover change, with 94.8% of respondents having subdivided their land for various purposes, including sales or family distribution, while 5.2% had not done so. Land subdivision impacts LUMC negatively in that after land is subdivided, the mew owner sets up residence on part of the land which results in reduction on the land under maize cultivation.

4.4.2: Socioeconomic Influence

Population increase in Likuyani Sub County has contributed to increase in land under structures and consequently reduction in land under maize cultivation. Family heirs shift to settle and build on different parts of the land parcel. Some end up selling part of their land parcel for diverse needs.

Table 4.24: Response on purpose for relocation on land

Response	No of respondents	Percentage
Heirs	102	35.6
Sold	44	15.4
Heirs and sold	140	49
Total	286	100

Source: Researcher 2021

Respondents interviewed on purpose for shifting to different parts of their land parcel, 102 representing 35.6% were heirs shifting to their allocated portion, 44 respondents representing 15.4% were new buyers while 140 were both new buyers and heirs.

4.4.3 Diversification in type of plants cultivated

The researcher sought to find out the type of plants the respondents have shifted to cultivating on their land that may lead to shift in area under maize cultivation. Table 4.25 represents results from respondents on type of plants cultivated by farmers in Likuyani Sub County.

Table 4.25: Types of plants cultivated

Plants	Frequency	Percentage
Maize	195	67
Eucalptus spp	36	12
Other crops	55	21
Totals	286	100

Source: Researcher 2021

Respondents interviewed 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 apart from maize (21%) cultivate other crops, (Fodder, Coffee, and Horticulture), whereas 36 respondents (12%) have planted *Eucalptus* spp trees and maize. This blue gum tree species 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.

4.4.3: Market Forces

Market forces play a pivotal in any given economy. Maize is a main cash crop in Likuyani Sub County. When the market praises are attractive most farmers are encouraged to put much of their land under maize. The opposite will happen when market praises drop. Results from respondents interviewed aided in analyzing how market forces were determining LULCC in Likuyani Sub County in respect to land under maize cultivation. Table 4.25 represents response on effects of market forces on maize cultivation in Likuyani Sub County.

Table 4.25: Effect of market forces on maize cultivation

Response	Frequency	Percentage
Unattractive market prices	157	54.9
Reduced yield	70	24.5
Competitive crops	33	11.5
Government policy	26	9.1

Source: Researcher 2021

Among the respondents interviewed, 157 (54.9%) gave reason for preferring to shift from maize cultivation to unattractive market prices which was blamed on cheap imports by the government. Reduced yield over the years was reason for 70 (24.5%) respondents preferring to try growing of other crops. 33(11.5%) of the respondents 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. Market forces is a determinant factor as it dictates what is favorable for farmers to grow which comes out as land cover change.

4.4.4 Regression analysis of Determinants influencing LULCC on land under maize

To analyze validity of hypothesis three, statistical data was retrieved from the questionnaire. 87.8% Respondent alluded land subdivision as the main cause in LULCC, socioeconomic factors, market factors and government policy. According to the study's findings and data assessment in SPSS software, variations in the dependent variable (land under maize cultivation) can account for roughly 83.6% of the variance in the independent variable (determinants of LULCC). This implies that 16.4% of the factors influencing LULCC 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 maize cultivation. Table 4.26 presents the regression analysis on the determinants of land use land cover changes on land under maize production.

Table 4.26: Regression analysis of causes of LULCC on land under maize cultivation.

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 cultivation										

Source: Data (2021)

Thus, the hypothesis that "There were no significant determinants influencing Land use land cover change on land under maize culitivation" was rejected.

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

5.2.1 Determine LULCC that occurred in Likuyani Sub County from 1997 to 2017

The study investigated land cover changes in Likuyani Sub County using Landsat 5, for 1997, Landsat 7, for 2002, 2007 and 2012 imagery. Sentinel 2A imagery for 2017, achieving a classification accuracy of 90.93% with a kappa coefficient of 0.8856 in 1997. The distribution of land cover classes in 1997 was as follows: Forest (13.66%), Grass/Shrub (14.97%), Bareland (23.06%), Buildings (4.15%), Swamp (4.14%), and Farmland (26.75%). The area under maize cultivation, represented by the combined percentages of Bareland and Farmland, totaled 49.81%. Land cover distribution for the years 2002, 2007 and 2012 were also quantified. In 2017 classification accuracy of 80.51% and a kappa coefficient of 76.24% were achieved. Land cover was as follows: Forest 14.72%, Grass/Shrub 16.78%, Buildings 9.01%, Swamp 4.89%, Farmland18.33%, and Bareland 20.14%. Land under maize cultivation was 38.47%. Noting significant impacts on local communities, such as poverty leading to sell and subdivision of land, climate fluctuations resulting in low yield that promote diversity from maize farming, and habitat destruction. Detailed land cover maps for different settlement schemes (Sango, Soy, Sergoit, and Nzoia) illustrated the distribution of various land cover classes.

5.2.2 Evaluate spatiotemporal LULCC affecting different land cover classes in respect to land under maize cultivation from 1997 to 2017

The study analyzed Land Use and Land Cover Change (LULCC) in Likuyani Sub County, using classified maps and error matrix analysis from 1997, 2002, 2007, 2012 and 2017. Ground visits and surveys further verified the findings. In 2002, the classified map indicated that the area was predominantly bare land (21.83%), with Farmland accounting for 24.4%. Forest cover was 11.42%, grass/shrubs 13.0%, buildings 7.54%, and swamps 3.45%. This distribution highlighted the region's extensive agricultural activities and ongoing land changes.

Analysis of the settlement schemes (Sango, Sergoit, Soy, and Nzoia) in 1997 and 2002 showed varying percentages of land use. Farmland ranged from 16.81% in Sergoit to 28.81% in Soy. Bare land was significant, particularly in Nzoia (32.89%). This pattern indicated extensive plowing and agricultural preparation. Swamp areas were minimal, with the largest swamp cover in Sergoit and the smallest in Sango. Building coverage was highest in Sango and lowest in Nzoia.

From 1997 to 2017, LULCC was influenced by land subdivision, population increase, and market factors. The R-square value of 80.2% from SPSS analysis indicated that 80.2% of the variance in land under maize cultivation could be explained by LULCC. The hypothesis test confirmed significant land use changes over this period. Between 1997 and 2002, there were notable shifts: forest and grass/shrub cover decreased, while bare land and farmland increased. Buildings and swamps also saw slight increases. This period saw a rise in building areas, correlating with land subdivision data.

By 2007, the land cover in Likuyani showed continued changes. Forest cover was 10.87%, farmland 21.22%, grass/shrubs 10.72%, swamp 4%, bare land 20.83%, and Buildings cover 7.69%. The classification accuracy for 2007 was 76.26%, indicating reliable data. The dynamics between 1997, 2002, and 2007 revealed a decrease in farmland and grass/shrubs, with an increase in buildings. Swamp cover remained relatively stable. These changes reflected population growth and urban expansion.

In 2012, Likuyani's land cover data showed continued trends. Forest cover rose to 12.72%, grass/shrubs 9.77%, buildings 8.53%, swamp 3.87%, farmland 20.22%, and bare land 14.33%. The increase in Buildings cover corresponded with population growth and land subdivision activities. Farmland decreased, while bare land fluctuated due to plowing activities. Grass/shrub cover also increased, mainly due to sugarcane cultivation. Statistical data from respondents revealed that approximately 55.9% of the variation in land under maize cultivation was due to LULCC, with the remaining 44.1% influenced by other unaccounted factors.

5.2.3 Asses the determinants influencing LULCC in the maize-producing areas of Likuyani Sub County from 1997 to 2017

The study analyzed the determinants influencing LULCC in land under maize cultivation from 1977 to 2017. The main factor was land subdivision. Subdivided land encouraged new developments on cover, significant being buildings that replace the maize cover. Land subdivision maps of Sango, Soy, Sergoit and Nzoia were analyzed in in detail through application of GIS SQL that brought-out very small subdivided land parcels unsustainable for sustainable maize production. Market forces played an important role in a determinant influencing LULCC. Respondents interviewed 54.9% agreed LUMC is influenced by market forces. Better prices encouraged putting more land under maize. Reduction in maize yield over the years, introduction of competitive crops with better market prices like sugarcane, horticulture and fodder, influenced reduction in land under maize cultivation. Government interventions like fertilizer subsidies, cheap maize imports during harvest plays a role in determining maize cultivation. 9.1% of the respondents interviewed agreed that Government policy did influence maize cultivation. Regression analysis on determinants influencing LULCC from SPSS data analysis indicated variations in dependents variable land maize cultivation accounts for roughly 83.6% of the variance variable (determinants influencing LULCC). Moderating term p of 0.07>0.05 implies the hypothesis "There were no significant determinants influencing LULCC on maize producing areas between the years 1997 to 2017 in *Likuyani* sub-county" does not hold.

5.3 Conclusions

5.3.1 Determine LULCC that occurred in Likuyani Sub County from 1997 to 2017,

The study effectively classified land cover in Likuyani Sub County using Landsat 5, Landsat 7 and Sentinel 2A imagery, providing understandings into land cover distribution and maize cultivation areas from error matrix computation of classified imagers. However, the coarse resolution of Landsat and Sentinel 2A sensors limits their effectiveness in extracting detailed crop cover. The study was limited to the period from late December to early March, missing seasonal variations. It did not compare the performance of different sensors in detail or delve deeply into specific socioeconomic drivers of land use changes.

Additionally, the study only utilized data from 1997 to 2017, lacking long-term trends and recent data to understand ongoing impacts on land cover changes. Future research should address these gaps to enhance the understanding and management of land use dynamics.

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.

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 significant.

5.3.2 To Evaluate SLULCC on various LC classes in Likuyani sub-county from 1997 to 2017

The study's findings underscore significant land use changes in Likuyani Sub County over the past decades, driven by agricultural activities, population growth, and land subdivision. The data reveals a dynamic landscape with shifting patterns in forest cover, farmland, grass/shrubs, and buildings. . This study showcased the effectiveness of utilizing remote sensing and GIS to bring out issues stemming from shifts in land use and cover change. GPS data and direct observations facilitated the validation of ground information. While the study identifies population growth and market factors as influences on various land cover classes, a more detailed analysis of socioeconomic variables could provide deeper understandings into these changes.

5.3.3 Asses the determinants influencing LULCC in the maize cultivating areas 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-count. The study concludes that the main determinants influencing land use land cover change in Likuyani Sub County are: Population growth which comes with urbanization and land subdivision, market forces that bring about diversity in crops grown, socioeconomic influence, Government policy and agricultural practices. However, the study primarily focuses on quantifiable land cover changes but lacks a deeper investigation into the socio-economic drivers behind these changes leaving room for future research to address these gaps.

5.4 Recommendations

5.4.1 Determine LULCC that occurred in Likuyani Sub County between 1997 and 2017

To comprehensively address the land use and land cover changes (LULCC) that occurred in Likuyani Sub County between 1997 and 2017, the study recommends establishing a continuous monitoring system will also help track changes in real-time, enabling timely interventions to mitigate adverse effects on local communities and the environment and Collaborative efforts with local authorities and stakeholders will be crucial to ensure that land use policies and practices are sustainable and aligned with the community's needs.

5.4.2 To evaluate spatiotemporal LULCC affecting different land cover classes in

respect to land under maize cultivation from 1997 to 2017

To evaluate the spatiotemporal LULCC affecting different land cover classes concerning land under maize cultivation, the study recommends the integration of Geographic Information System (GIS) tools with advanced statistical and machine learning models. This integration will allow for a more nuanced analysis of land cover dynamics and their correlation with socio-economic and environmental factors.

5.4.3. To assess the determinants influencing LULCC in the maize-producing areas of Likuyani Sub County from 1997 to 2017

To explore the determinants influencing LULCC in maize-producing areas, the study recommends conducting detailed case studies and interviews with local farmers, policymakers, and other stakeholders will provide insights into the socio-economic, cultural, and environmental factors driving LULC and promoting policies that support sustainable land management practices and incentivizing the cultivation of maize and other essential crops can help balance agricultural productivity with environmental conservation

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 impact of increased sugarcane farming on land used for maize production.
ii. Using high spatial resolution imagery, evaluate how land subdivision and population growth in the rural areas is affecting land under food cultivation.
iii. Examine impact of socioeconomic factors on land policy in maize cultivation regions

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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 SPATIOTEMPORAL LAND USE/LAND CHANGE COVER ON LAND UNDERMAIZE CULTIVATION IN LIKUYANI SUB COUNTY

1, Select your age group:

40 and below ☐ 41 – 50 ☐ 51 – 60 ☐ Above 61 ☐

2, How did you acquire the piece of land you currently live in?

Inheritance ☐ Purchase ☐ Other ☐

3, How long you been owning the farm?

10 years and below ☐ 11 to 30 years ☐ Over 30 years ☐

4, Have you constructed on what as initially LUMC

Yes ☐ No ☐

5, Do you prefer to cultivate sugarcane instate of maize

i, Yes ☐ ii, NO

6, For how long have you been cultivating maize?

i, 10 years and below ☐ ii, 10 to 30 years iii, Over 30 years

7, Did you at one point prefer any other crop cultivation other than maize?

Yes ☐ No ☐

If yes, why did you prefer other crops?

1, more profit. ☐

3, Maize harvest has reduced ☐

4, Need to venture in new crops. ☐

8, Which plants would you prefer to cultivate instate of maize?

1, Blue gum Trees, ☐

2, Sugar cane ☐

9, Have you subdivided your land for relocation?

Yes ☐ No ☐

If yes, what purpose? ☐

1, To family heirs ☐

2, Sold ☐

3, Family heirs and sold ☐

10, How many acres of land did you cultivate before the decision 8.

1, Under 5 acres ☐

2, 5 to 10 acres ☐

3, 10 to 20 acres ☐

4, More than 20 acres ☐

How many acres of land are you currently cultivating?

Under 5 acres ☐ 5 to 10 ☐ 10 to 20 20 acres and above ☐

11, Have you increased or reduced acreage under maize cultivation?

a) Reduced ☐ b) Increased ☐

If reduced, explain ☐

1, Subdivided part of the land ☐

2, ventured into other crops ☐

3, Left the land idle ☐

12, 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)

1, Very likely ☐

2, More likely ☐

3, Less likely ☐

4, Not likely ☐

12, What is making maize farming unpopular

1, Poor market praises ☐

2, Reduced yield ☐

3, Other competitive crops ☐

4, Poor government policy ☐

13, Are you witnessing any land use change in your area?

Yes ☐ No ☐

If yes to what cover

1, Forest ☐

2, Sugar Cane ☐

3, Settlement ☐

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

1, Half acre, ☐

2, One acre ☐

3, One and half acre ☐

15, Have you witnessed any changes in land cover since 1997 to date.

1, Yes ☐

2, No ☐

16, Among the elements mentioned, which one causes a major shift in land under maize cultivation?

1, Land subdivision ☐

2, Population increase ☐

3, Market forces ☐

QUESTION	Number of respondents		Percentage
4	Yes	109	38.11
	No	177	61.89
5	Yes	84	29
	No	206	71
6	i	251	87.8
	ii	22	7.8
	iii	13	4.4
7	Yes	9	30
	No	200	70
	1	228	80
	2	20	7

	3	37	13
8	1	9	3
	2	277	97
9	Yes	271	95
	No	14	5
	1	102	36
	2	43	15
	3	140	49
10	1	23	8
	2	180	63
	3	71	25
	4	11	4
11	a	240	84
	b	45	16
	1	251	88
	2	31	11
	3	6	2
12	1	157	54.9
	2	70	24.5
	3	33	11.5
	4	26	9.1
13	1	54	19
	2	143	50
	3	68	24
	4	17	6
14	Yes	286	100
	1	31	11
	2	9	3
	3	246	87
15	1	3	1

	2	23	8
	3	260	91
16	Yes	119	93
	No	20	7
17	1	157	55
	2	71	25
	3	48	17

APPENDIX 111: 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

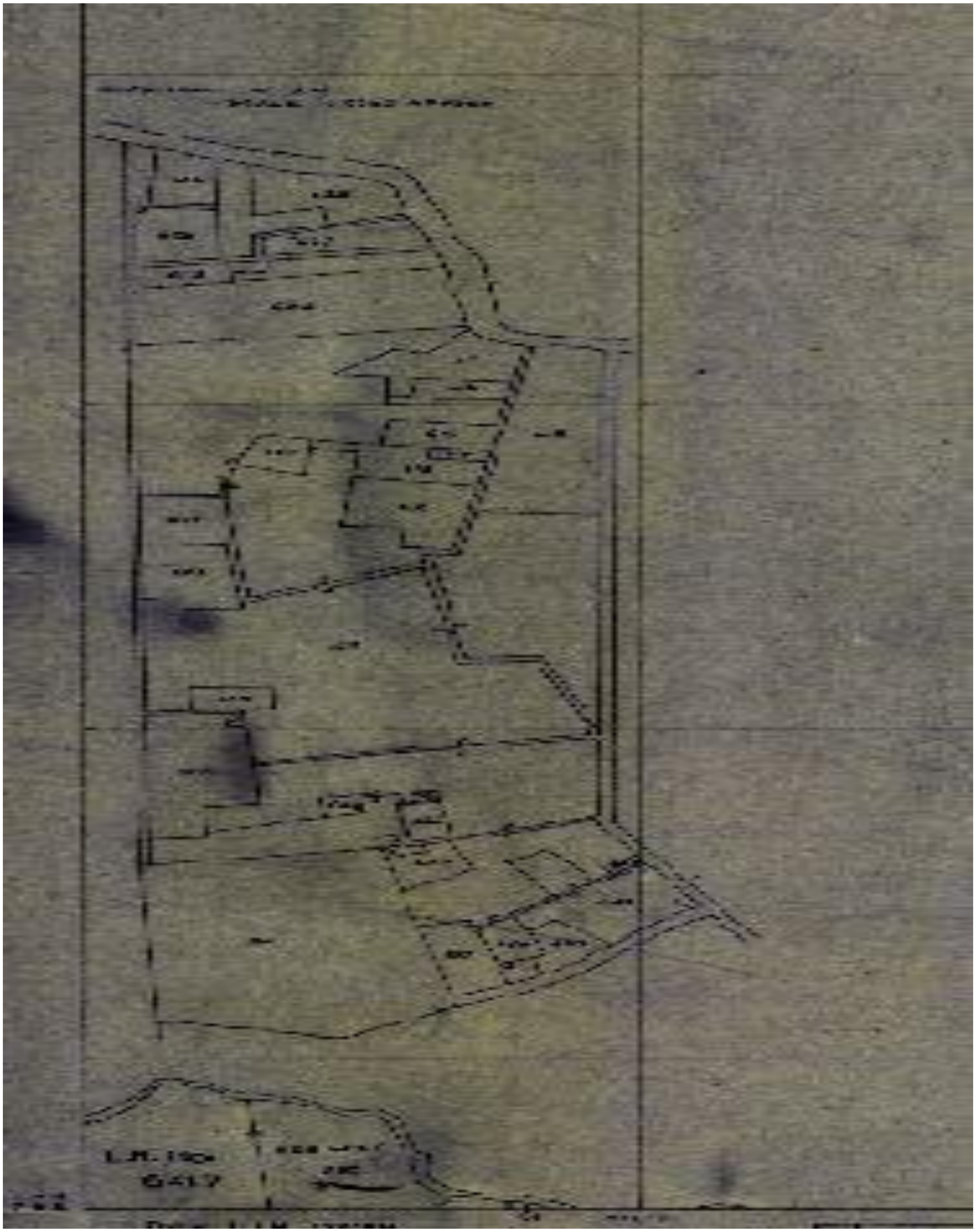
2015 1727 TONS

2016 6444 TONS

2017 5304 TONS

2018 2564 TONS

APPENDIX: 1V Nzoia RIM sheet 2



APPENDIX V: Part of Nzoia RIM Sheet3

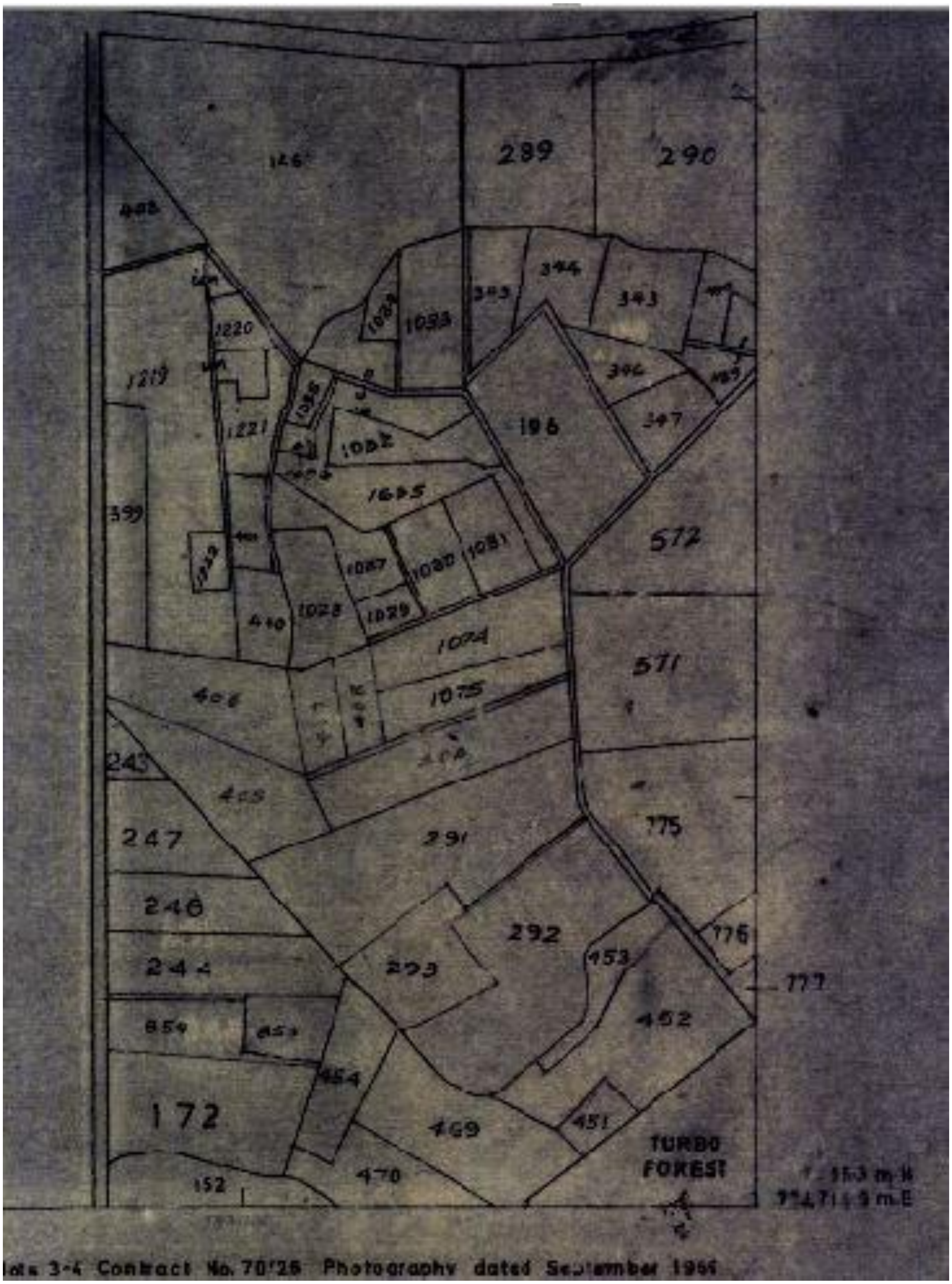
APPENDIX VI: part of Nzoia rim **sheet 1**

APPENDIX VII: Part of Sango Sheet 1

APPENDIX V111: Part of Sango sheet 2

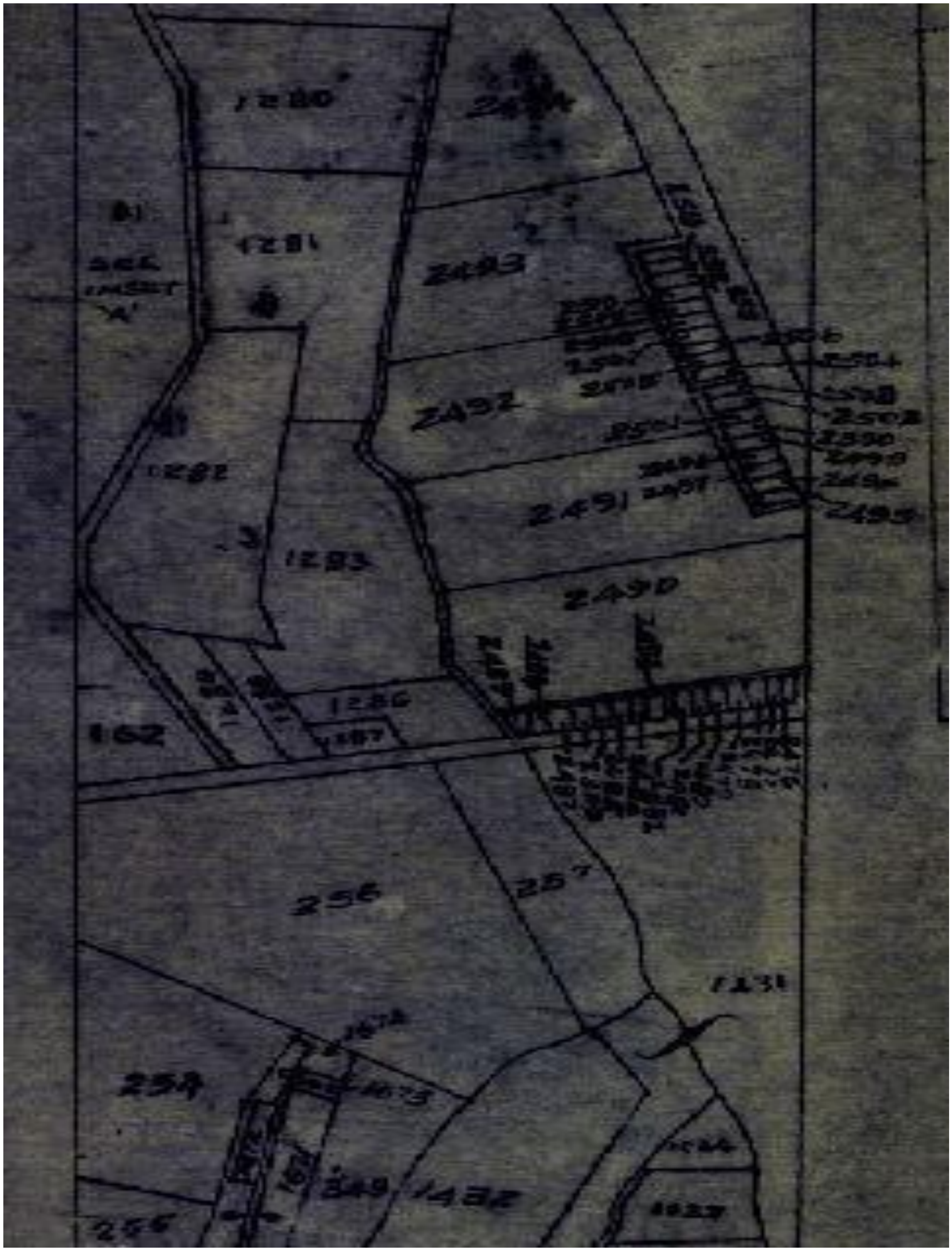
APPENDIX 1X: PART OF SANGO SHEET 3

APPENDIX X: PART OF SOY SHEET 1



APPENDIX XI: PART OF SOY SHEET 2

APPENDIX XII: PART OF SOY SHEET 3

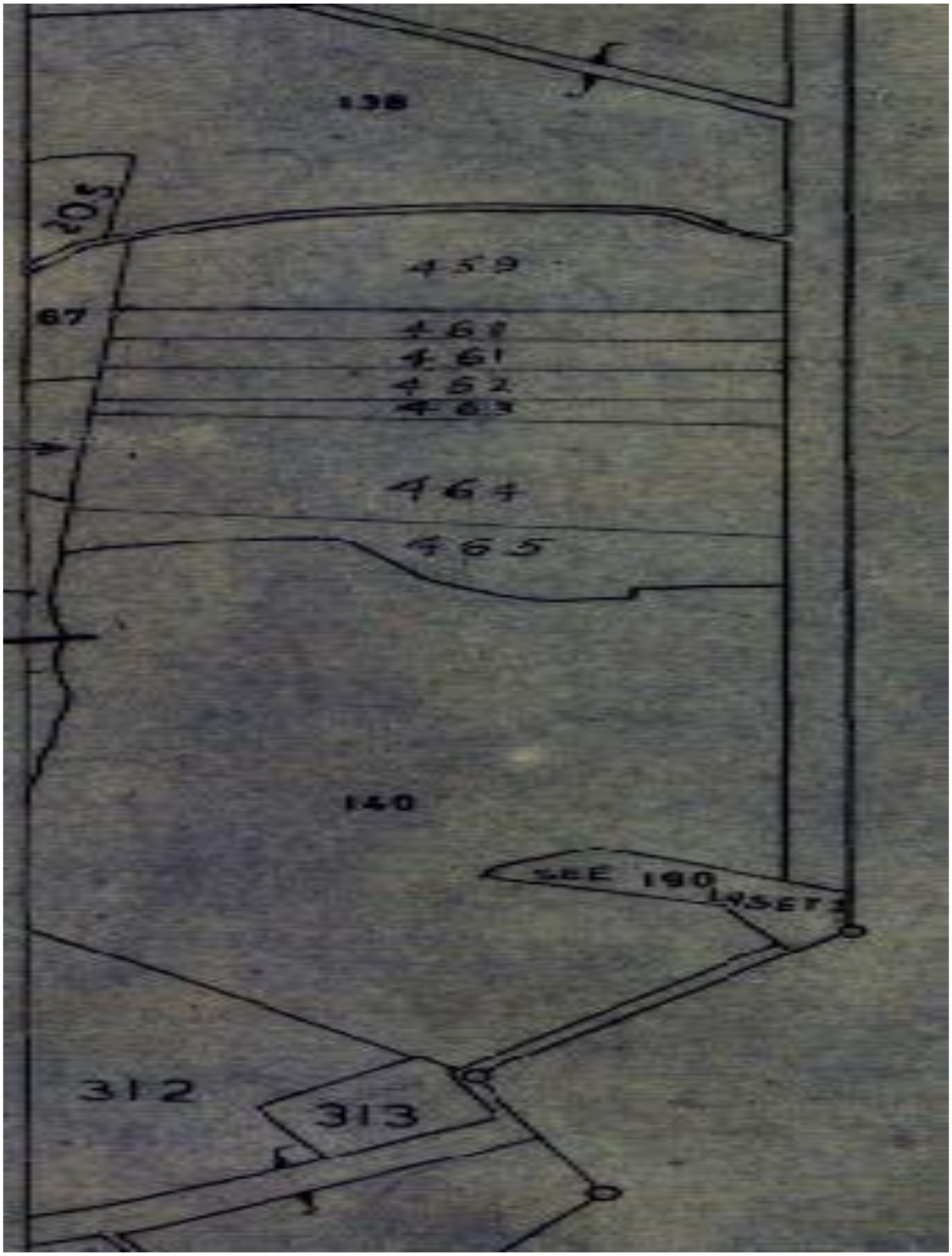


APPENDIX XI11: PART OF SOY SHEET 4

APPENDIX 1V: PART OF SERGOIT SHEET 1

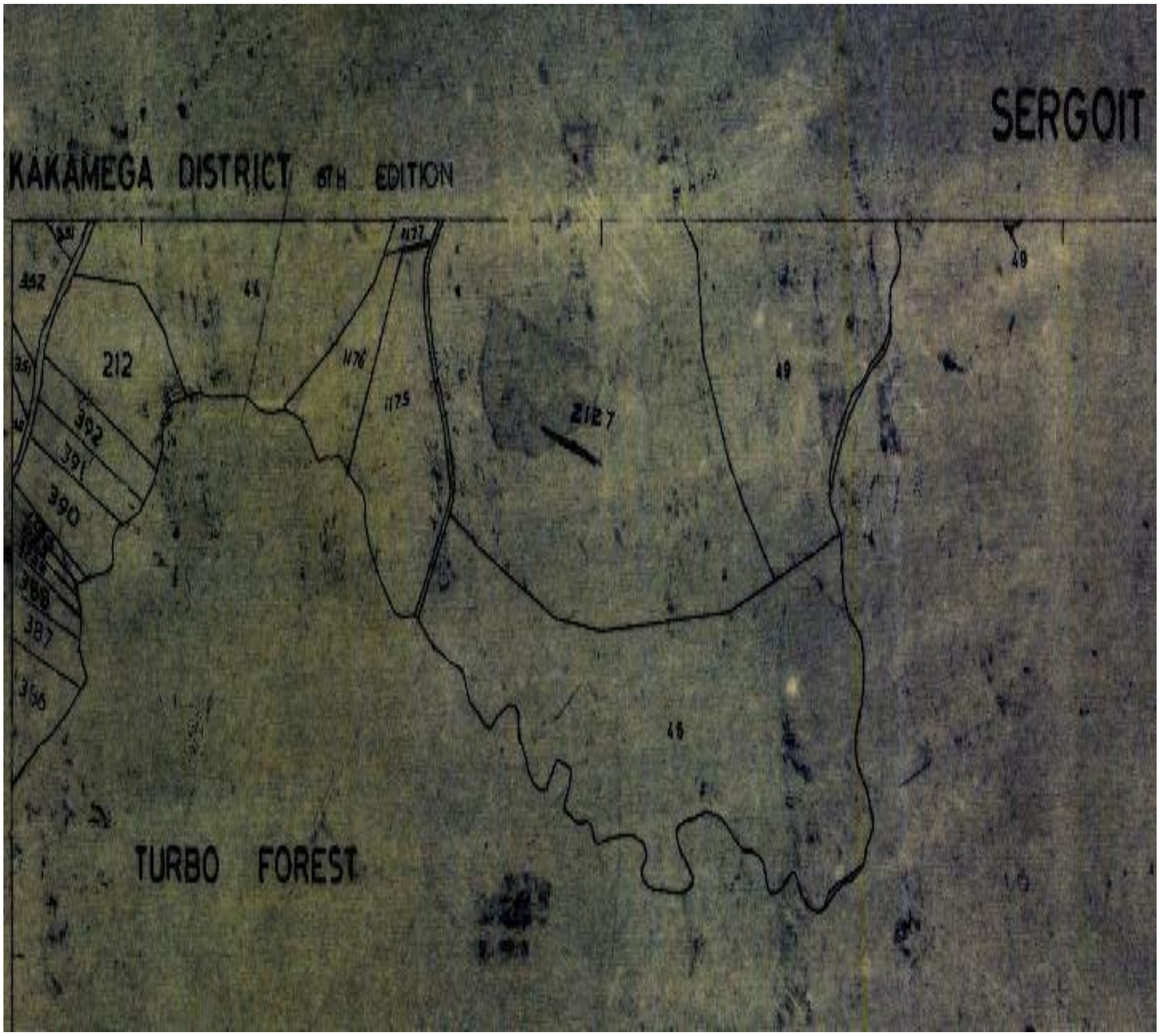
APPENDIX XV: PART OF SERGOIT SHEET 2

APPENDIX XVI: PART OF SERGOIT SHEET 3



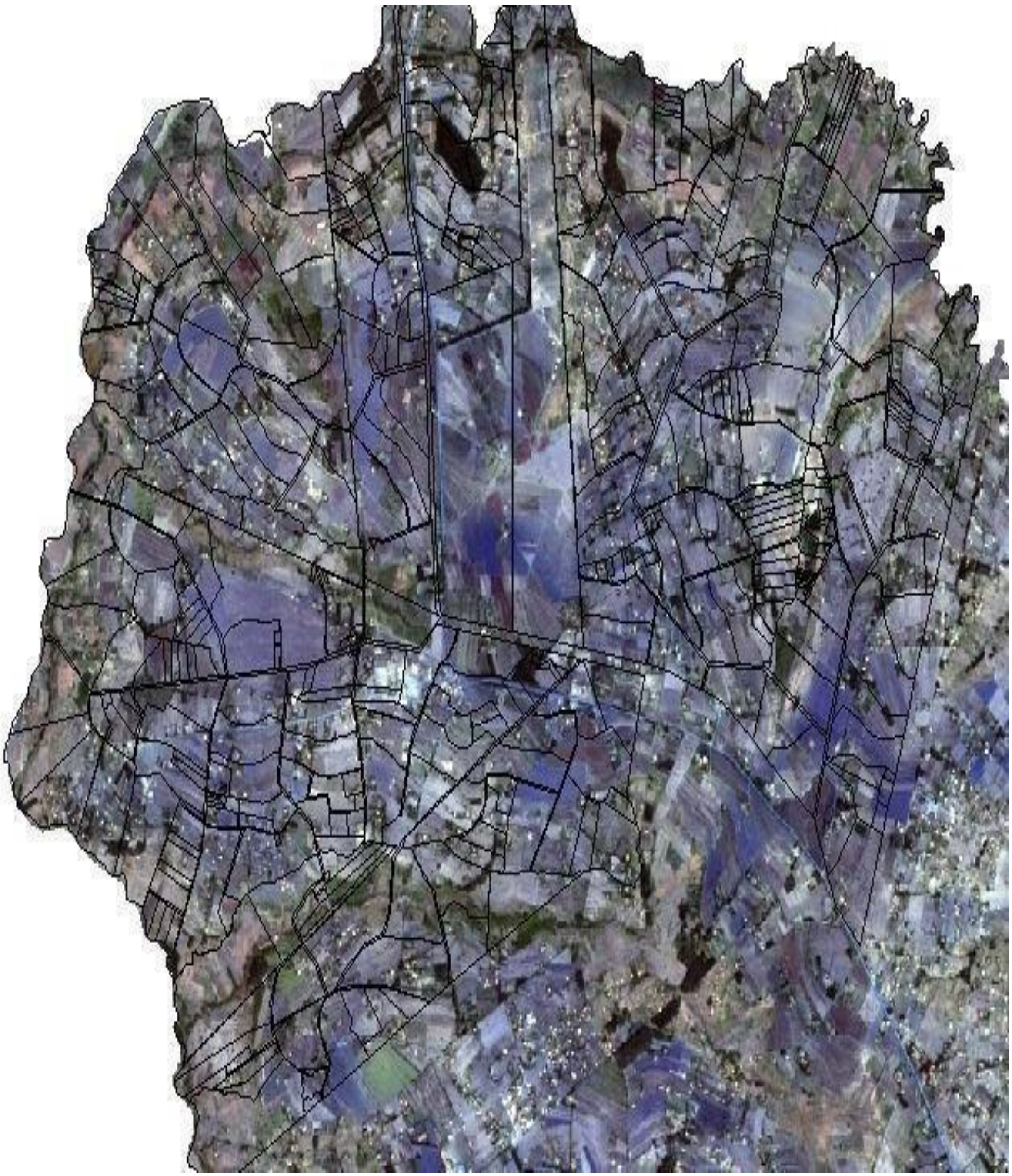
APPENDIX XVII: PART OF SERGOIT SHEET 4

APPENDIX XI11: PART OF SERGOIT SHEET 5

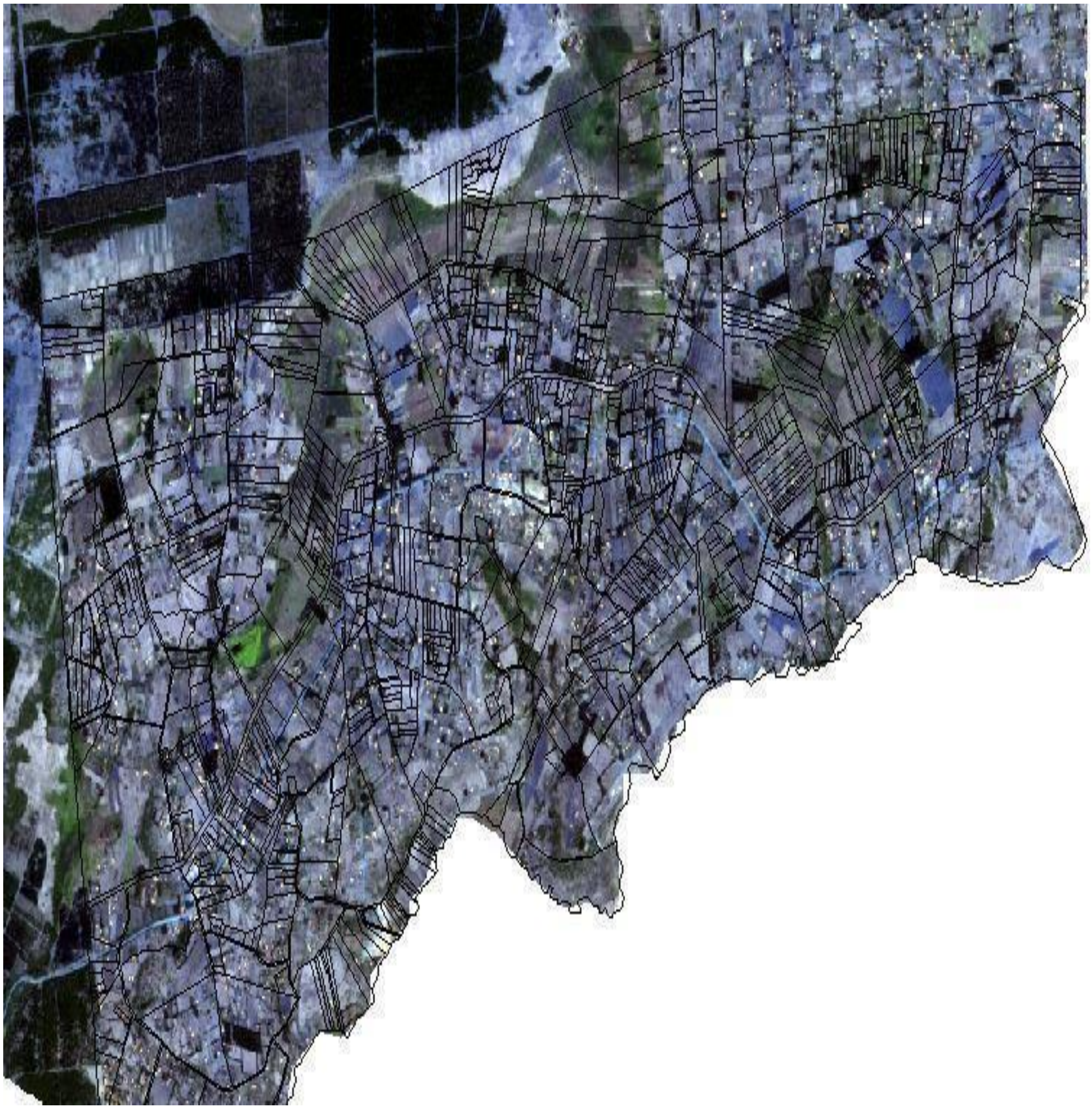


APPENDIX XIX: DIGITIZED SOY SETTLEMENT SCHEME

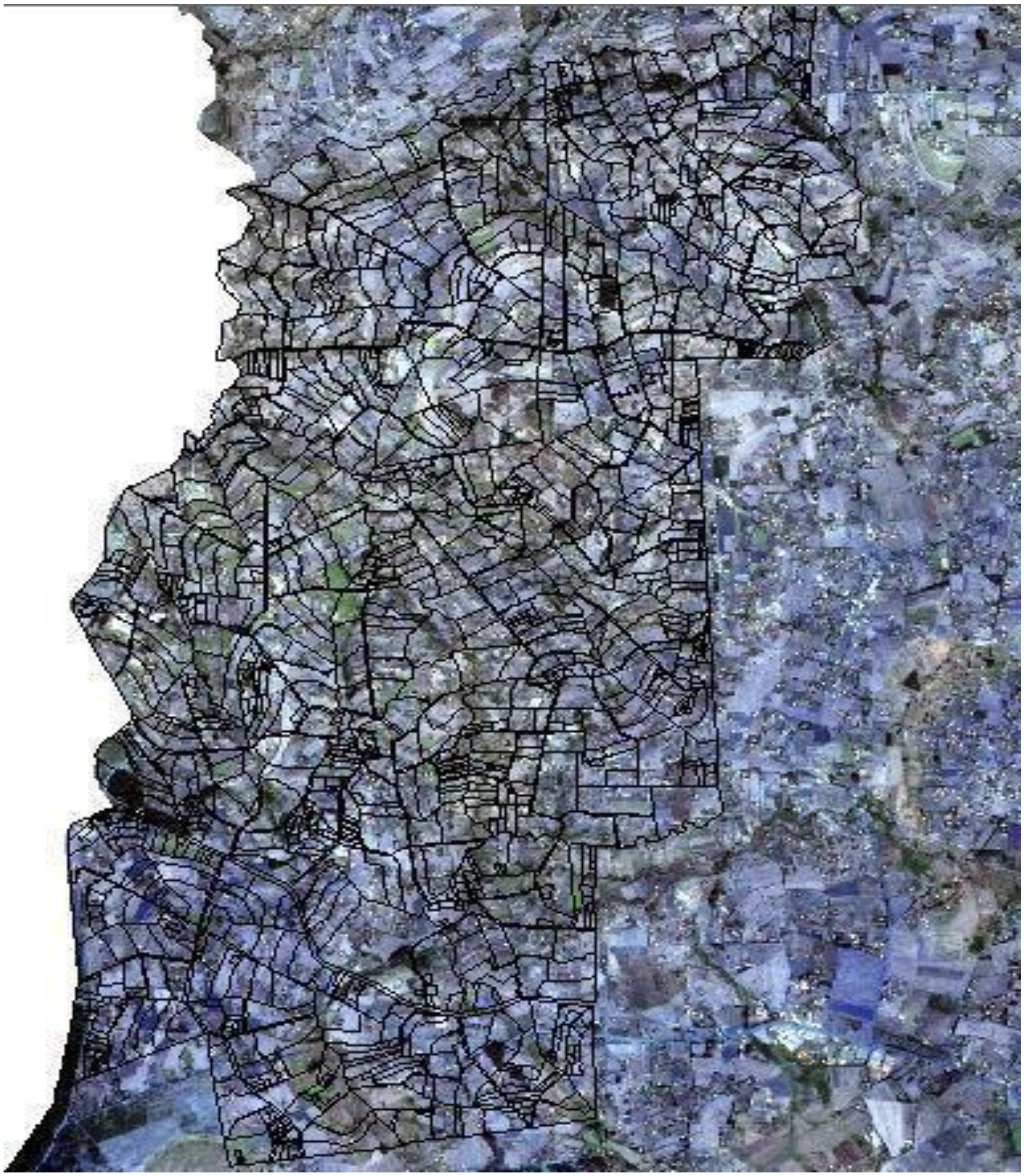
APPENDIX XX: DIGITIZED NZOIA SETTLEMENT SCHEME



APPENDIX XXI: DIGITIZED SERGOIT SETTLEMENT SCHEME



APPENDIX XXII: DIGITIZED SANGO SETTLEMENT SCHEME



APPENDIX XX111: GPS Data

Eastings	Nothings	description
729345.61 m E	88874.45 m N	Bareland
729247.78 m E	89176.48 m N	Cane
729869.18 m E	89285.45 m N	Forest
727687.83 m E	98898.01 m N	Forest
727632.23 m E	98747.79 m N	Farmland
728449.90 m E	98176.42 m N	Farmland
730929.93 m E	96293.58 m N	Farmland
731074.23 m E	94691.38 m N	Cane
731960.24 m E	97406.83 m N	Swamp
735317.85 m E	87329.47 m N	Bareland
735314.19 m E	86799.70 m N	Grass/Shrub
735744.10 m E	86071.82 m N	Grass/Shrub
734403.85 m E	85527.64 m N	Forest
729656.09 m E	77310.68 m N	Swamp
730183.65 m E	76068.04 m N	Forest
729633.48 m E	77382.18 m N	Swamp
734306.75 m E	73869.09 m N	Cane
735353.04 m E	78967.70 m N	Cane
733259.12 m E	79157.21 m N	Grass/Shrub
734416.81 m E	79426.71 m N	Forest
736128.51 m E	81164.09 m N	Bareland
738533.91 m E	74953.66 m N	Cane

APPENDIX XX1V: Research Permit

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NATIONAL COMMISSION FOR
SCIENCE, TECHNOLOGY & INNOVATION

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Date of Issue: 21/June/2021

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