ASSESSMENT OF THE IMPACTS OF FOREST COVER CHANGE ON WILDLIFE AND FUTURE PREDICTION FOR FOREST COVER CHANGE: A CASE OF GALEMA FOREST, ARSI ZONE, OROMIA, ETHIOPIA

Chala Daba Tafa

A Thesis Submitted to

The Department of Geomatics Engineering,

School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Geo-informatics

Office of Graduate Studies

Adama Science and Technology University

September, 2022

Adama, Ethiopia

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Advisor: Roba Gemechu (PhD)

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CANDIDATE'S DECLARATION

I hereby declare that this Master Thesis entitled "Assessment of Impacts of Forest Cover Change on wildlife and Future Prediction for Forest Cover Change: A Case of Galema Forest, Arsi Zone, Oromia, Ethiopia" is my original work. That is, it has not been submitted for the award of any academic degree,, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Chala Daba	__________________	__________________
Name of Candidate	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled “Assessment of Impact of Forest Cover Change on wildlife and Future Prediction for Forest Cover Change: A Case of Galema Forest, Arsi Zone, Oromia, Ethiopia” prepared under our guidance by Chala Daba submitted in partial fulfillment of the requirements for the degree of Mater’s of Science in Geo-informatics Engineering. Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

Roba Gemechu (PhD)	__________________	__________________
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Keredin Temam (PhD)	__________________	__________________
Co-Advisor	Signature	Date

APPROVAL SHEET

We, the advisors of the thesis entitled "Assessment of Impacts of Forest Cover Change on Wildlife and Future Prediction for Forest Cover Change: A Case of Galema Forest Arsi Zone, Oromia, Ethiopia" and developed by Chala Daba, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Roba Gemechu (PhD)	________________	____________
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Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Chala Daba have read and evaluated the thesis entitled "Assessment of Impacts of Forest Cover Change on Wildlife and Future Prediction for Forest Cover Change: A Case of Galema Forest Arsi Zone, Oromia, Ethiopia" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geo-informatics Engineering

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Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

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Office of Postgraduate Studies, Dean	Signature	Date

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TABLE OF CONTENT

Contents Pages

LIST OF TABLES.

Table NumberandTitle **pages**

LIST OF FIGURE

Figures number and titles **Pages**

LIST OF ACRONYMS AND ABBREVIATIONS

CSA: Central Statistical Authority

DEM: Digital Elevation Model

ERDAS: Earth Resource Data Analysis System

ETM: Enhanced Thematic Mapper

FAO: Food and Agriculture Organization

FAP : Forest Action Program

GIS: Geographic Information System

GCP: Ground Control Point

GPS: Global Positioning System

LULC: Land Use and Land Cover

MoA: Minister of Agriculture

NDVI: Normalized Difference Vegetation Index

NFPA: National Forest Program Actions

NIR: Near Infra-Red

RS: Remote Sensing

SPSS: Statistical Package for Social science

TIFF: Tagged Image File Format

UTM: Universal Transfer Mercator

USGS: United state of Geological Survey

ABSTRACT

The forest of Galema provides an array of ecosystem services, including the provision of fuelwood, timber, and trees for timber production and service as a habitat for different wildlife living in the area. However, this forest was currently declining due to anthropogenic activities and natural factors. Due to the forest being changed at an alarming rate, wildlife faces different problems in this area. Thus, the aim of this study was to identify the impact of forest change on wildlife and make future predictions for forest change by using ERDAS 2015 Furthermore, a 22-year forecast was made using QGIS to suggest how the forest might change in the future. The study used two Landsat7 images from 2000ETM, 2011ETM and a Sentinel-2A image from 2022 to analyze forest change. These satellite images revealed five major land cover classes: high-density forest, dense forest, sparse forest, grassland, and farmland. Therefore, as a result of change detection, high density and dense forest were decreased by 5.4% and 20.9%, respectively, in the first eleven years and by 7% and 12.1 % in the second eleven years. Inversely, other land classes increased by 20.83%, 23.3%, and 1.4%. The frequency analyzed driving factors of forest change were farmland expansion, firewood collection, and charcoal production. Timber production, population growth, and wildfire Because of these factors, the forest was degraded, and all large mammals such as the Ethiopian wolf, Menelik bush back, Mountain nyala, Warthog, leopard, common jackal, hyena, and red jackal lost their habitat; there was a conflict with local people; they were killed by farmers; they died because of starvation, and they migrated to other areas. Thus, *five wildlife populations decreased and Ethiopian wolf and redjackal were disappeared from the area. As the prediction result shows, high-density and dense forests were changed by 12.5 % and 33%, respectively. If this trend continues, the wildlife will lose their habitat and face the above problems. Therefore, in order to hold back the problem of forest cover change and its impact, corrective measures have been suggested that can be implemented both in the short-term and long-term phases.*

Keywords: *forest change, LULC, geospatial technologies, wildlife, prediction.*

CHAPTER I: INTRODUCTION

1.1 Background of the study

Forests constitute one of the world's most valuable natural resources and play a key role in global ecological balance. These resources have been and continue to be degraded and depleted globally(Macdicken, 2015). Depletion forest area threatens the sustainability of agricultural production systems and endanger the economy of the country (Desclée et al., 2006). Forests also play an important role in the hydrological cycle, contribute to disaster risk reduction, and provide a variety of ecosystem services, such as the provision of fuelwood and timber, materials and areas for human settlement and agriculture, and raw materials for wooden and non-wood forest products (Monitoring of forest resources, 1998).

The amount of land covered by forests and trees is an important indicator of environmental health and provides a habitat for a variety of mammal species(Sandker et al., 2015).Forests indirectly influence not only the global but also the micro-climate by providing range, serving as wildlife habitat and a genetic pool for biotic diversity, and providing critical ecosystem services such as watershed protection and erosion control.Regardless of this significance, forest cover decline is a serious problem throughout the world. According to Zone et al., 2020 at the worldwide level, forest area declined by 3%, from 4128 million hectares in 1990 to 3999 million hectares in 2015 by anthropogenic and natural factors. It is predicted that forest areas are projected to continue to decline at alarming rates (Sandker et al., 2015).

As reported by the World Bank (2017), between 1990 and 2015, East Africa's forest cover decreased annually by 1% while the human population increased at an average annual rate of 2%. Thus, it is possible to correlate forest cover change with population growth. People are converting forests and other land covers to agricultural lands to meet the demand of the growing population. According to (Fahrig, 2008), agricultural expansion into forest land, timber logging, charcoal production, and firewood harvesting are the major drivers of deforestation in Africa. Forests are used as habitats for wildlife. Due to these, any loss of forest and wildlife habitats is a direct threat to biodiversity conservation and affects local livelihoods adversely (Thapa et al., 2018).

According to Girma et al., 2018, wildlife habitat degradation, fragmentation, and loss are common phenomena worldwide. Habitat degradation, fragmentation, and loss affect the survival of wildlife populations by reducing the number of available habitats. According to International Union for Conservation of Nature and Natural Resources (IUCN, 2016), around 86% of threatened mammals are at risk due to habitat loss. Wildlife habitat threats are enormous in developing countries where the livelihoods of many are highly dependent on subsistence use of natural resources and agriculture(Girma et al., 2018).

According to FAO, 2011, from 1995 to 2010, Ethiopia lost about 141,000 ha of forest. This forest declined due to factors like conversion to agriculture, timber production, and wildfire and fuel wood consumption(Million, 2011). Consistent with Abera, 2019, in Ethiopia, the cultivated area has increased from 9 million hectares in 2001 to 15 million hectares in 2009 alone, resulting in forest decline. And Ethiopia faced the threat of deforestation and loss of wildlife resulting from the expansion of agriculture, grazing land encroachment(Berhanu & Teshome, 2018). Habitat degradation due to deforestation, encroachment of incompatible land uses, and uncontrolled fire create ever-increasing human-wildlife conflicts (Tefera, 2011).

In particular, forest decline was a serious problem in the Galema forest . This forest decline was primarily caused by factors such as farmland expansion, charcoal extraction, timber production, population growth, and wildfire. Consistent with this, the forest change driving factors were clearing the forest for agricultural land, and this was the reason for the reduction of forest in Ethiopia as discussed by Lemenih et al. 2008 and Teketay, et al., 2010 . Forest depletion in the study area causes wildlife habitat loss, climate change, low agricultural production, high soil erosion, and wildlife loss. Due to the information gap about forest cover change and species living in the forest, the problem in the study area was increased in alarming rate.Therefore ,a responsible bodies have to take a decision on forest management to reverse the problem of forest loss in the area. Thus, a better understanding of forest patterns, change, interactions between anthropogenic activities and phenomena, wildlife and forest, and local people helps to encourage forest management and environmental decision making.

Currently, satellite images are used to analyze forest change detection with other land classes and predict its change for the future. As stated by Kumar et al., 2014 ,Remote sensing datasets are very useful and very important for forest cover mapping and monitoring. Furthermore, data from community-based interviews conducted in selected kebele was used to identify the most influential factors influencing forest change in the study area.

Many researchers explore the study of forest change analysis by using remote sensing data. But not focused on the impact of forest change on wildlife. Therefore, this study aimed to fill the existing research gap by using geospatial technologies to evaluate the impact of forest cover change on wildlife and future prediction of forest cover change for the next 22 years..

1.2 Statement of problem

Forest cover decline is a commonly known problem in Ethiopia (dessise, G,& Christiansson, 2008). And according to IFMP, 2000, in Ethiopia, the current rate of deforestation is estimated at 160,000 to 200,000 hectares (ha) per year. Large-scale forest cover change has its own negative impact on wildlife habitats and the environment. The study area represents one of the areas in which forest cover has changed and loss of some wildlife has taken place. A large area was covered by high-density and dense forest before a few years, but currently, this forest is changing at an alarming rate due to the impact of the local community. This affected both wildlife and the environment. Deforestation has exposed large areas of dense forest, resulting in environmental degradation and a serious threat to wildlife (Oljirra, 2019).

In this study area, the majority of rural people live in the forest and near the forest boundary. Their livelihood depends on the forest for shelters, fuelwood, fodder, and timber, and they generate income from the forest to maintain their daily needs. Besides this, they use intentional fire as a tool for clearing forests to execute their temporal demand for grazing and agricultural land. But nevertheless, the best conservation and protection for forests and wildlife were not given well. Thus, forest cover decline and loss of wildlife are serious problems in the study area.

As information obtained from Lemu and Bilbio environmental protection authorities and field observation, the natural environment as well as the ecological balance of the area are under a serious threat due to the persistent disturbance of the forest resources by the local community. Currently, available information on the status and trends of forests and wildlife helps decision-makers with orienting forestry policies and wildlife conservation.

LULC and forest change maps provide the basis for discussions with responsible bodies and local users on improving forest management practices to achieve sustainability. Unfortunately, the forest is changing rapidly, and consequently, the environmental problems have increased due to forest change and a lack of current LULC information. Therefore, the stakeholders have to produce a LULC or forest change map or new documented information about forest change by using remote sensing data.

The rate and extent of forest cover change and the current status of the wildlife in the district have not been determined until now. However, from available information from community elders and field visits, it is evident that forest cover change and loss of wildlife are very widespread and continuing at an alarming rate. The process involves the shrinking of forest lands through the selective cutting of tree species to complete clearance of forest-covered land into other land uses or land cover systems and degrades wildlife habitats. Therefore the aim of this study is to identify the impact of forest cover change on wildlife and future predictions for forest cover change through geospatial technologies (GIS, RS, ERDAS, and QGIS). Also, GIS and remote sensing are used to detect forest cover change in Galema forest over the last 22 years between 2000 and 2022.

1.3 General objective

The general objective of this study is to evaluate the impact of forest change on wildlife specifically on large mammals and future prediction for forest cover change of the study area by using geospatial technologies.

1.3.1 Specific objectives

The specific objective of this study was to:.

- Detect the spatial change of forest cover for the study area between selected years.
- Identify driving forces for forest cover change and consequences
- Evaluate the effect of deforestation on wild life.
- Predict the forest cover change in the study area for the future 2044 years.

1.4 Research question

- ✓ What are the spatial changes in forest cover between the selected three years?
- ✓ What are the major causes of the forest cover change and concequesnces in the area?
- ✓ What are the impactt of deforestation on wildlife
- ✓ What will be the pattern of forest cover for the future of 2044?

1.5 Significance of the study

This study will address the rate of deforestation, the impacts of deforestation on wildlife, and driving factors in more scientific ways. The main beneficiaries of this study are policymakers, foresters, and researchers. Furthermore, the Oromia forest and wildlife enterprise office, the Ethiopian wildlife conservation authority office, the Lemu - Bilbilo environmental protection authorities, and the Sirka environmental protection authority office are expected to benefit from the findings of this study by providing the following:

- For policy makers to provide a feasible path to solutions for those responsible for taking measures to mitigate the problems of forest reduction and habitat loss,
- researchers to generate first-hand information on the problem of forest cover change and its future prediction in the study area for those who are interested in conducting further research on the issue.
- For Lemu - Bilbilo environmental protection authority, Sirka environmental protection authority, and Oromia forest and wildlife enterprise office to obtain reliable data about forest coverage, its change, and wildlife status. This helps them to give direction to take some measurements and minimize the problem.

1.6 Scope of the study

The spatial scope of this study was limited to Galema forest in Oromia Regional State,Arsi zone, Ethiopia. The contextual scope was mainly focus on impact of forest cover change on wildlife from 2000-2022 using geospatial technology and this research was carried out to determine and calculate the trend of forest cover change, the relationship between forest cover and wildlife. to identify the forest change and its impact,satellites image and interview data from local poeople were used .as well as DEM, slope and road were used in molusce plugin to determine future forest cover change for the last 22 years.

1.7 Limitation of the Study

For the future prediction of forest cover, different variables were used, like population growth, DEM, slope, road, and river. However, population map and river flow were not considered because there was no new settlement and river within the boundary of the study area. In addition to this, outdate data was used,that collected from Lemu - Bilbilo as well as from sirka environmental protection authority Office instead of updated data about wildlife.Beacuse there no recently recorded data about wildlife in the study area in both office.Thus, outdated data made some sort of errors in the study.

1.8 Organization of the Thesis

The thesis is organized into five chapters. The first chapter is an introduction that includes the following sections: background of the study; problem statement; objectives of the study; basic research questions; the significance of the study; scope and limitations of the study. Chapter Two provides a literature review with an overview of related studies conducted in other parts of the world with previous works in an Ethiopian context. The background of the study area as well as the various data sets, materials, and methodology that are manipulated in this research are presented in chapter three. The results obtained with the various methods are outlined in chapter four. First, the contribution of Landsat image and Sentinel 2A with other ancillary data and the results from various digital image processing, as well as LU/LC, forest cover change detection and mapping outputs, are documented. Secondly, the statistical analysis describes the major causes and impacts of forest cover change in the study area and future prediction mapping results are presented. Finally, conclusions and recommendations are presented after chapter four as a sub-section.

CHAPTER II: LITERATURE REVIEW

2.1 Concept of forest cover change

The rapid conversion or degradation of forest environments is thus of important international concern. Forest monitoring mainly focuses on detecting and estimating the land conversion rate and, more recently, on assessing carbon stocks in the forest ecosystem. Operational systems for monitoring and updating forest maps are thus needed for many applications such as forest management, carbon budgeting and habitat monitoring(Blower, 2021). Satellite remote sensing is widely used to detect forest change and update existing forest maps. Many change detection techniques have been developed since the early days of earth observation.(Blower, 2021).

2.2 Land-use and land-cover change

Land cover denotes the physical and biological cover over the surface of the land, including vegetation, water, bare soil, and/or artificial structures(Ellis, 2007). Land cover may be a characteristic of the land which will be observed physically, as by remote sensing but Land use is a more complicated term. Natural scientists define land use in relations to conditions of human activities like agriculture, forestry, and building construction that alter land surface processes including biogeochemistry, hydrology, and biodiversity(Ellis, 2007).

The Earth's surface is experiencing rapid LULC changes as a result of numerous socioeconomic activities and natural phenomena (Kanth & Hassan, 2010). According to(Ellis, 2007) humans have been modifying land to obtain food and other essentials for thousands of years, current rates, extents and intensities of LULC change are far greater than ever in history, driving unprecedented variations in ecosystems and environmental processes at local, regional and global scales. Changes in Land Use Land Cover (LULC) can also affect biological diversity, alter ecosystem services, and lead to soil erosion, disrupt socio-cultural practices and increase natural disasters, like flooding.

2.3 Uses, Extent and Trends of Forest Cover Change: A Global Perspective

Forests are playing a key role globally as important natural resources, improving the livelihood of poor people through meeting their daily subsistence necessities(Siraj, 2019).Not only have this Tropical forests played a key role in climate change mitigation by sequestering and storing carbon from the atmosphere. There is growing recognition among the scientific community and policy makers that sustainable forest management is affected by multiple factors associated with global change(Ramsfield et al., 2016). Forests are of vital importance to humanity as they provide a wide range of essential ecosystem services (Ramsfield et al., 2016).

Currently forests cover 30.8 percent of the global land area and the total forest area is 4.06 billion hectares (FAO, 2020), but forests are not equally distributed around the globe. More than half of the world's forests are found in only five countries like: The Russian Federation, Brazil, Canada, the United States of America and China. And two-thirds (66 percent) of forests are found in ten countries as shown.

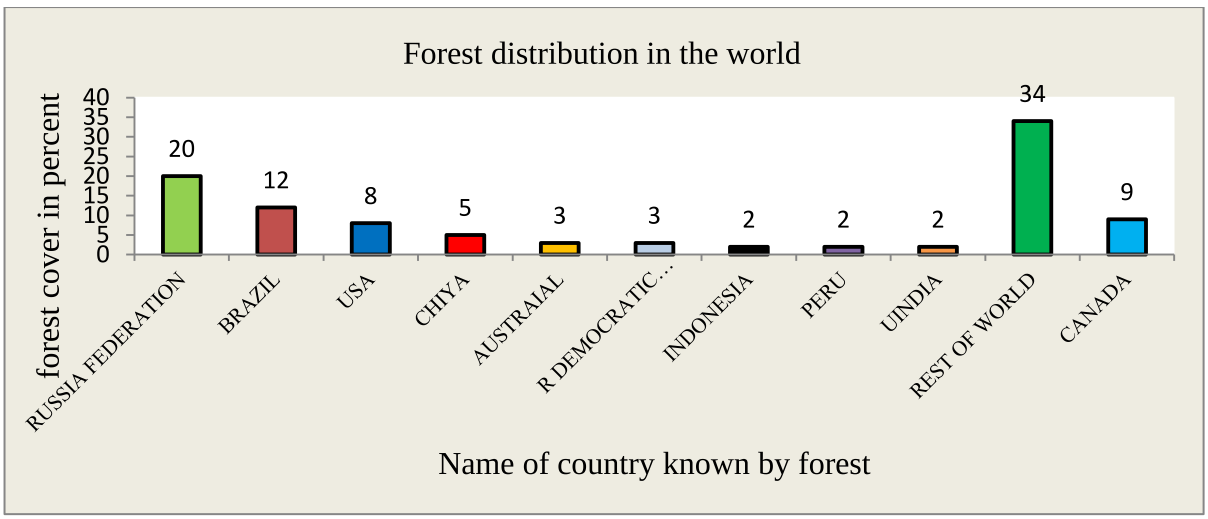

Figure 2.1forest distribution of in 2020

Source: FAO 2020

The world's population is increasing from time to time. For instance, in 2015 the world population is about 7.3 billion, and expected to reach 9.7 billion in 2050, and 11.2 billion in 20100 (UN 2015). People are converting forest, and other land cover to agricultural lands to meet the demand of growing population and the conversion of forest is to agricultural lands is expected to be continued in the future(Siraj, 2019). According to (Fahrig, 2008) Agricultural expansion into the forest land, timber logging, charcoal production and fire- wood harvesting are the major drivers of deforestation in Africa.

Forest gains, on the other hand, are driven by two main factors: natural forest regrowth on abandoned agricultural land and tree planting for consumption, either as timber or energy wood. Many studies suggest that wood is indeed increasingly used as an energy source at the global level, not only in developing countries(Sandker et al., 2015).

2.4 Extents of forest cover in Ethiopia

Ethiopia's plants and wildlife resources are uniquely diverse. The plants comprises about 6500- 7000 species of higher plants out of which 12% are endemic and the countries natural forests and woodlands covered 15.1 million ha in 1990 and declined to cover 13 million ha in 2005(Bekele, 2011). In other words, our country lost over 2 million ha of forests, with an annual average loss of 140 000 ha between 1990 and 2005. In 2009, the area is estimated at 12.3 million ha, 11.9 % of the total land area. Out of this, the remaining closed high forests are 4.12 million ha or 3.37% of Ethiopia's land (FAO, 2010). This indicates that the coverage of forest resources is declining at an alarming rate. The area of forest is unevenly distributed in the country. Oromia, Southern Nations, and Nationalities Regional State and Gambela region account for 95% of the total high forest area(Takano et al , 2010).

2.5 Trends and cause of Forest Cover Change in Ethiopia

The concepts of forest change detection analysis is not new, the emergence of new imaging sensors and geospatial technologies has created a need for image processing techniques that can integrate observation from a variety of different sensors and datasets to map, detect and monitor forest resources.(Forkuo & Frimpong, 2014).Forest change detection studies seek to know: pattern of forest cover change, processes of forest cover change, and human response to forest cover change. Changes in forest cover are often the result of anthropogenic pressure (e.g. population growth) and natural factors such as variability in climate (Forkuo & Frimpong, 2014).

Management criteria for sustainable forest management have been developed within Ethiopia's Forest Action Program (FAP), but have not been implemented. According to FAP, natural forests are primarily used for conservation, commercial utilization being a secondary objective(Forests & Papers, 2003). Two million ha of natural forests selected in priority for development could not be effectively administered. Management plans were prepared for eight forests, but only two were brought into being.

The national forest programmed has proposed 60% of the natural high forests to be under conservation while 40% is intended for production(Forests & Papers, 2003).The forestry administration both at federal and regional levels is trying to develop a management system that would minimize any further destruction of natural forests, balancing protection objectives with productive interests of the state and local communities.

With respect to wildlife, the management of protected areas is planned to be a participatory endeavor, allowing the sharing of grazing, of water resources and of revenues generated by the forests and tourism.(Forests & Papers,2003).Forests ,woodlands ,the wild plants and animals they contained were the main source of food for many early hunter-gather societies and still are for forest-dependent communities(Seyoum & Teketay, 2015).

According to (Monitoring of forest resources,1998) , in Ethiopia only negative impacts on the High Forest are registered, which means that the forest resources are under severe human pressure .The forest degradation in Ethiopia is closely linked to the ongoing population growth. More people generally lead to an increasing demand on land for living and for agricultural production (Planner et al., 2000).Rapid population growth, extensive forest clearing for agriculture, over grazing, movement of political centers and exploitation of forest for fuel wood without replanting reduced the forest area of the country(Menker et al., 2012).

2.5.1 Cause of Deforestation

Deforestation is clearing the Earth's forests on a large scale worldwide and resulting in many land damages. One of the causes of deforestation is to clear land for pasture or crops(Oljirra, 2019). Not only this, The rural poor living around forests heavily depends on biodiversity to satisfy their basic needs such as food, water, housing, and social services. The economic dependency of the people on the forest which offers firewood and area that can be converted to agricultural land is one of the main causes for deforestation.

Global Forest Resource Assessment (FRA) (FAO, 2010) to suggest that agriculture is by far the largest direct cause of deforestation; according to their estimations between 70% and 80% of forest conversion is to agriculture in Africa, around 70% in subtropical Asia and >90% in Latin America(Macdicken , 2015). Other studies equally indicate agricultural expansion as the largest direct cause of deforestation in Africa, Asia and Latin America (Sandker et al., 2015).

Due to the media-presence of large-scale deforestation in Latin-America, south-east Asia and Central Africa the world community does not take note of the comparable small-scale depletion of tropical forests in Ethiopia. Mainly during the last century, Ethiopia’s forests have been declining both in size (deforestation) and in quality (degradation). According to(Reusing, M. 2001) high forest cover of Ethiopia decreased from 4.75 % to 3.93% of the total land area from 1973-1990 The current annual loss of the high forest area has been estimated by Efap to be between 150,000 and 200,000 ha.

If this tendency does not stop, the country will soon lose one of the most sophisticated ecosystems of the world with a unique genetic diversity(Monitoring of forest resources, 1998).These findings, (Bekure, 1997), stated that the increasing demand for croplands, grazing land, construction poles, and fuel wood including charcoal production is the main reason for the forest cover change in Ethiopia. In addition, forests are cleared to acquire constructional materials, to provide a source of energy, to make space for grazing, farming, and building and layout infrastructure networks, and to supplement raw materials such as input for agricultural production and livestock grazing (Mesfin, 1991).

According to Ethiopian environmentalist, 5% of deforestation is due to cattle ranching, 19% due to over-heavy logging, 22% due to the growing sector of palm oil plantations, and 54% due to slash-and-burn farming. Deforestation causes the loss of habitat for millions of species and is also a driver of climate change(Oljirra, 2019) .In Ethiopia Deforestation occurs for many reasons: trees are cut down to be used or sold as fuel (sometimes in the form of charcoal) or timber, while cleared land is used as pasture for livestock, plantations of commodities and settlements. The removal of trees without sufficient reforestation has resulted in damage to habitat, biodiversity loss (Oljirra, 2019).

2.5.2 Impact of deforestation

Deforestation leads to the disappearance of sustainable development. (Monitoring of forest resources, 1998) . Also Deforestation is causes habitat fragmentation and loss of biodiversity, but it also degrades environmental conditions and has an impact on global greenhouse gas emissions (GHG) by releasing CO2 to the atmosphere. This causes changes in the global carbon cycle and alters the surface energy and water balance(Romijn et al., 2015).

The destruction of the tropical forests results directly in the loss of uncounted plant and animal species as well as in a shortage of fuel-wood, timber and other forest products. Indirectly it leads to soil erosion, deterioration of the water quality, drought and flooding, reduction of agricultural productivity and finally to an increasing poverty of the rural population. Finally it is obvious that the depletion of forest resources contributes significantly to the world-wide climatic change All these effects, which have their origin in the ongoing deforestation, should be reason enough to draw consequences to a sustainable management of forest resources and to conserve them for future generations(Monitoring of forest resources, 1998).

2.6 Concept of wildlife

Even though tropical rainforest makes up just 6 percent of the surface area of the Earth, about 80-90 percent of the entire species of the world exist here. Due to the massive felling of trees, about 50 to 100 species of animals are being lost each day (Oljirra, 2019). The outcome of which is the extinction of animals and plants on a massive scale. The effects on animals are very heartbreaking. They not only lose their habitat and protective cover, but they are also pushed to extinction. Many beautiful creatures, both plants and animals have vanished from the face of the earth(Oljirra, 2019).

Dispute over land-use between the local people and wildlife conservation agencies is becoming a serious problem in developing countries. It has now reached crisis levels in some areas where the local people used to utilize land until they were declared conservation areas. The recently increase in disputes over land-use is caused by combined factors such as expansion of cropland due to rapid population growth, policy change for tenure, and mismanagement by the conservation agency. (Blower, 2021).It is certainly encouraging that a start has at last been made in the field of wildlife conservation in Ethiopia. But it is only a small beginning and a great deal has yet to be done both in the development of national parks and other conservation areas, in the introduction of effective protection of wildlife elsewhere against widespread poaching and destruction of the habitat, and also in ecological surveys to provide the necessary data on which to base management plans(Blower, 2021).

Understanding relationship between local people and natural resources is critical in designing and sustaining effective conservation strategies. Such relationships have particular relevance to the management of protected areas (PAs), where long-standing tensions over land tenure, local use of natural resources, and human–wildlife conflicts may limit local acceptance of conservation goals(Tessema et al., 2010).An important first step in creating sustainable and collaborative resource management systems is to understand local attitudes toward wildlife and conservation. In Ethiopia, such attitudes are likely to be influenced by the country's unusual sociopolitical history and its historic systems of common property resource management. Unfortunately, few studies have been conducted in Ethiopia to understand local views about conservation (Tessema et al., 2010).

Ethiopia has designated many protected areas throughout the country that includes national parks, wildlife reserves, National Forest Priority Areas, biosphere reserves and community conservation areas(Forest, 2015). There are 58 protected forest priority areas, 21 national parks, 2 wildlife sanctuaries, 3 wildlife reserve areas, 6 community conservation areas, 2 wildlife rescue centers, 20 controlled hunting areas, 2 botanical gardens and 4 biosphere reserves. Additionally, the previous "Forestry and Wildlife Conservation Development Department of the MoA has been endeavoring to formulate forest management plans for those areas .However, the NFPAs have not been gazette, which contributed to uncontrolled, illegal cutting, encroachment and clearing of forest land(Monitoring of forest resources, 1998). protected forests did not yield the expected results as they are increasingly degraded and is being converted for subsistence and commercial agriculture, timber used for fuel wood and construction, protected grasslands used for livestock grazing(Forest, 2015).

2.6.1 Habitat loss

Habitat loss is known to be the main cause of the current global decline in biodiversity, and roads are thought to affect the persistence of many species by restricting movement between habitat patches.(Kostin et al., 2019).Habitat loss and land degradation are the most significant threats to mountain nyala and the majority of Ethiopia's wildlife(A et al., 2008) and has negative consequences for populations and communities. The effects of the loss of habitat on Wildlife populations are usually evaluated using separate variables in landscape-scale studies. The effect of habitat loss is generally measured by the correlation between the amount of habitat in the landscape and species distribution (Fahrig, 2008).Wildlife habitat degradation, fragmentation, and loss are common phenomena worldwide. Habitat degradation, fragmentation, and loss affect the survival of wildlife populations through reducing the amount of available habitats, reducing habitat quality, and creating edge effects(Girma et al., 2018). Habitat fragmentation creates small Meta populations that are vulnerable to a number of population extermination factors such as inbreeding, predation, disease, and poaching that may lead to direct population extinction According to International Union for Conservation of Nature and Natural resources (IUCN, 2016), around 86% of threatened mammals are at risk due to habitat loss. Wildlife habitat threats are enormous in developing countries where the livelihood of many is highly dependent on subsistence use of natural resources and agriculture(Girma et al., 2018).

The amount of forest in the landscape is known to be important predictors of amphibian species richness, distribution and abundance. Many species of amphibians require upland habitat in the landscape along with ponds or wetlands for breeding (Fahrig, 2008). Forests can provide both upland habitat and help maintain the moist microclimate that facilitates the dispersal of amphibians and the amount of forest in the landscape around breeding ponds and wetlands is known to be positively associated with amphibian species richness. In additionally the amount of forest in any area have great role to predict the habitat loss(Fahrig, 2008).

2.7 Use of remote sensing and geographic information system

The use of remote sensing data in recent times has been of immense help in monitoring the changing pattern of forest cover. It provides some of the most accurate means of measuring the extent and pattern of changes in cover conditions over a period of time(Forkuo & Frimpong, 2014).we require new technologies like satellite remote sensing and Geographical Information Systems (GISs). These technologies provide data to study and monitor the dynamics of natural resources for environmental management(Mallupattu et al., 2013).Change detection has become a major application of remotely sensed data because of repetitive coverage at short intervals and consistent image quality(Volcani et al., 2005). Remote Sensing and Geographic Information System (GIS) have been used in order to study forest changes analysis(Journal & Geomatics, 2011).

Remote sensing and GIS are being increasingly used in combination for spatial analysis. GIS data bases are used to improve the extraction of relevant information from remote sensing imagery, whereas remote sensing data provide periodic pictures of geometric and thematic characteristics of terrain objects, improving our ability to detect changes and update GIS data.

Both remote sensing (RS) and geographic information systems (GIS) have been widely applied and recognized as powerful and effective tools in detecting the spatiotemporal dynamics of land use and land cover.

2.8 Image Classification

Image classification is the process of sorting pixels in to a finite number of individual classes and making thematic maps from satellite imagery. A thematic map is an information representation of an image that shows the spatial distribution of a particular theme (Lillesand & Kiefer, 2000). Remotely sensed data of the world could also be analyzed to extract useful thematic information for various purposes. The aim of image classification procedures is to automatically categorize all pixels in an image into LULC classes or themes (Lillesand, T., and Kiefer, 2000).

2.9 Accuracy assessment

Each thematic maps derived from remote sensing contain some sort of errors due to several factors which range from classification technique to method of satellite data capture. These errors must be quantitatively explained in terms of classification accuracy. An error matrix is a square array of numbers structured in rows and columns which expresses the number of sample units allocated to a particular category relative to the actual category as indicated by reference data (Congalton, 2001). The average accuracy is that the average of the accuracies for every class, and therefore the overall accuracy may be a similar average with the accuracy of every class weighted by the proportion of test samples for that class in the total training or testing sets. Thus, the overall accuracy is a more accurate estimate of accuracy (Foody, 1992). The importance and power of the Kappa analysis is that it is possible to test if a LULC map is considerably better than if the map had been generated by randomly assigning labels to areas (Congalton, 2001). The Kappa coefficient represents the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance (Foody, 1992). According to(Forkuo & Frimpong, 2014) The Kappa coefficient lies normally on a scale between 0 and 1. Kappa values are also characterized into 3 groupings: (i) a value greater than 0.80 (80%) represents a strong agreement, (ii)a value between 0.40 and 0.80 (40 to 80%) represents a moderate agreement, and(iii) a value below 0.40 (40%) represents poor agreement Kappa can be used as a measure of agreement between model predictions .According to (Jensen, 1996),Kappa is computed as,

$$\mathrm{K} = \frac{\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi + xx + i)}{N^2 - \sum_{i=1}^{r}(xi + xx + i)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . eq\ 2.1$$

Where;

N is the total number of sites in the matrix,

r is the number of rows in the matrix,

xii is the number in row i and column i,

x+i is the total for row i, and

xi+ is the total for column i

2.10 Normalized Difference Vegetation Index (NDVI)

NDVI is used to determine the density of green on a patch of land. And directly associated with the photosynthetic capacity and hence energy absorption of plant canopies. (Myneni et al., 1995). R and NIR channels of the sensors onboard satellites are particularly well suited to the study of vegetation ((Mather, 1999).According to (Bannari et al., 1995). Several vegetation indices have been developed of which, NDVI is still the most widely used one despite the development of many new indices that take into account soil behavior. NDVI value ranges between -1 to +1. Measured value range from -0.35 (water) through zero (soil) to +0.6 (dense green vegetation). The more positive the NDVI the more green vegetation.

Mathematical formulae for calculating NDVI is as follows;-

$$\mathrm{NDVI} = \frac{NIR-R}{NIR+R!} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . eq\ 2.2$$

Where; NIR = the spectral reflectance measurements acquired in the near-infrared region.

R = the spectral reflectance measurements acquired in the red region (band).

2.11 CA modelling for future prediction

Several techniques have been used to provide an estimation of LULC prediction models, such as the Markov chain (MC) model, the Cellular Automata (CA) model, and the conversion of land use and its effects (CLUE) model, have been developed in recent years to forecast the LULC and their change detections (Alam et al., 2021).

Among this the CA model has been used for land-use and forest change analysis among the several modeling approaches. MOLUSCE (Modules of Land Use Change Evaluation), new QGIS plugin that can estimate potential LULC changes is built with CA model and also includes a transition probability matrix, And designed to analyze, model and simulate land use/cover changes. and more suitable to: Analyze land use/ land cover and forest cover changes among special time periods(Willayat, 2017).

Model land use/cover transition potential or regions vulnerable to deforestation, and simulate future land use and forest cover modifications. Not only had these MOLUSEC offered a user-friendly and intuitive plugin, which make it easier for users to perform modeling and simulation. It’s used to obtain land cover change map and to establish the trend of change for the study area. As stated by (Willayat, 2017),the plug-in incorporates well-known algorithms, which can be used in LULC change analysis, urban analysis as well as forestry applications.

Its measure the percent of area change in a given year, provide transition matrix shows the proportions of pixels changing from one land use/cover to another and carried out the area change map.Under MOLUSCE plugin the graphical user interface (GUI) is comprised of seven main components: Inputs: the initial (period 1) and final (period 2) land use/ land cover maps as well as spatial variables such as slope, road, aspect, and DEM loaded in the panel of spatial variables.

The land use/ cover change information and the spatial variable well be used for modeling and simulating land use/ cover changes. In this step will check geometry if all inputs matched then moved to next step,- Evaluation correlation: this tab comprises three methods, namely the person’s correlation, joint information uncertainty, and crammer’s coefficient, which are used to check correlation among the spatial variables, Area change: In this tab, land use/ cover change and transition probabilities are computed. Also land use/ cover change map produced. The land use/ cover units can expressed in square meter, square kilometer, and hectares.- Transition potential modeling: While many method available for computing transitional potential map, Artificial Neural Network (ANN), Multi Criteria Evaluation (MCE), Weights of Evidence (WoE), and Logistic Regression (LR) are available in this plugin. Each method uses land use/cover information and the spatial variable as inputs for calibrating and modeling land use / cover change.

- Cellular Automata simulation: transitional potential map, certaincy function, and simulated land use/ cover maps are generated under this process. The cellular automata approach is based on Monte Carb algorithm.- Validation: validation computes Kappa statistics (standard kappa, kappa histogram, and kappa location, misses and false alarms are produced under this component,- Message: this tab presents the progress of the modeling and simulation, error message or warning to the user(Willayat, 2017).CA model includes a transition probability matrix that shows the proportions of pixels changing from one LULC to another and the plugin carried out the area change map between different periods. (Rangarajan, 2022). Thus depending on the previous area covered the transition matrix was calculated.The transition probability (Pij) matrix in a state which is calculated as follows;-

$$\|\mathrm{Pij}\| = \left\| \begin{matrix} P_{11} & P_{12} & P_{1N} \\ P_{21} & P_{22} & P_{2N} \\ \vdots & \vdots & \vdots \\ P_{41} & P_{42} & P_{4N} \end{matrix} \right\| \qquad \text{thus, } (0 \le pij \le 1)$$

Where: pij mean the probability of land use change from period i and j.

2.12 Gap and knowledge observed from previous study

Many studies have been performed to analyze forest cover change and identify factors that cause changes in forest cover in different areas. Those (Forkuo & Frimpong, 2014), used Landsat and aster imagery to map and analyze structural changes in forest cover as well as the factor of forest cover change in the Owabi forest in Ghana. One of those factors is population expansion, rapid urbanization, sand-winning activities, and uncontrolled grazing. In addition to this, another study was conducted on forest cover change detection using Geographic Information Systems and remote sensing techniques in Komto Protected Forest in Wolega, Ethiopia(Zone et al., 2020). This was used with Landsat imagery and a maximum likelihood classification algorithm. They used focused group discussions (FGD), key informant interviews (KII), and a household questionnaire survey. The obtained results were forest change detection over a three-year period and the factors driving forest cover change, such as agricultural expansion, forest logging, firewood harvesting, and increased built-up area (settlement).

However, one study was conducted by Zerihun. Girma 2018, on the impact of tree removal and livestock encroachment on mountain nyala and Menelik bushbuck scat counts (recorded in different seasons). And identified fire, encroachment by livestock, and agriculture have been known to be the major driving forces for the degradation, fragmentation, and loss of mountain nyala and Menelik's bushbuck habitat. But the current study shows key drivers for forest cover change, a forest change detection map, quantifying the percent of forest cover change for different images, and the impact of forest change on other wildlife, which was not included in the previous study (Zerihun. Girma 2018). and cannot use remote sensing data. Other previous studies (Forkuo & Frimpong, 2014) and (Zone et al., 2020) can only conduct forest change analysis, not include the impact of forest change on wildlife. But the present study will include all parts of the Galema forest and identify the impact of forest change on wildlife by using remote sensing data and interview data .and using the train vector support machine classifier algorithm instead of the maximum likelihood classification to obtain high accuracy of classification.

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CHAPTER III: MATERIALS AND METHOD

3.1 Description of study area

3.1.1 Location

Galema forest is located in Arsi National park (Chilalo-Galema forest) .Based on UTM WGS 1984 The forest is Found between 7.48 to 7.88∘Nand 39.27to39.51∘E and located between the inter boundary regions of four Woredas (Districts), namely, Tena, Degeluna-Tijo, Sirka, and Lemu-Bilbilo .

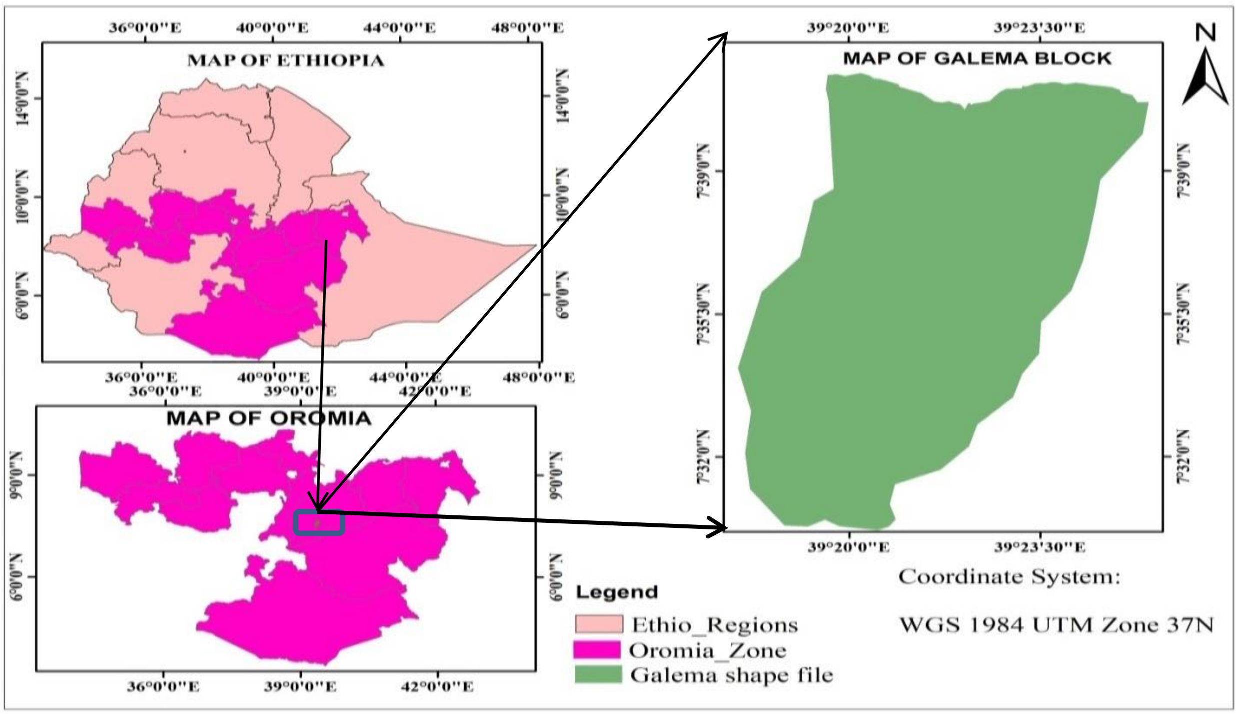


Figure 3.1 Location map of study area

3.1.2 Population

Lemu - Bilbilo district as well as Sirka district, are found in the Arsi zone.Lemu - Bilbilo has 25 kebeles but sirka district has 33 kebeles.the total kebeles found in both district are 58. According to the projection made from the 2015(2007) Central Statistical Agency of Ethiopia (CSA), the total population of both woreda was 386308 of whom 191,929 were men and 194,3379 were women;.12.92% of its population were urban dwellers.

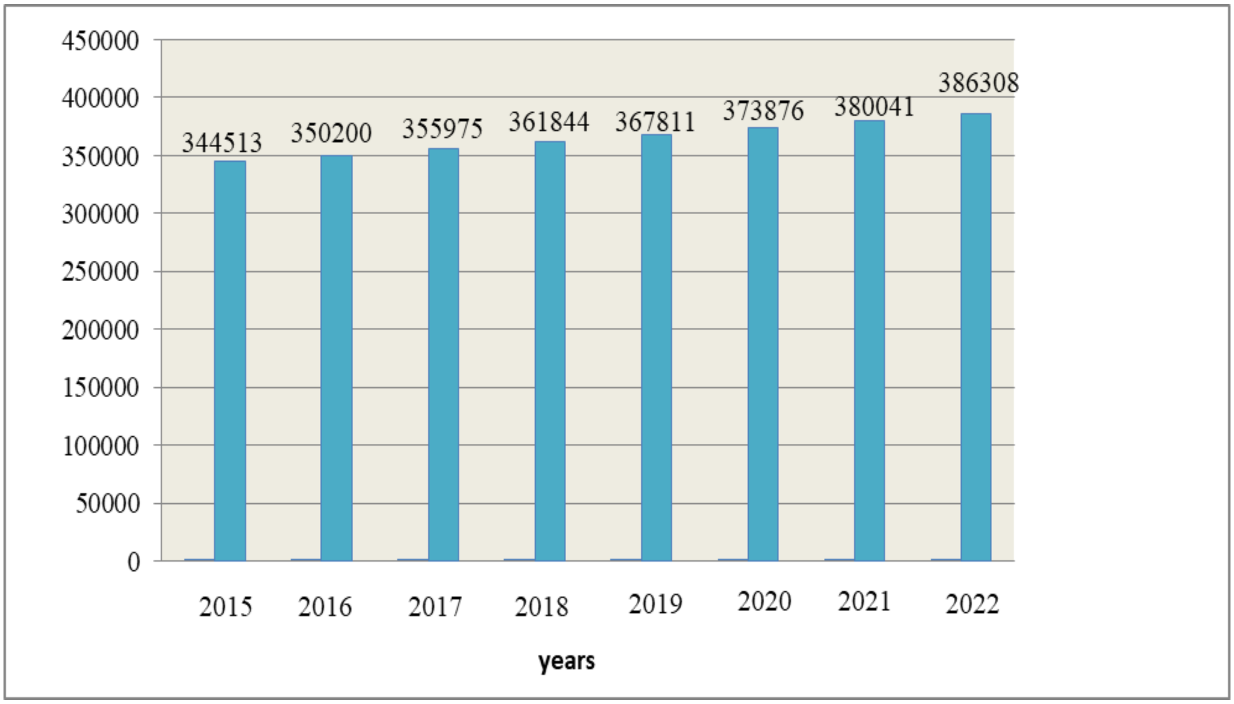


Figure 3. 2 Shows increment in Population size of the district.

From the above figure the average annual incerement of both district population is 5,971.

3.1.3 Economic source

According to information gathered from the agricultural office of the lemu Bilbilo and Sirka districts, the economy of the community was mostly dominated by agriculture and livestock farming practices. Mixed farming dominates the area and produces crops like wheat, barely beans, and pea.From this, wheat and barley are produced in large quantities in the area, and various vegetables and fruits are extensively cultivated in the area. Furthermore, the local community's income is based on livestock(cows,sheep and goats)sales to customers for meat and other uses and sale a food crops. Source (Lemu Bilbilo and Sirka district agricultural office).

3.1.4 Land use land cover of the study area

The Study Area was mostly dominated by forest , grassland and agricultural land. both woreda has very dense forest and vegetation in the past nowadays it is sparse due to increased demand for farmland, deforestation, and increased population pressure. Now, major types of land use dominant in study area high dense ,dense forest, sparse vegetation ,grassland and farmland . (include savannas and shrubland), built up, agriculture include (grassland and sparse vegetation),now aday, the study area dominated by sparse forest which covers 50.3% (8733.2ha) and next the dominant land use type is a grassland which covers 26.1% (4526.24ha) of total area. High density, dense forest, and farmland land cover 3.9 % (679.45ha), 6.7% (1166.56) and 13% (2249.7) respectively. Galema forest, covers 17355.15ha of the total area.

3.1.5 Climate

The climatic condition of lemu-bilbilo and sirka woreda largely governed by altitude and causes climatic zone ranges from Kolla, to Afro alpine . The climate of those woreda are dominated by woina dega and dega climate. Besides to this, due to high altitude of the chilalo mountain, the central part of this woreda consists of extremely harsh climatic conditions such as an erratic rainfall, usually wet and waterish air, icy and frostiness. Total rainfall of the woreda is 1203 mm(Kassu et al., 2017).The study area is characterized by humidmontane climate with bimodal rainfall pattern. The mean annual rainfall ranges from 778.7 to 1089.65mm and area has a mean monthly maximum temperature of 22.4∘C and minimum of 11.1∘C(Girma et al., 2018). As indicated in the following figure ,woreda characterized by having nine months rainy season (frebruary to October) and followed by another three months dry season (November to January). The area experiences driest month during december and wettest month during July.

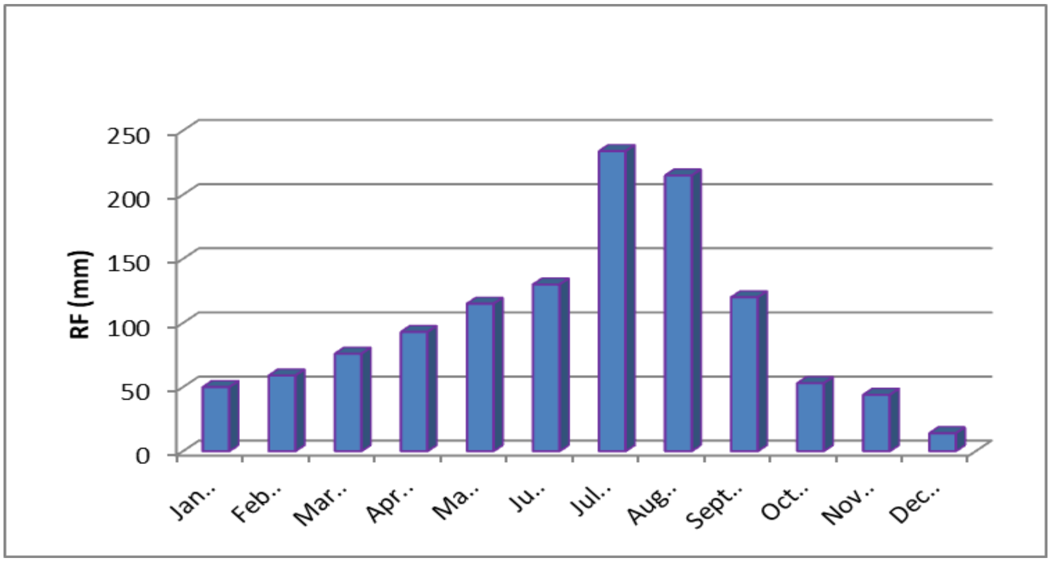


Figure 3.3 The mean annual rainfall.

3.1.6 Forest and Wildlife Composition

Lemu-bilbilo and sirka District are covered with ever green forests with various types of vegetation such as higher trees, riverian trees, small trees, shrubs and ground cover grasses . The entire high lands of the district are believed to have been covered once with dense forest resources. Currently, the Galema forest area is found in the this District and characterized by Afro-alpine vegetation at higher altitudes (3600–4008m), dominant ericaceous vegetation in the middle altitude(3539–3889m),and remnant Afro-montane (2843–3456m) natural forest and mixed plantations (3181–3340) (Girma et al., 2018).

The Galama forest have been reported to harbour metapopulations of endemic and endangered large mammals like Tragelaphus buxtoni (mountain nyala), Canis simensis (Ethiopian wolf), and Tragelaphusscriptusmenelik(Menelik'sbushbuck), Pantherpardus(Leopard),canis aureus (common jackal), lepusstark(Ethiopian highland hare), Potamochoerus africanus(warthog), beira(antelope), Crocuta crocuta(hyena) and Canis aureus(Red jackal)(Girma et al., 2018) and (lemu-bilbilo environmental protection authority).

3.2 Data collection and data source

To achieve the Specific objective of this study ,data were used and collected from satellite image data, field survey data, literature reviews, and GPS data.

Satellite images of Landsat 7-ETM" for the years 2000 and 2011 were collected from the United States Geological Survey (USGS) (http://glovis.usgs.gov). But sentinel 2A of 2022 was collected from Copernicus. During the field survey, data about forest change, factors for forest change, and the impact of forest change in the area were collected directly from the community through questionnaires and physical observations of the study area. Furthermore GPS points for ground truth were taken, and detailed information on previous forest cover and general management practice was observed during the field survey. Not only this data, but the literature review was collected from Google scholar, books, and published articles. This collected data was both primary and secondary data and was collected from different sources.

3.2.1 Primary data

Primary data was collected directly from community-based interview data (depth interviews with community elders and manager of lemu-bilbilo environmental protection authority, key informant interviews with community elders, and observation), and twenty-five GPS points were collected for ground truth. These points were taken on a sample of points in the selected area of high-density forest, dense forest, sparse forest, grassland, and farmland for accuracy assessment.

3.2.2 Secondary Data

This type of data was collected from internet, books, published and unpublished works on this area, useful documents, records of offices regarding the issue(wildlife data). Secondary data sources included the Lemu - Bilbilo Environmental Protection Authority, the Agricultural Offices, and the CSA (Central Statistical Authority), the United States Geological Survey (USGS), and Copernicus. The data collected from these sources were used to know the information about the driving factors and the impact of forest change on wildlife. These data included: the local community's economic source; the type and name of recorded wildlife living in the area; a DEM; a slope; a road; and satellite images from 2000, 2011, and 2022.

The following table shows both spatial and non-spatial data which are gathering from different source . Including: format, the source and resolution.

Table3.1: Data type and Source

S.no	Data and sensors used with its ID	Source	Data format	resolution	Acquisition date	Used
1	Landsat-7_ETM" image of 2000	USGS	Raster(.tiff)	30*30	3/6/2000	Forest change analysis
2	Landsat-7_ETM" image of 2011	USGS	Raster(.tiff)	30*30	8/2/2011	
3	Sentinel-2A image of 2022	Copernicus	Raster(.tiff	10*10	22/2/2022	
		Other data used for this study and its source				
4	Ethio- boundary	google(open Africa)	Shape file	-	-	For map of study area
5	Questionnaires data	community		-	-	For frequency analysis
6	25 GCP point	Field survey		-	-	For ground truth
7	Wildlife data	Lemu-Bilbilo environmental protection authority				To know current status of wildlife
8	Road Data	bbbike.org/community		-	-	For prediction
9	DEM	USGS		30m	-	For prediction
10	Slope	DEM		-	-	For prediction

3.3 Software and material used

Different material and software were used in this study like: SPSS, ARCGIS 10.8,1, Earth resource data analysis system (ERDAS) imagine 2015, and Mendeley desktop. Which were illustrated in the table below.

Table3.2: Software used

S.no	Name of software	Purpose
1	SPSS	for questionnaires data analysis
2	ArcGIS 10.8.1	Data processing and thematic map preparation
3	ERDAS Imagine 2015	For processing and analyzing satellite Image
4	ENVI 5.3	For image classification
5	Google Earth Pro	Use as a base map in visual image interpretation,
6	QGIS	For future prediction
7	Mendeley desktop	For referencing
		Material used
8	Handle GPS	For GPS point collection

3.4 Data Processing and Analysis Method

After the data were collected from its sources, the data were analyzed by using different formula and software like ArcGIS, QGIS, ENVI5.3, SPSS and ERDAS IMAGINE 2015.

3.4.1 Image pre processing

Image processing is an important step that should be done before using the raw digital satellite image directly for the intended purpose. It involves operations that are normally required prior to the main data analysis and extraction of information. Therefore, image preprocessing in this study was done after layer staking and clipping of the study area.

Layer stacking is a primary process after obtaining satellite images from different sources, as most images are provided in separate bands. All of the bands from that specific satellite image are stacked into a single file under a layer stack. Therefore, for all the Landsat images, Landsat 7-ETM" of 2000, 2011, and Sentinel2A of 2022, layer staking is done in ERDAS 2015. Following layer stacking, band combinations were used (for Landsat7, bands 1, 2, 3,4,5,7, and 8; for Sentinelbands, bands 2, 3,4, and 8). The true color RGB (3, 2, 1) for Landsat 7 and for Sentinel 2A RGB (4, 3, 2) were done after layer stacking.

Landsat images of 2000, 2011, and Sentinel 2A were downloaded from the USGS and Hub Copernicus prior to layer stacking. During this, some images have errors like scanline errors.But this error was fixed or removed using ArcGIS by downloading the Landsat toolbox. There are no scanline errors in other Landsat images from 2000 or in Sentinel 2A. However, the 2011 Landsat image contains scanline errors during download from the USGS website. The scanline errors make identifying features for classification difficult. Due to this, the image needs to be corrected using ARCGIS after downloading the Landsat toolbox and adding it to the arc toolbox. Each band scanline error was fixed in Arc GIS separately.

After layer stacking and band combination, radiometric corrections were made for the images of 2000, 2011, and 2022, including, noise reduction and haze reduction, to improve the image quality. Atmospheric effects can cause imagery to have a limited dynamic range, appearing as haziness or reduced contrast. Due to this, haze reduction is used to correct this effect. whereas noise reduction reduces the amount of noise in a raster layer.

Clipping: the process of extracting an interesting area from a satellite image using a shapefile or by digitizing the area of interest is known as clipping. In this study, the interesting areas were extracted from three images of different years (2000, 2011, and 2022) by using shape file

3.4.2 Image classification

Image classification is the process of categorizing pixels based on their data file values into a finite number of individual classes or categories of data. Hence, if a pixel satisfies a certain set of criteria, then the pixel is assigned to the class that corresponds to that criteria. For this study, image classification was done after carrying out all digital image processing operations such: as image enhancement (spatial and spectral) by using ERDAS IMAGINE 2015. Then classification was done in ENVI 5.3. Extracting different types of information about the target under investigation is largely possible classification to the raw digital satellite imagery. In this regard, supervised classification techniques have been employed. Then, after supervised classification has been made based on training areas. Post classification techniques such as confusion matrix and kappa statistics have been used to assess the accuracy of the classified image. Statistical data was used to determine the pattern of change in cover types between 2000, 2011 and 2022. A brief description of each task regarding image classification is described in the next section.

3.4.3. Supervised classification

Supervised classification is also another classification technique that clusters pixels in a data set into classes corresponding to user-defined training classes. Training classes are groups of pixels or individual spectral. In this classification, representative samples for each land cover class were selected. The software then uses these "training sites" and applies them to the entire image. According to (Forkuo, Eric K. Frimpong, and Adubofour, in supervised image classification, the study area was taken through three stages to generate land cover classes of the study area. These include (1) feature extraction; (2) selection of training data (signatures); and (3) selection of suitable classification approaches. That was the same for this study, and the Train support vector machine classifier algorithm was applied to Landsat images of 2000, 2011, and Sentinel 2A of 2022.

Train support Vector machine (SVM) is one of the most popular supervised learning algorithms, which is used for classification as well as regression problems in machine learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n–dimension space into classes so that we can easily put the new data in the correct category in the future. Also, SVM works by mapping data to a high-dimensional feature space so that data points can be categorized even when the data are not otherwise linearly separable.

3.4.4 Change detection analysis

Change detection analysis is used to identify, describe, and quantify differences between images of the same scene at different times or to identify which land class was changed to other land classes and how much change occurred in hectares and percent. In this study, a different set of three imageries was used, and a change detection analysis was performed on these imageries (2000, 2011, and 2022). To analyze change Between various land classes, a post-classification comparison method was employed to analyze changes between various land classes.

Specifically, to determine the detection of forest cover change and the rate at which it changes. This kind of change detection method identifies and provides where and how much change has occurred. In this forest cover change detection, the selected three dates of satellite imagery are used to determine the change by generating information on spatial and temporal distribution.

In the meantime, four aspects of forest cover change detection characteristics, such as detecting the changes that have occurred, identifying the nature of the change, measuring the areal extent of the change, and assessing the spatial pattern of the change, are being investigated. Moreover, a change detection matrix has been generated to investigate the trends and patterns of land use and land cover change detection in general and forest cover change detection in particular. Besides, different statistical results were documented, and the rate of forest cover change was also computed using the following equation.

$$R= \frac{Q2-Q1}{t} \text{ ....…………………….equation 3.1}$$

Where, R= is rate of change , Q1= is initial year forest cover in ha

Q2=recent year forest cover in ha T=the interval year between initial and recent year

Total LULC change = Area $_{\text{final year}}$ -Area $_{\text{initial year}}$........................equation 3.2

$$\text{Percentage of LULC change} = \frac{(\text{Area}_{\text{final year}} - \text{Area}_{\text{initial year}})}{\text{Area}_{\text{initial year}}} *100\text{…… equation 3.3}$$

After the change detection was computed by using equation 3.1, land use and land cover change map were generated form the image of 2000.2011 and 2022.

For more information see result section of change detection. In addition to these NDVI (normalized difference vegetation index) value was used to know the coverage of vegetation change between each selected year. Which range between -1 and 1.Thus based on the reflectance the feature class, classes can be identified. For image of selected years (2000, 2011 and 2022) NDVI value are Calculated by using the equation below.

-For Landsat image of 2000 and 2011

NDVI = NIR (Band4) -red (band3) / NIR (band4) +red (band3)………equation 3.2

-For Sentinel 2A image of 2022

NDVI =NIR (Band8) -red (band4) / NIR (band8) +red (band4)…………equation 3.3

3.4.5 Accuracy Assessment

Each LULC map derived from remote sensing always contains some sort of errors due to several factors, which range from classification technique to method of satellite data capture. These errors must be quantitatively explained in terms of classification accuracy. Whether the output meets expected accuracy or not is usually determined by the users themselves, depending on the type of application the map product will be used for later.

The accuracy levels that are acceptable for specific tasks are determined by the kappa value. According to (Forkuo & Frimpong, 2014), the ranked kappa values ranging from 0 to 1 are characterized into 3 groupings: a value greater than 0.80 (80%) represents a strong agreement and a value between 0.40 and 0.80 (40 to 80%) represents a moderate agreement, and a value below 0.40 (40%) represents poor agreement. kappa can be used as a measure of agreement between model predictions and reality or to determine if the values contained in an error matrix represent a result significantly better than random.

The accuracy of the years 2000, 2011, and 2022 classifications was assessed for each year classification using the collected GCP points of each class from classified images and Google Earth. Each point is taken as ground truth for the classification the locations of each class were compared to the ground truth by using the following formulas. And according to (Forkuo & Frimpong, 2014),kappa value is calculated by using equation 3.6

$$\text{User accuracy} = \frac{\text{Number of correctly classified pixels in each class}}{\text{Total number of pixels in each catagory}} * 100 \ldots equation\ 3.4$$

$$\text{overall accuracy} = \frac{\text{Total number of correctly classified diagonal pixel}}{\text{Total number of referance pixecatagory}} * 100 \ldots \text{equat } 3.5$$

$$\text{coefficient of kappa K} = \frac{\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi + xx + i)}{N^2 - \sum_{i=1}^{r}(xi + xx + i)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \text{equation } 3.6$$

3.4.6. Statistical Analysis Used

Statistical analysis is used in this study to become more scientific about decisions that need to be made. SPSS software is used to analyze the data obtained from the respondent. So, to obtain the information needed in this study, four kebele were selected from Lemu Bilbilo Woreda, two kebele from Sirka Woreda, and one person from eight workers of the Lemu-Bilbilo environmental protection authority office. From five kebele, twenty five and from one kebele twenty four respondents are selected.. Totally from six kebele and one government office, one hundred fifty samples are selected.All of these respondents filled out questionnaires about the key factors influencing forest change and the problems it causes, particularly for wildlife.

3.4.7 Analysis for Future prediction

The data used for future prediction was all in vector format, whereas MOLUSCE works with raster data. Therefore, the first thing was to convert all vector data to raster data to be able to deal with the plugin. Another term to deal with the plugin is to set the same coordinate system for all layers, which is (WGS_1984_UTM_Zone_37N). applied the resample process to all layers to determine the same pixel size. Finally, to set a fixed extent for all layers. By all these processes, the data was able to be used in the MOLUSCE plugin. The plugin measures the percent of area change in a given year and provides a transition matrix that shows the proportions of pixels changing from one LULC to another(Rangarajan, 2022). The plugin carried out the area change map, which presents the change in the land from 2011 to 2022 in all 5 classes. Thus, depending on the previous area covered, the transition matrix was calculated as follows.

The transition probability (Pij) matrix in a state which is calculated as follows;-

$$\|\mathrm{Pij}\| = \left\| \begin{matrix} P_{11} & P_{12} & P_{1N} \\ P_{21} & P_{22} & P_{2N} \\ \vdots & \vdots & \vdots \\ P_{41} & P_{42} & P_{4N} \end{matrix} \right\| \qquad \text{thus, } (0 \le pij \le 1)$$

Where i mean initial year,j is the second selected year, pij mean the probability of land use change from period i to j and N mean the last seleted period

The image used for this study as earlier and later were 2011 and 2022 LULC maps .Based on the projection of these two image of different years, the transition matric for the next 2044 were created.For validation two LULC were used ;the first one is the real LULC of the year 2022 and the second one is predicted LULC map of 2022.In addition for validation , kappa value were used to evaluate the accuracy of prediction (Rangarajan, 2022).

Kappa statistics ($K_{location}$, $K_{overall}$ and $K_{histogram}$) gives the amount of agreement that exists between the raster's and their probability. Where; $K_{location}$ is used to evaluate the ability of the simulation to identify location and $K_{overall}$ is employed to evaluate the overall success of the simulation.

Kappa statistics with 0% indicates that there is no agreement while 100% indicates perfect agreement. These kappa value are used to evaluate the accuracy of model .which are calculated as given below.

$$K = \frac{P(A)-P(E)}{P(1)-P(E)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. Equation\ 3.7$$

1 kappa location

$$K\mathrm{Kloc} = \frac{P(A)-P(E)}{Pmax - P(E)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Equation\ 3.8$$

2 kappa histogram

$$Khisto = \frac{Pmax - P(E)}{1 - P(E)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Equation\ 3.9$$

Where

$$\mathrm{P(A)} = \sum_{i=1}^{c} \mathrm{Pij} = \sum_{1}^{c} = 1\mathrm{PitPtj}, \mathrm{Pmax} = \sum_{i=1}^{c} \min(\mathrm{Pitptj}),$$

pij is the i,jth cell of contingency table, pit is the sum of all cells in the ith row, ptj is the sum of all cells in the jth column, and c is count of raster categories, kappa statistics obtain From above formula gives the amount of agreement that exists between the raster’s and their probability. To produce valuable data and conclusions, selection of appropriate research method is a key issue at the outset. So, both quantitative and qualitative research methods were used for this study which is shown in the figure below.

3.5 Methods

The methods were procedures followed in this study to obtain the desired result, and they show the technical steps followed in primary and secondary data to achieve the required objectives. This includes: the classification method, change analysis, community data sampling method, and future prediction. Thus, based on the obtained data and the research objectives, the methods used to attain the research goal are shown in the next.

3.5.1 Classification method

The following procedures were used for image classification to produce LULC map and forest cover map of 2000,2011 and 2022

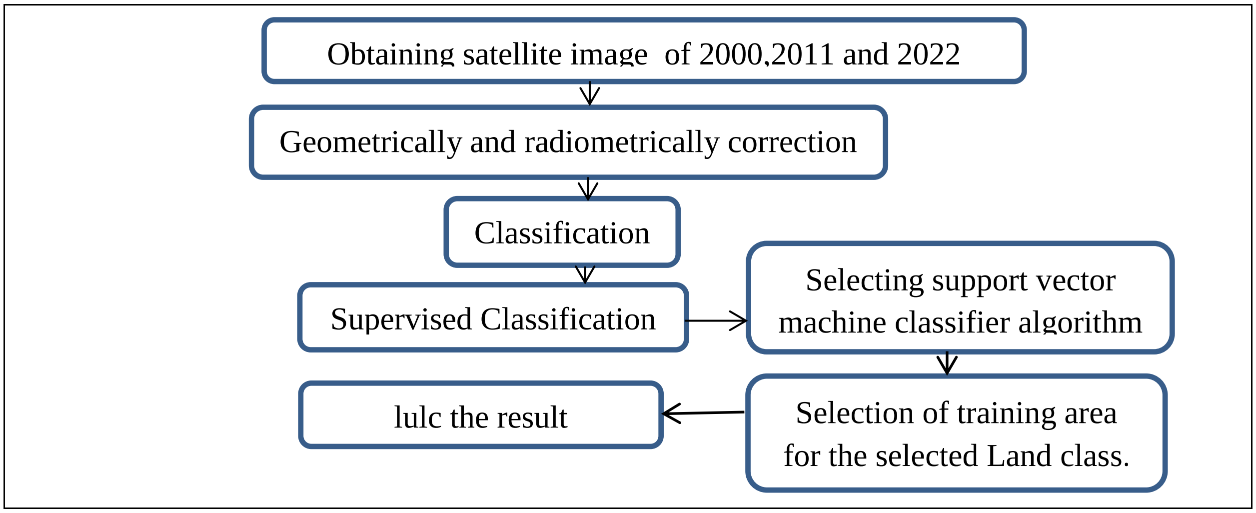


Figure 3.3 Classification procedures

3.5.2 Change analysis.

This steps is show the change analysis between LULC of 2000, 2011 and 2022.including the forest cover change between selected three years.

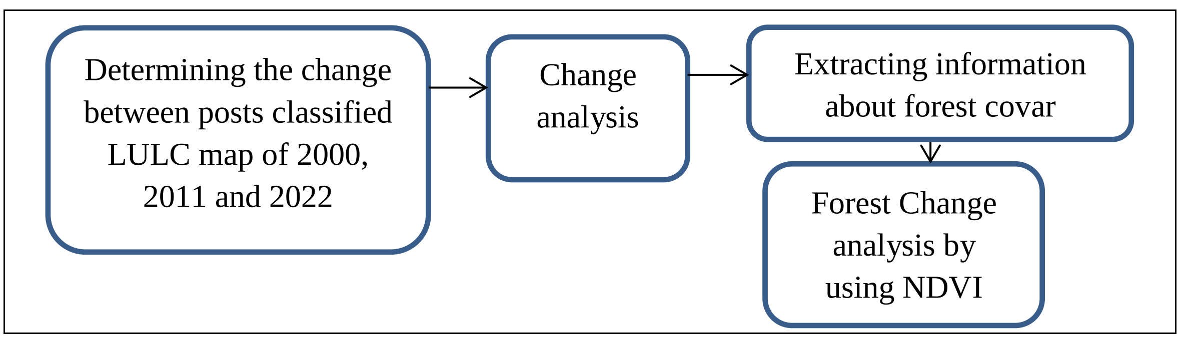


Figure 3.4 procedures for change analysis

3.5.3 Community Data Sampling

In this method partitioning the population into groups called strata is as kebele, and then drawing a sample (respondents) independently from each stratum (kebele) is known as stratified sampling. In stratified random sampling, the population of N units is first divided into subpopulations of sizes N1; N2; …; Nn, respectively. From the set of sizes $n1$; $n2$; …; nn will be taken from each stratum (kebele) by treating each stratum as a separate population.

This sampling method was chosen because the selected kebele is better known by a mixed forest and bounded the study area .

$$n = \frac{(p)(q)z^2}{(e)^2} + \cdots \textit{equation } 3.10 \text{ (Cochran 1963)}$$

where , n = sample size

p = proportion of the population containing the major interest

q=1-p

e = acceptable/allowable error = 0.08

p=0.5 and q=1-p = 1-0.5= 0.5,

Z = 1.96

$$n = \frac{(0.5)(0.5)(1.96)^2}{(0.08)^2} \qquad n = 150$$

The study used 95 percent of confidence level (Z=1.96). The maximum variability principle suggested by Cochran (1963) was used. Therefore, p = 0.5, and q = 0.5. Using an allowable error of 8 percent, the total sample size was 150.

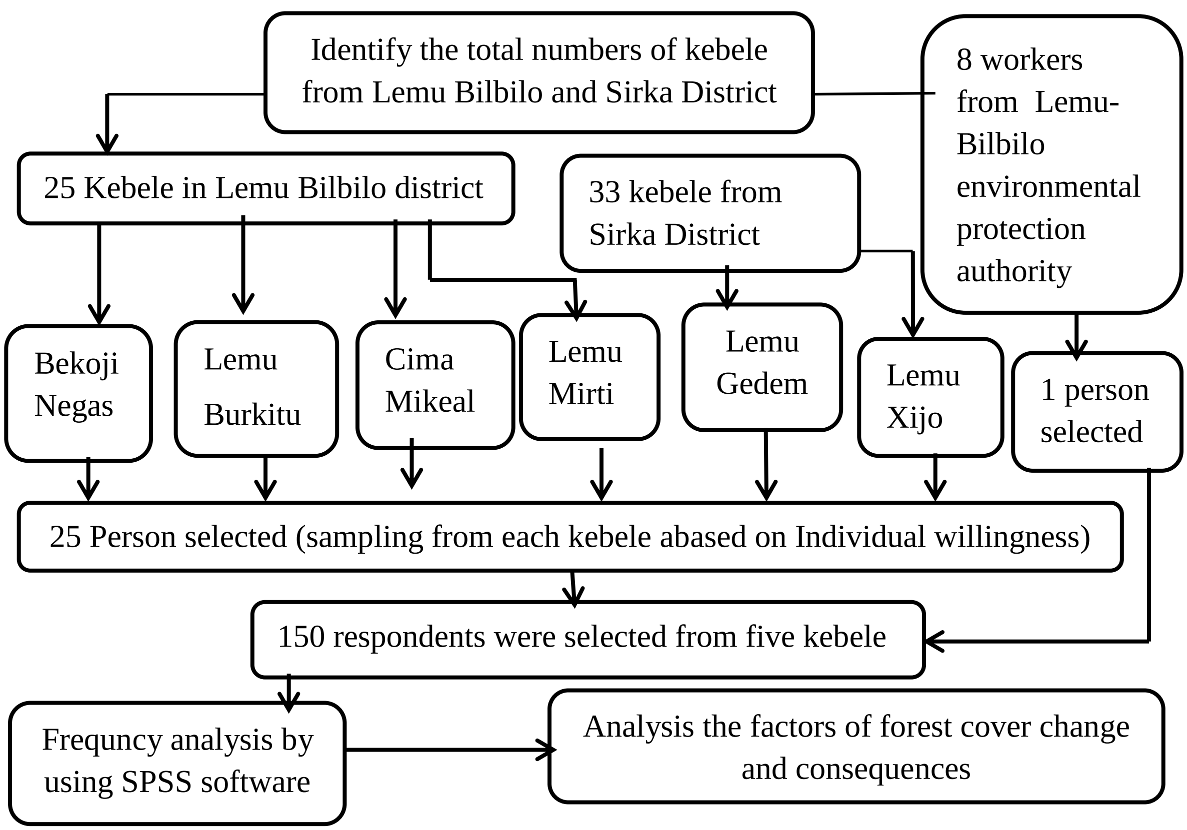


Figure 3.5 Chart of Stratified sampling procedures.

3.5.4 Future forest cover change prediction

This steps were followed after all variable or data were analyzed .which was explained in data analysis method.ThusThe procedure followed to get the future prediction of land use land cover and forest cover of galema forest for 2044 year were as follows.

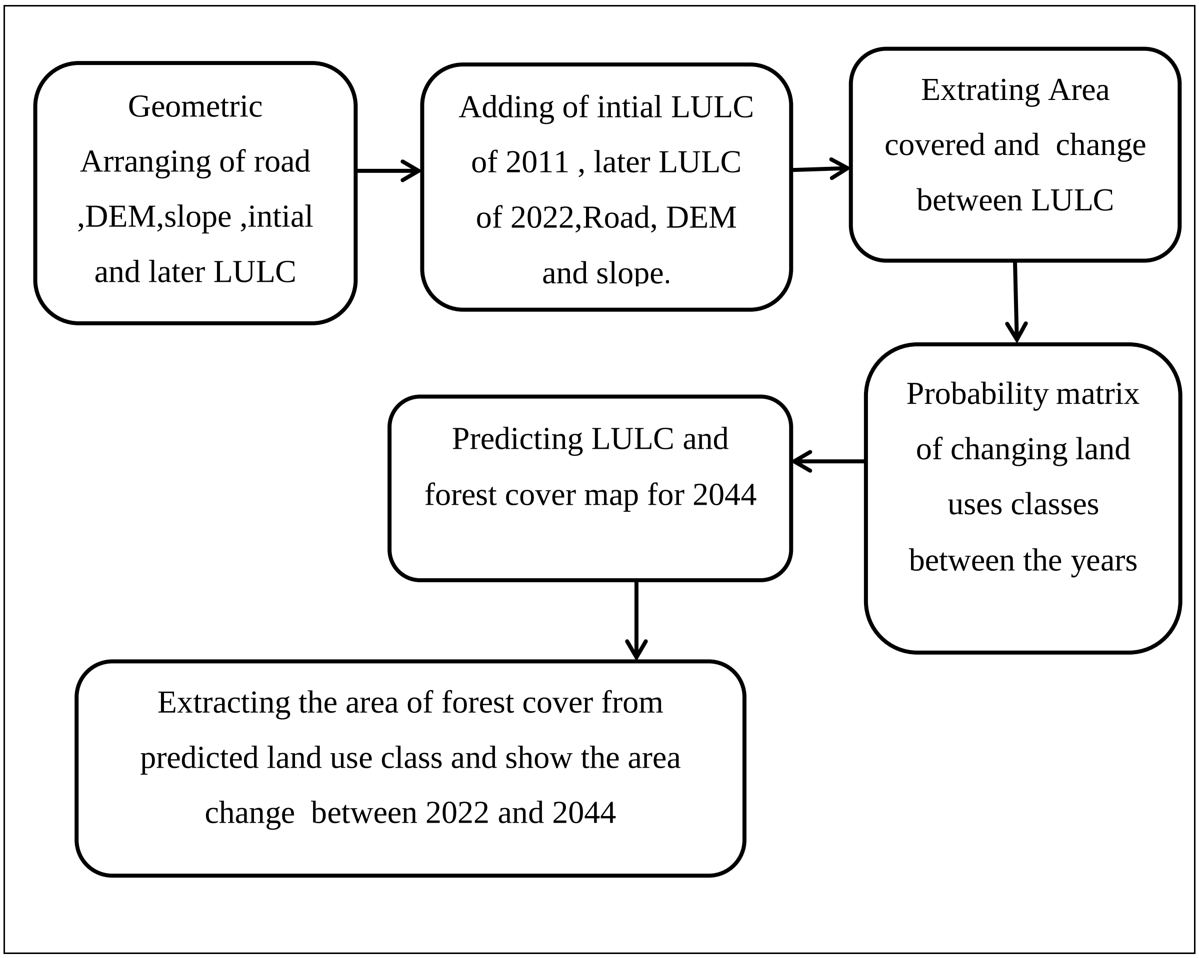


Figure3. 6 procedure for future prediction

All the above methods are the set of procedures which is seriously and carefully followed to attain the specific objective of the research and used to achieve the main objective of the study. So method of image classification, method of change analysis ,method of community based data analysis and method of future prediction are generalized in the following figure .

This the general work flow was summarize and contain all procedure of the study.

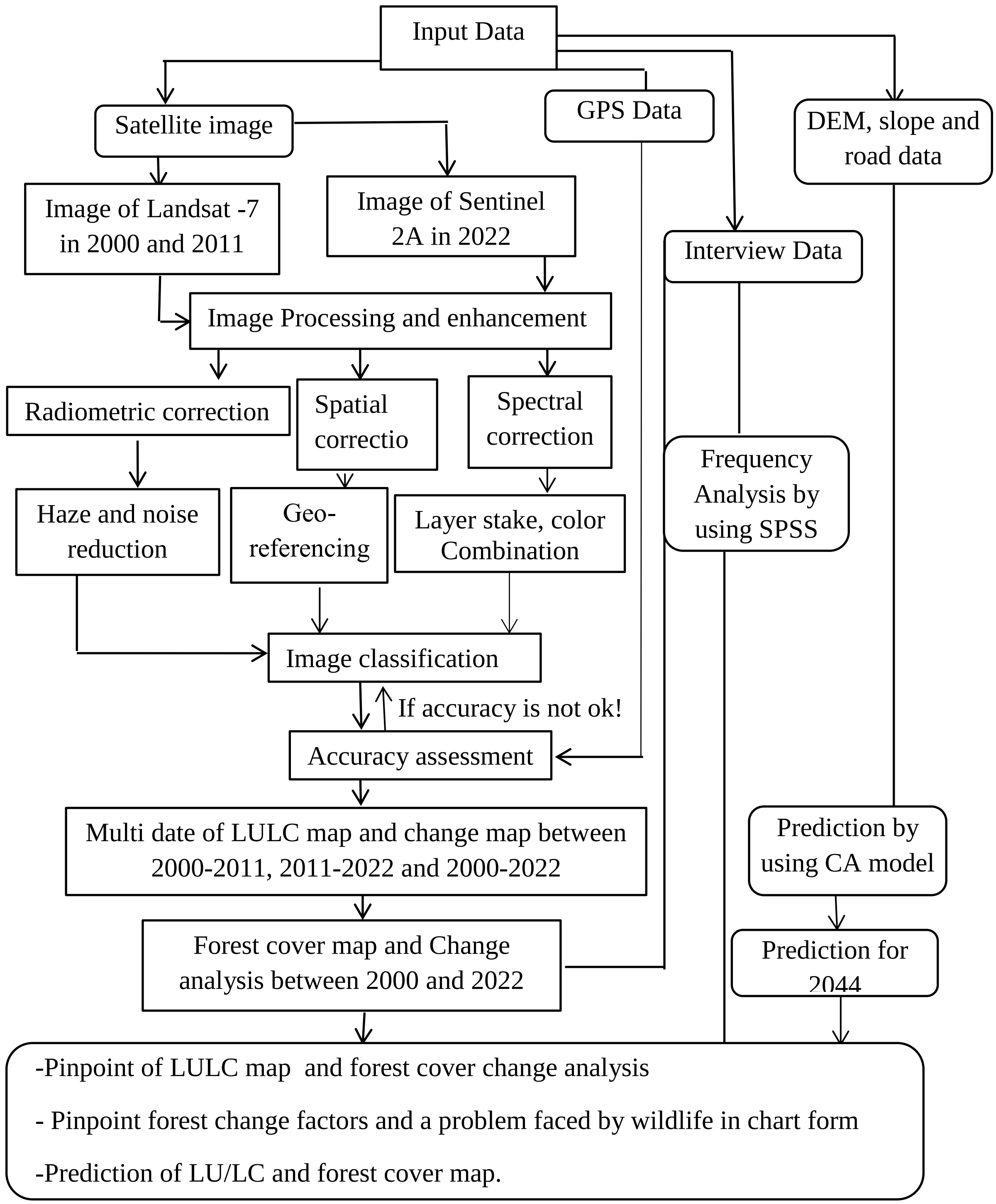


Figure 3.7 Methodological flow chart

CHAPTER IV: RESULT AND DISCUSSION

This section describes the results obtained through data processing and analysis methods, and it encompasses four major parts. In the first part, the LULC map of the study area and the nature of forest cover change detection and the magnitude of its change are documented using post-classification comparison change detection techniques and NDVI analysis. In the second part, an attempt has been made to present the driving factors of forest change. The problems that occurred to wildlife and the environment were presented, and the future prediction for forest change was described in the fourth section.

4.1 Trend of LULC Change

4.1.1 Image preprocessing and classification

Image preprocessing is an essential technique used to improve the quality of raw satellite data (Navin & Agilandeeswari, 2020). The 2011 Landsat image contains scanline errors that occurred during the download from the USGS website. And these scanline errors make it difficult to identify features for classification. The errors were removed by using ARCGIS after downloading the Landsat toolbox and adding it to the arc toolbox. Each band scanline error was fixed in Arc GIS separately. True colors for each image and the removed scanline error for the image Landsat 7 in 2011 are shown in the figure below.

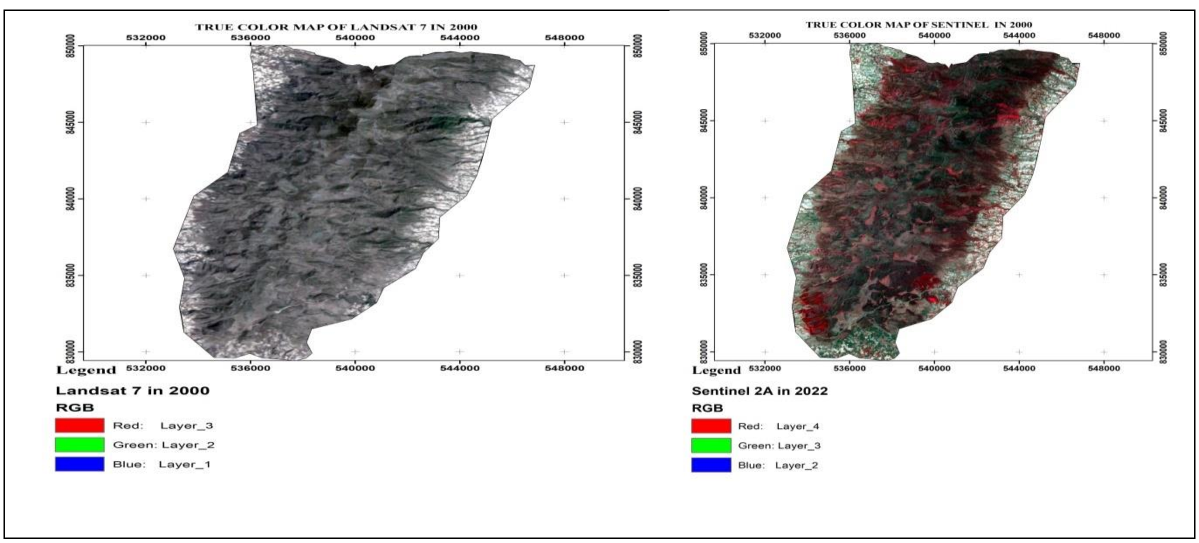


Figure4.1: True color maps of 2000 and 2022

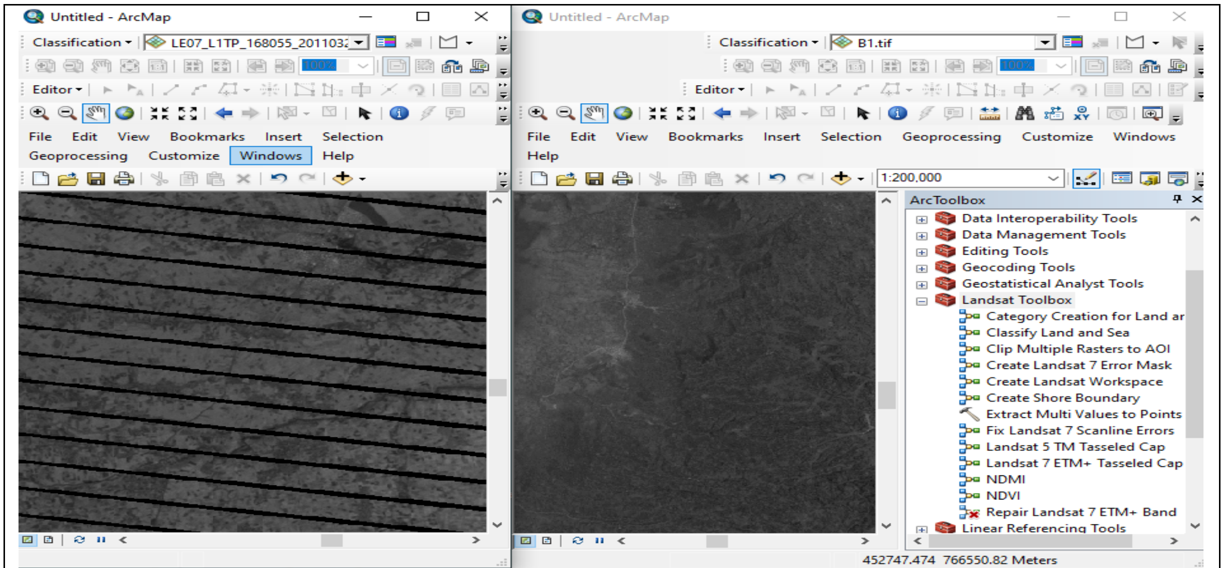


Figure4.2 corrections for 2011 image with scanline error

Acording to this study, the forest coverage of the area was further classified into high-density forest, dense forest, and sparse forest to suit the analysis of forest change. Besides this, farmland and grassland are categorized into different classes. In general, land use and land cover maps have been generated from the processed Landsat images of the years 2000, 2011, and 2022 for the area under investigation and summarized in table 4.1.

Table4.1: Major land use /land cover class for Galema forest and its description.

No	Land use classes	Descriptions
1	High density forest	Area covered by highly natural forest and tree plantation.
2	Dense forest	Area covered by medium natural forest and tree plantation.
3	Sparse forest	Area covered by scattered natural tree.
4	Grassland	A lands, where small grasses are the predominant natural vegetation
5	Farmland	a large area of land used or suited for farming

4.1.2 LULCs classification

LULCs of the study area were categorized in to five major types; these are: high density forest, dense forest, sparse, grassland and farmland.

4.1.3 Land use / cover

Based on the results extracted from the 2000 Landsat image, the LULC of the study area was classified into five major classes. This area has high-density forests, dense forests, sparse forests, grassland, and farmland. Therefore, the results of these classes are shown in the following figure.

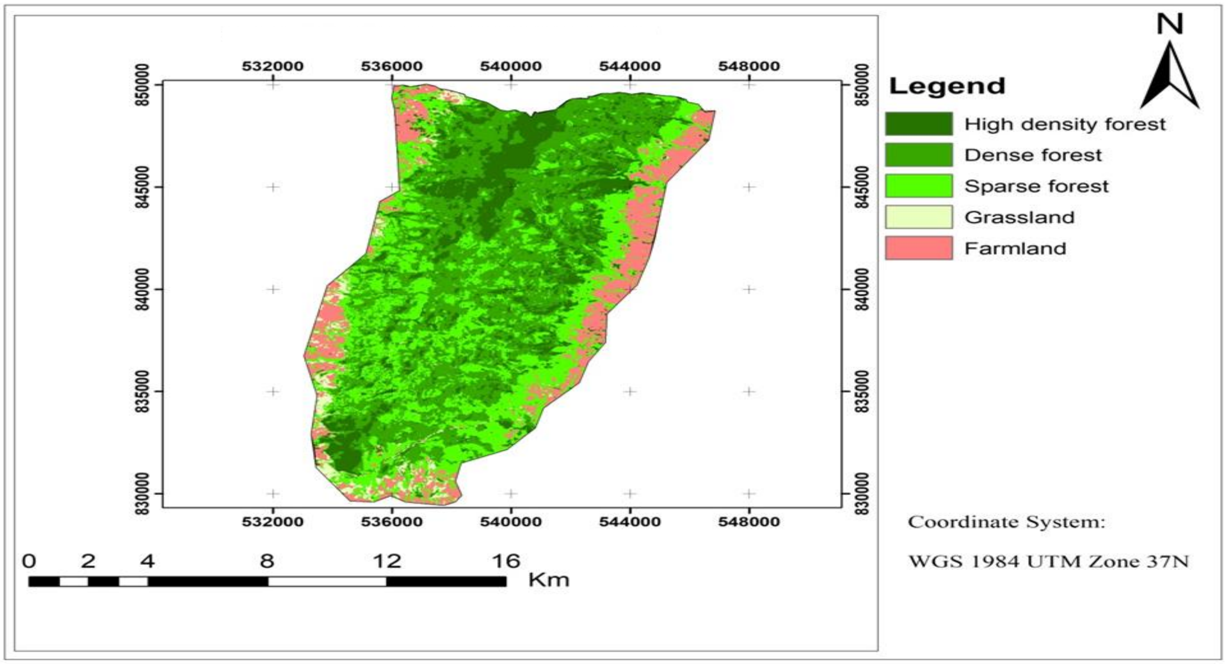


Figure4.3: land use and land cover of Galema forest in 2000

The area coverage by each land use classes were presented in the following table.

Table 4.2: Area covered by land classes in hectare and percent in 2000.

Year	Class name	Areain hectare(ha)	Area in percent (%)	Total
	High density forest	2846.28	16.4	
	Dense forest	6882.30	39.7	
2000	Sparse	5130.87	29.5	17355.15
	Grassland	477.37	2.8	
	Farmland	2018.33	11.6	

Source; From ArcGIS attribute table of 2000 year image classification.

The area coverage by each land use classes were calculated by using the following formula.

$$\text{Area of land use classs in hectare} = \frac{(30*30)*number\ of\ pixel/count}{10000} + \ldots \text{equation 4.1}$$

Where;-30*30 means pixel size

Count; mean the total number of pixels that represent the class.

According to the LULC Map in figure 4.5, high-density forest covered 16.4% of the total area, dense forest covered 39.7%, sparse forest covered 29.5%, and grassland and farmland covered 2.8% and 11.6%, respectively. The largest part of the study area was covered by dense forest, followed by sparse forest and highly dense forest, at 39.7%, 29.5%, and 16.4%, respectively. But the least covered was farmland.

The result of LULC for Landsat image in 2011 was shown in the following figure.

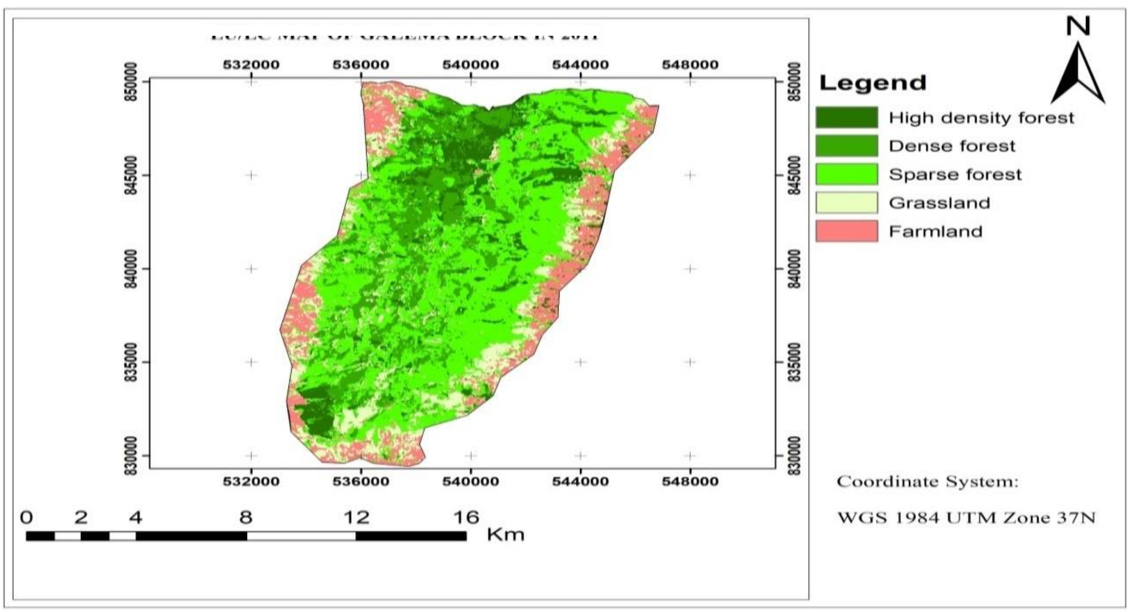


Figure4.4: land use / land cover map of 2011

The LULC result in 2011 was the same as the previous one .but the difference was the area covered by each land use class. Therefore, based on the results extracted from the Landsat image in 2011, the LULC of the study area was classified into five major classes. These were: high-density forest, dense forest, sparse forest, grassland; and farmland.

The area covered in hectares and the percent for each land use class were presented in the table below.

Table 4.3: Areas covered in hectare and percent for land use classes in 2011.

Year	Class name	Area in hectare(ha)	Area in percent (%)	Total
2011	Highly dense forest	1902.83	11	17355.15
	Dense forest	3265.24	18.8	
	Sparse	7807.24	45	
	Grassland	2260.06	13.1	
	Farmland	2119.78	12.1	

From the above table, each LULC has a different area coverage when compared with the 2011 result. Thus, high-density forest covered 1902.83 ha, dense forest 3265.24 ha, sparse forest 7807.24 ha, farmland and Grassland 2260.06ha, 2119.78 respectively. In this table largest areas were covered by sparse (45%) and dense forests (18.8%), but the amount of area covered in 2000 was greater than in 2011. The other land classes covered by: high-density forest, farmland, and grassland were 11%, 13.1%, and 12.1%, respectively. This shows that: high-density forests and dense forests were increased. But sparse, grassland and farmland decreased. Because when one land use class increased the other land classes decreased.

The result of land use /land covered of sentinel 2A was presented in following figure and table

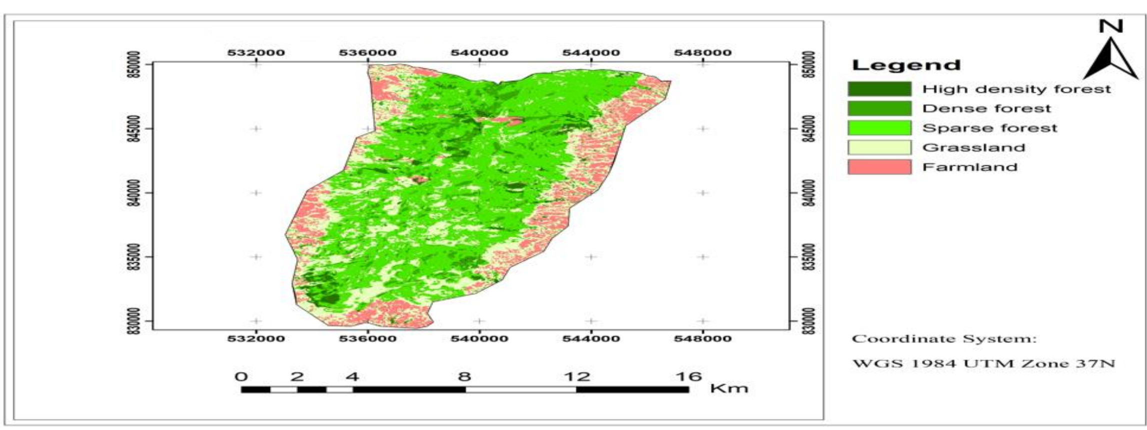


Figure4.5: LULC cover map in 2022

The LULC result in 2022 was the same as the previous ones (2000 and 2011). But the difference was the area covered by each land use class. Therefore, based on the results extracted from the Landsat image in 2022, the LULC of the study area were: high-density forest, dense forest, sparse forest, grassland and farmland. The area covered in hectares and percent for each land use class is presented in the following table.

Table 4.4: Land use /land cover map in 2022.

Year	Class name	Area in hectare(ha)	Area in percent (%)	Total
	Highly dense forest	679.45	3.9	
	Dense forest	1166.56	6.7	
2022	Sparse	8733.2	50.3	17355.15
	Grassland	4526.24	26.1	
	farmland	2249.7	13	

Source; From ArcGIS attribute table of 2022 year image classification.

In table 4.4, the largest area was covered by sparse forest (50.3%), followed by farmland (13%) and grassland (26.1%), respectively. The area change between land classes in 2000, 2011, and 2022 was presented in the following table by using the following formula. The areas covered were summarized in the bar graph and pie chart (in hectares and percent).

Change in ha =h2-h1

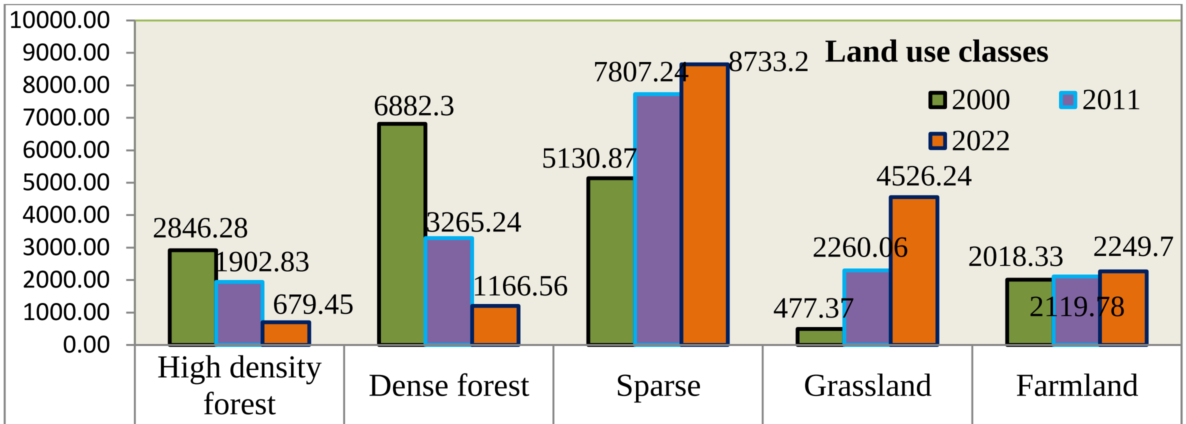
Change in percentage =P2-P1

Where :- (h1) Means the initial area of class in hectare and (h2) the final area of classes in hectare. (P1) Mean the initial area of class in percent and (P2) the final area of classes in percent. The area changed between selected three years are calculated by hectare or percent. Therefore the areas changed in the following table were calculated by percent.

Table 4.5: LULC Area Summary for each selected years

No		Selected years					
		2000		2011		2022	
		Area in%	Change b/n 2000-2011	Area in %	Change b/n 2011-2022	Area in %	Change b/n 2000-2022
1	High dense forest	16.4	-33.1	11	-64.3	3.9	-76.1
2	Dense forest	39.7	-52.6	18.8	- 64.27	6.7	-83
3	Sparse	29.5	52.2	45	11.9	50.3	70.2
4	Grassland	2.8	373.4	13.1	100.3	26.1	848.2
5	farmland	11.6	5	0.5	6.1	13	15.5
6	Total	100		100		100	

Figure 4.6 and figure 4.7 shows the area covered by each land use class in 2000, 2011, and 2022. Thus, it shows high density and dense forest were decreasing, but sparse forest, grassland and farmland were increasing. In total, forest cover (high density, dense forest, and sparse) was 85.6% in 2000, but it will be 60.8 in 2022. This shows that the forest cover decreased by 24.8% from 2000–2022. (sourced from tables 4.4 and 4.6). The area covered by each land use and the land cover in hectares and percent were presented in the following bar graph and pie chart, respectively.



	High density forest	Dense forest	Sparse	Grassland	Farmland
2000	2920.68	6812.73	5135.67	488.79	2015.10
2011	1943.46	3293.91	7729.92	2297.52	2108.16
2022	699.75	1207.26	8646.57	4556.25	2263.14

Figure 4.6: Bar graphs of LULC in hectare for 2000, 2011 and 2022.

The area coverage of different land use classes in selected years can be interpreted in many ways, like the bar graph shown above. Moreover, the pie chart below depicts the percentage of area coverage of each land use during different time series. Thus, to represent total land cover in percentage, the pie chart was easy and precise to convey the information as shown below.

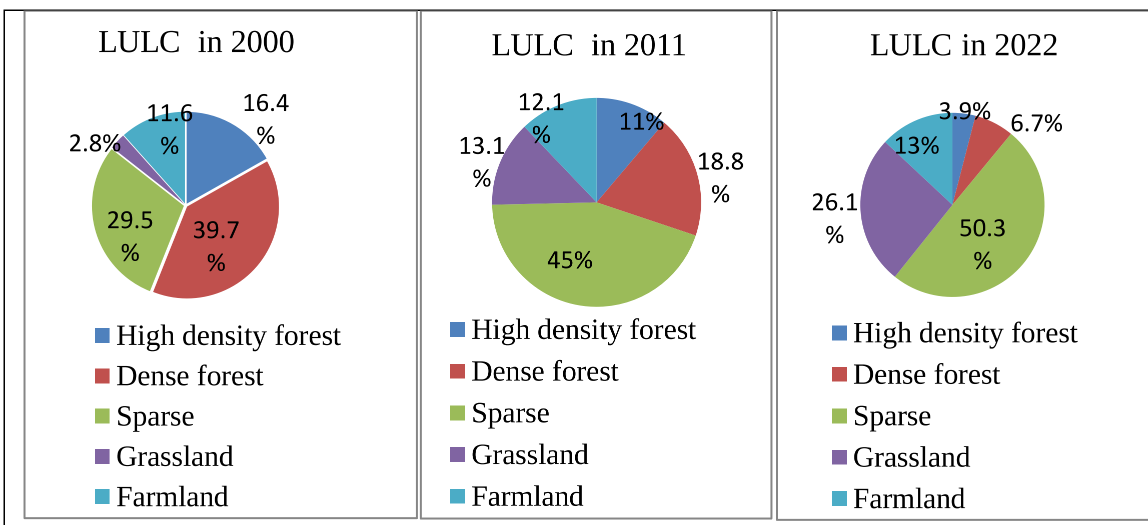


Figure 4.7:pie chart of LULC area coverage in percentage for 2000.2011 and 2022

4.1.6 Accuracy assessment

The overall accuracy, user accuracy and kappa value for the image of 2000, 2011 and 2022 were present in the following table. For more clarification see the appendix part of accuracy computation.

Table 4. 6: Accuracy assessment for image of 2000, 2011 and 2022.

Year		land use classes					Overall accuracy in %	Kappa Value %
		Highdensity forest	Dense forest	Sparse forest	Grass land	Farm land		
2000	User accuracy %	95	87.34	90.48	90.91	86.79	**89.97**	87.34
2011		95.75	95.71	96.77	93.06	76	**92.035**	90
2022		96.36	100	90.36	93.94	92.42	**95.35**	94.08

4.1.7 LULC Change detection based on post classification for selected years

4.1.7.1 Change detection between 2000 and 2011

From the change map shown in Figure 4.8, there is a conversion of one class into another class between the years 2000 and 2011. These conversions were between the same class and different classes. High-density forest to High-density forest, Dense forest to Dense forest, Sparse to Sparse, Grassland to Grassland, and Farmland to Farmland (i.e., between the same land use classes) show unchanged area during the period. In other words, the conversion from one class to another class alters the area coverage of the classes. For more information, see the following change map.

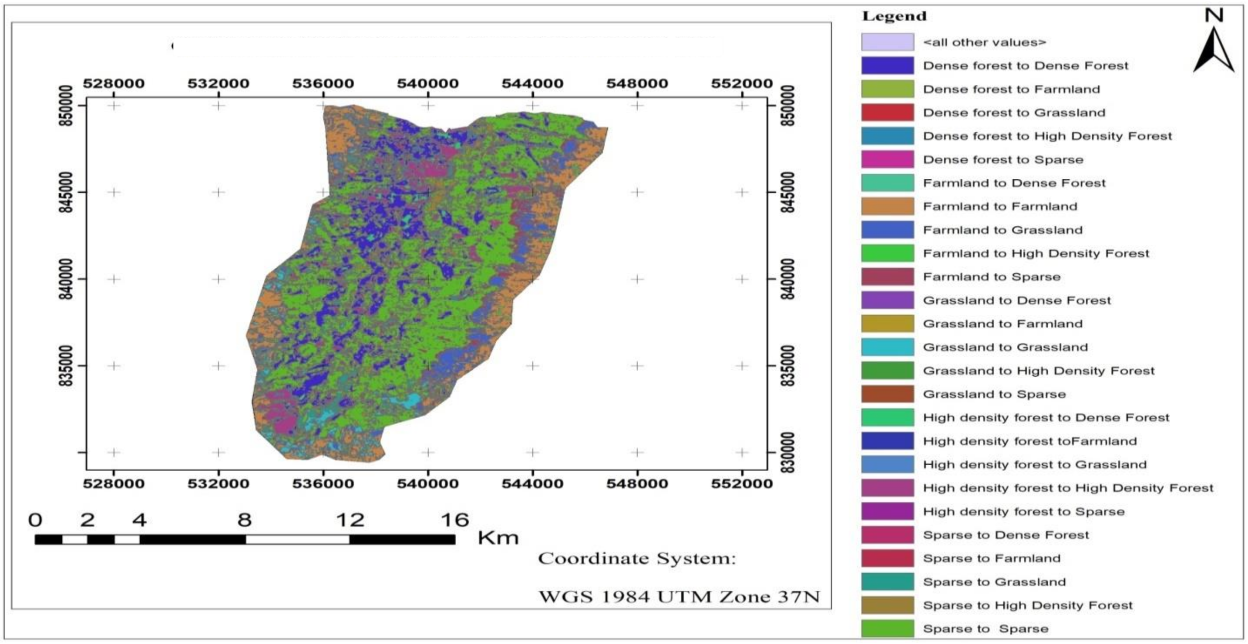


Figure4.8change map of between 2000 and 2011 year

These figure indicate that the conversion of one land use class into other land use class.

Table 4.7: Change matrix of land uses between 2000- 2011

Land class		Area of Land use class (ha) in 2011 (final**)**					
		High density	dense forest	sparse	grassland	farmland	Grand Total
Area of Land use class (ha) in 2000 (initial)	High density	1027.16	961.28	724.74	66.12	66.98	2846.28
	Dense forest	719.21	1949.4	4101.21	110.15	2.33	6882.30
	Sparse	105.39	348.83	2896.08	1438.24	342.24	5130.87
	grassland	0.81	3.70	32.21	365.94	74.70	477.37
	Farmland	50.26	0.03	54.90	279.60	1633.54	2018.33
	Grand total	1902.83	3265.24	7807.24	2260.06	2119.78	17355.15
	Change	-943.45	-3617.06	2676.37	1782.69	101.45	

Source; ArcGIS change matrix between 2000 -2011

According to the transition matrices between 2000 and 2011, high-density forest 1027.16, dense forest 1949.40, sparse 2896.08, grassland 365.94, and farmland 1633.54 are persistent. This means the diagonal number indicates an unchanged area. However, when compared to other land classes, high-density forest conversion to dense forest and sparse forest is high. Conversion from dense forest to sparse forest (4101.21) and sparse forest to grassland (1438.24) is also high, but conversion from one land use class to another is low. Finally, the grassland (74.70) is converted to farmland. Due to one land use class changing into another's land use class, the area coverage of one land class is changed. When one class is increased, the other class is decreased. The five land use classes reduce high-density forest by 943.45ha, dense forest by 3617.06 ha, and sparse, grassland, and farmland by 2676.37ha, 1782.69ha, and 101.45ha, respectively.

4.1.7.1 Change detection between 2011-2022

This period shows a similar trend to the previous period between the land classes. However large area of high-density forest decreased but the area of grassland increased (1243.71 and 2258.73) as compared with sparse, dense forest and farmland.

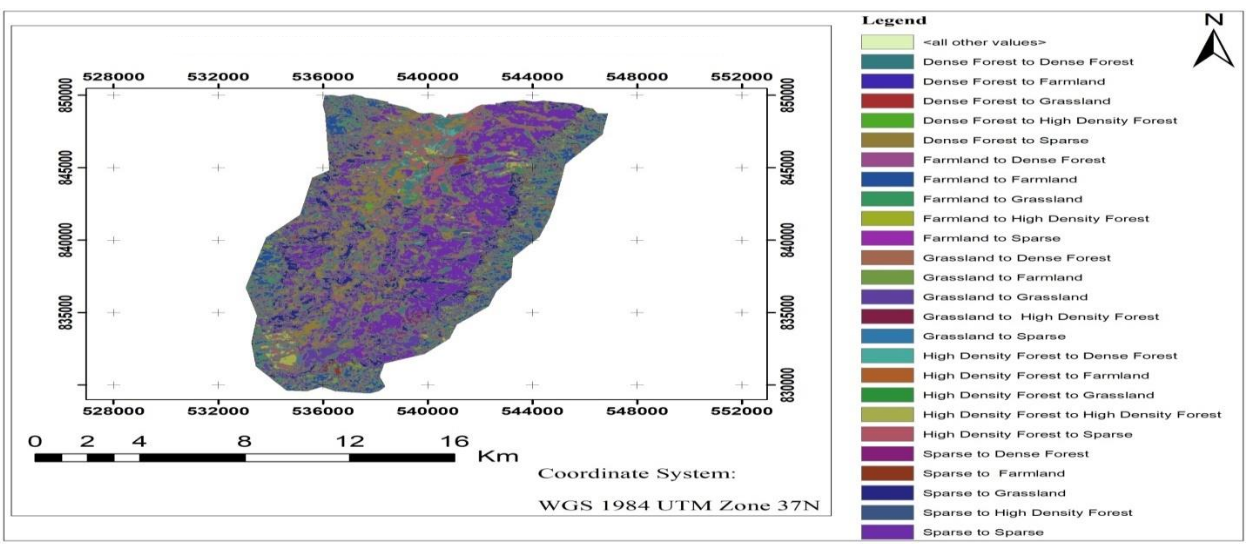


Figure 4.8: Change map of between 2011 and 2022

The following table shows the same conversion between land classes as in the previous period, but there is a change in area coverage. For example, the conversion of high-density forest to dense forest and spares is 267.14 and 1076.62, dense to sparse is 2158.61 and sparse to grassland is 1985.11 and farmland to grassland is 877.22.

Table 4. 9: Change matrix of land uses between 2011- 2022

Land use		Area of Land use class (ha) in 2022 (final)					
		High density .f	Dense forest	Sparse	Grassland	Farmland	Grand Total
Area of Land class (ha) in 2011(initial)	High density	344.39	267.14	1076.62	140.16	74.52	3265.24
	Dense forest	94.55	724.30	2158.61	260.35	27.43	2119.78
	Sparse	204.03	142.71	5189.95	1985.11	287.33	2260.06
	Grassland	23.98	26.88	287.52	1263.40	658.27	1902.83
	Farmland	12.50	5.52	22.40	877.22	1202.14	7807.24
	Grand Total	679.45	1166.56	8733.20	4526.24	2249.70	17355.15
	Change	-2585.79	953.22	6473.14	-2623.41	5557.54	

Source; ArcGIS change matrix between 2011 -2022

4.1.7.2 Over all Change between 2000-2022

The change between the 2000 and 2022 years shows the overall change between the initial year and the final year. During the initial period, most of the area was covered by high-density, dense forest, and sparse forest, and in the final (2022) year, the least coverage in hectares was high-density and dense forest. The high-density forest cover decreased from 2846.28ha in 2000 to 679.45ha in 2022, with a decrement of 2167.28ha. And dense forest cover decreased from 6882.30ha in 2000 to 1166.56ha in 2022, with a decrement of 5715.74ha between the years. Conversely, sparse, grassland and farmland show increments of 3602.33ha, 4048.87ha, and 231.37ha, respectively. as shown in the following figures and tables.

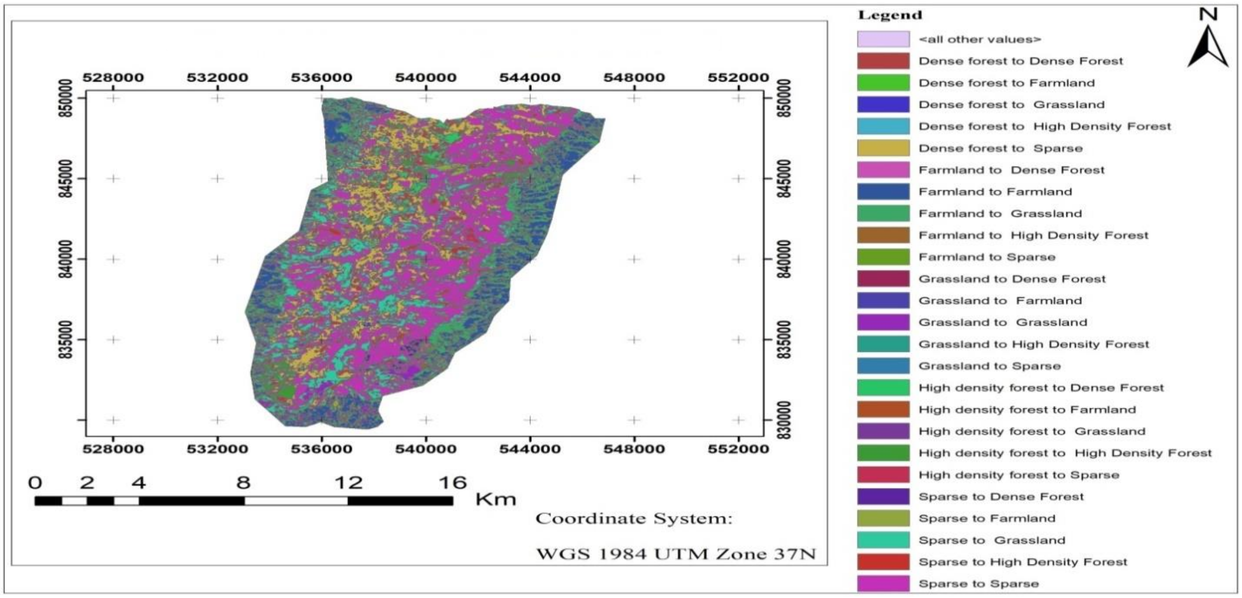


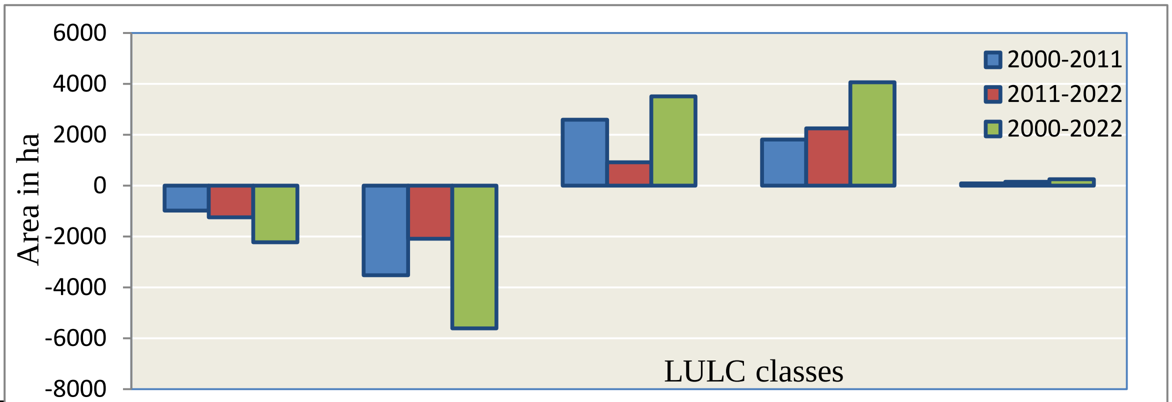
Figure 4.9: Change map of between 2000 and 2022

Table 4. 10: Change matrix of land uses between 2000- 2022

Land class		Area of Land use class (ha) in 2022 (final)					
		High density .f	Dense forest	Sparse	Grassland	Farmland	Grand Total
Area of Land class (ha) in 2000(initial)	High density.f	422.55	706.09	1435.08	217.23	65.33	2846.28
	Dense forest	144.78	379.98	5352.59	902.25	102.43	6882.30
	Sparse	98.45	76.07	1923.87	2405.19	627.30	5130.87
	Grassland	5.72	1.71	11.94	249.45	208.53	477.37
	Farmland	7.95	2.71	9.43	752.13	1246.11	2018.33
	Grand Total	679.45	1166.56	8733.20	4526.24	2249.70	17355.15
	Change	-2167.28	-5715.74	3602.33	4048.87	231.37	

Source; ArcGIS change matrix between 2011 -2022

As shown in Table 4.9, there is a conversion of land classes to other land classes from the initial (2000) year to the final (2022) years. During these conversions between 2000 and 2011, 2011 and 2022, there were area gains and losses for each land use class. This was the same for the overall change between 2000 and 2022, which is shown in the figure below.



Years	HighD.forest	dense forest	Sparse	grassland	Farmland
2000-2011	-943.45	-3617.06	2676.37	1782.69	101.45
2011-2022	-1223.38	-2098.68	925.96	2266.18	129.92
2000-2022	-2846.28	-5715.74	3602.33	4048.87	231.37

Figure4.10: Area gain and loss between selected years.

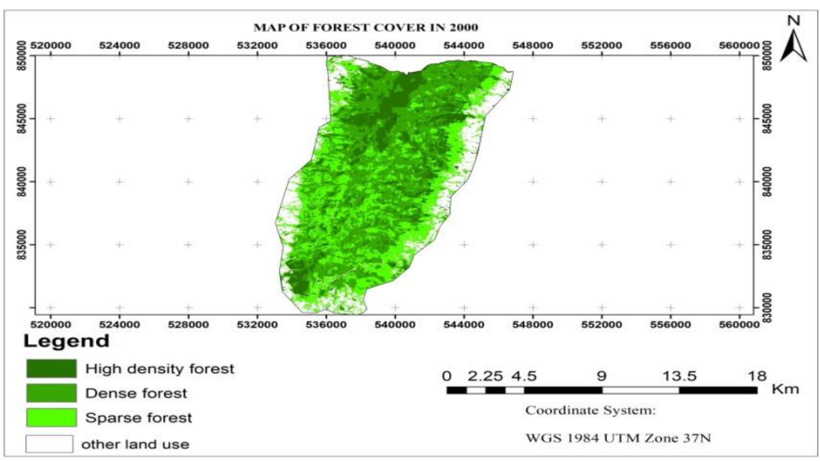
figure 4.10 indicate the area loss and gain in hectares between selected years (2000 and 2011, 2000 and 2011,2000 and 2022). Negative signs show that area's loss and positive signs show that area's gain. The area lost for high-density forest and dense forest between 2000 and 2011 is 943.45ha and 3617.06ha, respectively. The areas gained for sparse, grassland and farmland are 2676.37, 1782.69 and 101.45 respectively. The area lost for high density between 2011 and 2022 was 1223.38ha, and the dense forest was 2098.68ha. From 2000 to 2022, the total area lost for high density was 2846.28ha, while dense forest lost 5715.74ha. However, the area gained for sparse, grassland and farmland between 2011 and 2022 and the overall change were: 925.96ha, 3602.33ha, 2266.18ha, 4048.87ha, 129.92ha, and 231.37ha, respectively.

4.1.8 Forest covers in each selected years

From LULC, forests were the ones that were classified into high-density forest, dense forest and sparse forest for the Landsat and Sentinel images of 2000, 2011 and 2022. It is necessary to extract these forest cover maps that are used to visualize the distribution and rate of forest cover change. As shown in the LULC map, the total coverage of high-density forests and dense forest decreased from 2000 to 2022. The area coverage for classified forests was illustrated in the following bar graph and pie chart for each year.

4.1.8.1 Forest covers in 2000

Three types of forest coverage from LULC in 2000 were shown in the following figure.



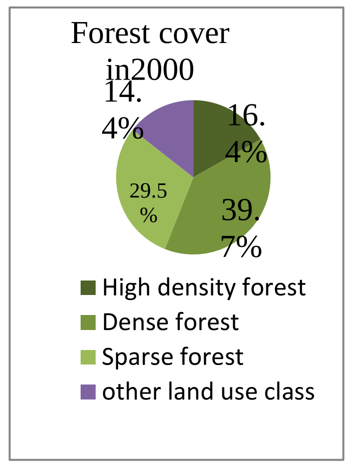
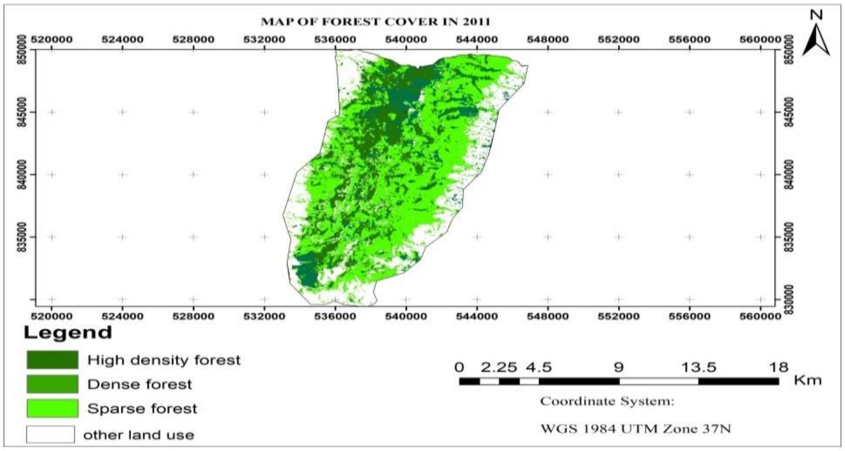


Figure4.11: forest map of Galema forest in 2000 Figure4.12: pie chart of forest cover in2000

Figure 4.13 High density, dense and sparse forest cover map in 2000 figure pie chart of forest cover in percent. In 2000 high density forest coverage units was about 16.4%, a dense forest was 39.7% and sparse forest 29.5% of the total area. The total area of forest cover was 85.6%.

4.1.8.2 Forest cover in 2011

From land use /land covered in figure 4. High density forest, dense forest and sparse forest map were shown in the following figure.



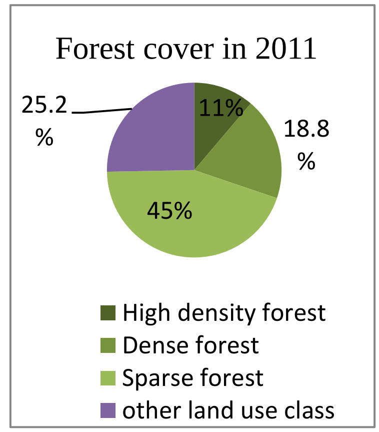


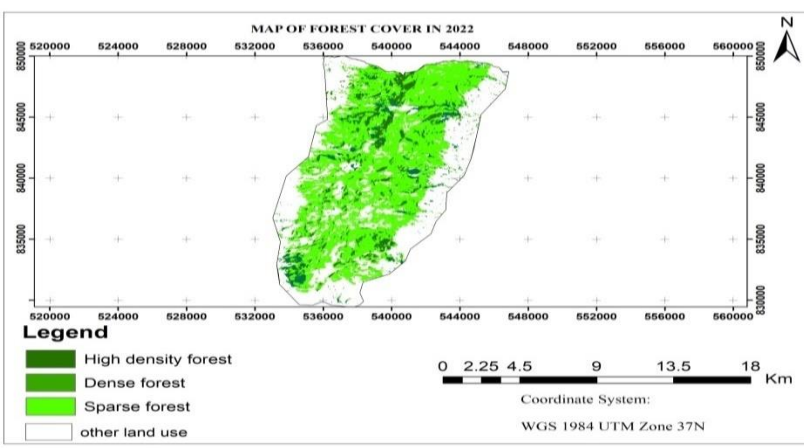
Figure4.13: forest map of Galema forest in 2011 Figure4.14:pie chart of forest cover in2011

Figure 4.15 High Density, dense and sparse forest cover map in 2011.

High-density forest, dense forest and sparse forest coverage were 11%, 18.8%, and 45% respectively. This shows that high-density forest changed from 16.4% to 11%, dense forest 39.7% to 18.8% and 29.5% to 45%. Due to this, the total area covered by forest was 74.8%.

4.1.8.3 Forest cover in 2022

From all classified image of 2000, 2011 and 2022 forest maps and area covered were extracted. Then the pie chart was included to shows forest cover area.



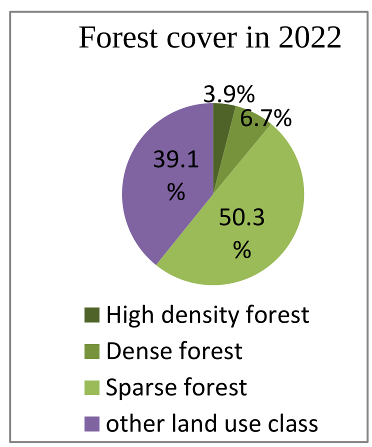


Figure 4.15 : forest map of Galema forest in 2022. Figure4.16:pie chart of forest cover in2022

From the above figure, high-density forest, dense forest, and sparse forest covered were 3.9%, 6.7% and 50.3%, respectively. The total coverage of the forest was 60.9% . This shows that high-density forest and dense forest have greatly decreased when compared with other land uses in 2000 and 2011. The inversely sparse forest increased between 2011 and 2022. But it is not suitable for the habitat of wildlife. Due to this, the study was more focused on high-density and dense forest change. Because these were heavily used for large mammal habitats in the study (source: community elder). As a result, the area covered by high-density and dense forest for selected years (2000, 2011, and 2022) is depicted in the bar graph below

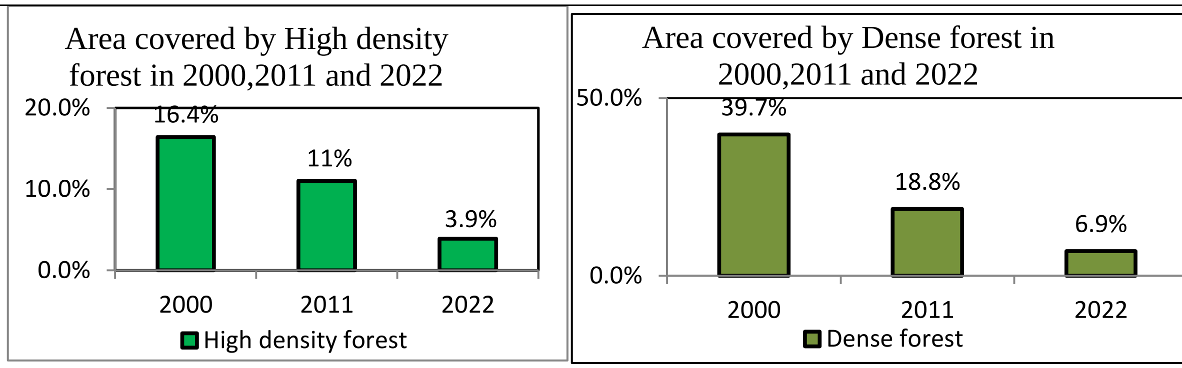


Figure4.17: Bar graph of high density and dense forest in percent for selected years

This figure summarizes the coverage of high density forest and dense forest for 2000, 2011 and 2022. From this high density forest covered 16.4%.11% and 3.9% respectively. But dense forest covered 39.7%, 18.8% and 6.7%.Simply this shows that both forest were continuously decreased in the study area.

Table 4.11: Forest loss and gain in ha and percent between 2000- 2022

No	Land Cover classes	year					Rate of change	
			2000		2022		Area loss in ha	Area Loss %
			ha	%	ha	%		
1	Forest cover and loss in ha and %	High density forest	2846.28	16.4	679.45	3.9	-2166.83	-76.1
2		Dense forest	6882.30	39.7	1166.56	6.7	-5715.74	-83
3	Total loss						-7882.57	-159.1

4.1.9 Change detection by using NDVI

NDVI values indicate the vegetation cover and give information about an increase or decrease in NDVI value. However, it cannot provide detailed change information. The NDVI values range from -1 to +1, with negative values representing non-vegetation and positive values indicating less dense or healthy vegetation. Therefore, from the above equations(3.2 and3.3) the NDVI value of the Landsat image 2000, 2011 and Sentinel 2A of the study area was generated as shown in the following figure.

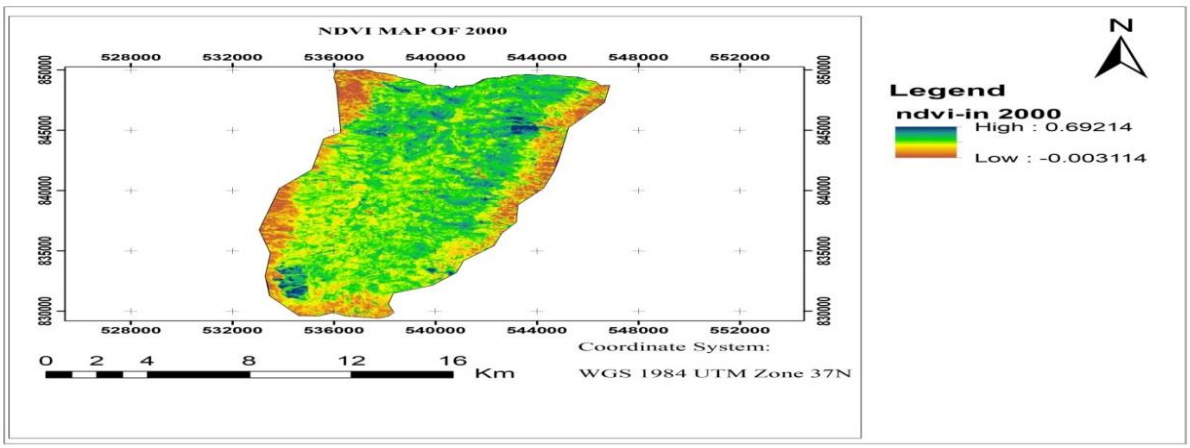


Figure 4.18: NDVI Map of 2000 with its maximum and minimum value

From the above figure, maximum value (0.69214) and minimum value (-0.0003114 shows that; dark green color indicate the high vegetation (forest) cover and yellows color indicates less vegetation cover.

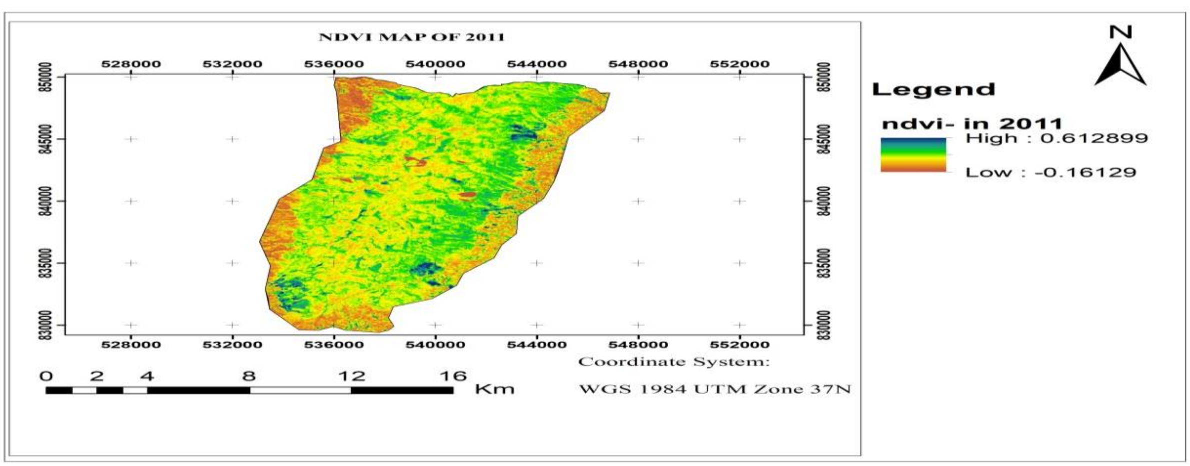


Figure 4.19: NDVI Map of 2011 with its maximum and minimum value.

From the above figure, the NDVI map in 2011 has a maximum value of 0.612899 and a minimum value of -0.16129. These indicate that the dark green color represents high vegetation cover and the yellow color is less vegetation cover.

However, the maximum and minimum values of image 2022 were decreasing as compared with the images of 2000 and 2011 shown in the figure below for the sentinel image of 2022.

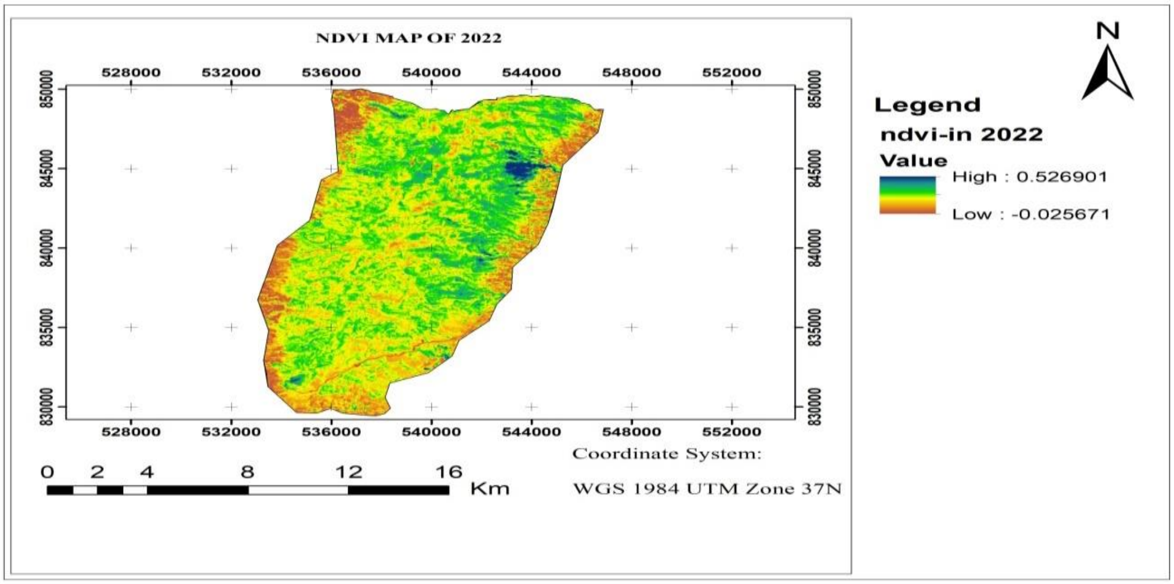


Figure 4.20: NDVI map of 2022 with its maximum and minimum value.

From the above result, the maximum NDVI value was 0.526901 and the minimum value was -0.025671, respectively. This value shows the vegetation cover was decreasing as compared with the images of 2000 and 2011. The NDVI value showed a slight reduction from 0.612899 in the year 2011 to 0.526901 in the year 2022. The darker the red color, the lower the NDVI value and shows other than vegetation and vice versa. This comparison result shows that the highest vegetation cover was observed in 2000, whereas average vegetation cover was observed in 2011, but the lowest vegetation coverage was observed in the year 2022.

4.1.10 Statistical analysis

4.1.10.1 Demographic data of the respondents

Demographic data refers to socio-economic information expressed statistically, including employment, level of education, income, marriage, sex age, rates of birth and death. Demographic data were used in this study to obtain the results.

Frequency analysis in SPSS software for the sample selected based on gender, level of education and duration in the study area of respondents is presented in the table below.

Table4.12: sex, gender, level of education and duration based frequency analysis of respondent

Item	**characteristics**	**frequency**	**percent**
Sex	female	43	28.7%
	male	107	71.3%
Age	40-45	22	14.7%
	45-50	38	25.3%
	50-55	46	30.7%
	55-60	23	15.3%
	60-65	15	10%
	Above 65	6	4%
Level of education	Unlettered	69	46%
	Elementary	41	27.3%/
	Secondary	19	12.7%
	Preparatory	21	14%
Duration	10-20 years	76	50.7%
	20-30 years	59	39.3%
	30-40 ears	15	10%

As a result, as shown in table 4.11, out of one hundred fifty respondents, 43(28.7%) were female and 107(71.3%) were male. This implies more information was gathered from the male than the female. because the daily activities of each male were around Galema forest.These respondents were 69(46%) unlettered, 41(27.3%) completed elementary school, 19 (12.7%) completed secondary school, and 21(14%) preparatory school. This shows that most of the respondents were unlettered because they were farmers and daily laborers around this study area.

As a result, they paid a few birrs and were denied an education. Some of them were not interested to learn because they had a low understanding of education. Thus, lack of education forced them to engage themselves in clearing forest for different purposes, which caused land degradation and loss of wildlife from the area. In addition to this, a few of them participated in different illegal activities such as deforestation, hunting, and burning grasslands. From these respondents, 22 (14.7%) were 40-45 years old, 38 (35.3%) 45-50 years, 46 (36.7%)50-55 years, 23 (15.3%) 55-60 years, 15 (10%) 60-65 years and 6(4%) above 65 years old .This indicates that the average age of respondents was 45–50 and 50–55 years old. But the duration of each respondent in the study area was 76(50.7%) for 10-20 years, 59(39.3%) for 20-30 years and 15(10%) for 30-40 years. Therefore, based on respondent responses key factors for forest change, the problem happened due to forest change and the impacts on wildlife were clarified in the next section. And for more information about the total number of the respondent that participates in factors for forest change, the present status of forest and wildlife, a problem that occurred due to forest change, the responsible bodies,the most wildlife conflict with humans and hunting you can see from the appendix.

4.1.10.2 The key drivers/factors for forest cover change

The community's interview data was collected in order to identify the most influential factors that cause the forest in the study area to change. About 150 people from six different kebele took part in this. From the total respondents, 43 females and 107 males responded properly to each question. To analyze the collected community-based data, SPSS software was used and the results of frequency analysis for the present status of the forest, the key factors for forest cover change and the problems that occurred due to forest change were illustrated in the table and figure below.

Table 4.13: Current status of the forest.

No	Response	Frequency	Percent
1	Increasing	3	2
2	Decreasing	146	97.3
3	No change	1	0.7
	Total	150	100.0

Before 22 years, the Galema forest was covered with more high-density, dense and sparse forest, where different wildlife was found. These forests are used as habitats, food sources, and other uses for different wildlife. (Source: community elders and local society). It was also the area where people found charcoal trees, timber trees, firewood and different wildlife that were used as a source of food for the local society. Currently, as shown in the above table, 3(2%) answered that forest cover had increased, and 1(0.7%) answered there were no changes in the forest. However, around 146(97.3%) of respondents answered that the coverage of forests had greatly changed due to different factors, which are illustrated in the table below.

Table 4.14: Factors of forest change and Numbers of respondents in percent.

No	factors of Forest change	Respondents			
		Female	male	total	Total in percent
1	Expansion of farmland	32	105	137	91.3
2	Fire wood collection	39	93	132	88
3	Making charcoal	38	84	122	81.3
4	Timber production	12	44	56	37.3
5	Population Growth	36	70	106	70.7
6	wildfire	41	98	139	92.7

Result shows in table 4.14, there are several reasons for the loss of high density, dense forest and sparse Forest. Some of them are Expansion of farmland, Fire wood collection, making charcoal, Timber production, Population Growth and Wild fire.from the result , 92.7% of the respondents replied that wildfire was cause forest loss; 91.3%, 88%, 70.7%, and 37.3% of the respondents answered that expansion of farmland, firewood collection, making charcoal, population growth, and timber production were other factors for forest change, respectively. From this result, wildfires and the expansion of farmland were the major factors for forest change. Also, during the dry season, wildfire can destroy a large hectare of forest that is used as grassland and farmland(source: community elders). Therefore, based on this result, it is possible to generalize that there are multiple factors that cause forest cover change and wildlife loss.

4.1.10.3 Problem Occurred due to forest change in the study area

Forest is one of the natural resources that use to maintain the biodiversity of the ecosystem. It is home for wildlife, it holds and improves soil fertility, filters water, prevent soil erosion and remove toxic gasses and maintain environmental quality(Romijn et al., 2015) .Therefore, forest cover change is associated with many effects as shown in the following table.

Table 4.15: a problem occurred due to forest change and total number of respondents.

No	**Problem occurred due to forest change**	**Respondent**			
		Female	Male	Total	Total in percent
1	Climate change	25	87	112	74.7
2	Losing Habitat of all mammals	29	102	131	87.3
3	Losing wildlife	21	97	118	78.7
4	High soil erosion	11	74	87	58
5	Low agricultural production	11	48	59	39.3

Source: from community based interview data.

As indicated in table 4.14, 131(87.3%) of the respondents said that the habitat of all mammals was decreased or lost immediately due to forest cover change, and 118 (78.7%) of the respondents answered that the wildlife had migrated or been loosed from the area. 112 (74.7%), 87 (58%), and 59(39.3%) respondents replied that climate change, high soil erosion, and low agricultural production can occur in the study area. This implies that forest loss is linked to wildlife habitat loss, wildlife loss, climate change, soil erosion, and low agricultural production. The number of respondents to the problem that occurred due to forest change was presented in the figure below.

As result show in table4.14: Many problems were occurred due to loss of forest and as the information was gathered from local community and manager of lemu-bilbilo environmental protection authority have been responsible for the forest loosed and problem appeared in the study area. This is shown in the following table and figure.

Table 4.5: Responsible bodies for the forest change and problem occurred.

Responsible Bodies	Frequency	Percent
Kebele leader	39	26
Woreda leader	55	36.7
Local society	56	37.3
Total	150	100

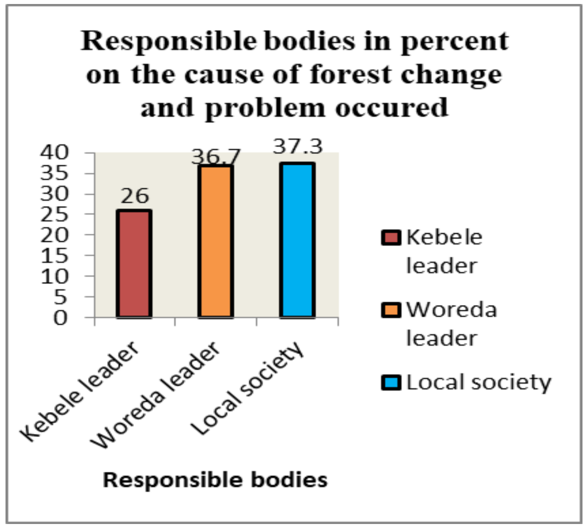


Figure4.21: Bar graph of responsible bodies in percent

As indicated in table 4.15, 37.3% of respondents replied that local societies have more responsibility for the loss of forest and that problem occurred. Furthermore, 36.7% and 26% of respondents said the woreda and leader were to blame for forest change and problems, respectively.

4.1.10.4 Problem Faced by large mammals due to forest change

As the response of the respondents shows, different large mammals live in the Galema forest. Because this block (Galema) contains high-density, dense and sparse forest (source: community elders). Some of the large mammals living in the study area include the Mountain nyala, Ethiopian wolf, Menelik's bush back, leopard, common jackal, Ethiopian highland hare, warthog, antelope, hyena, and red jackal (source: Lemu - Bilbilo environmental protection authority). However, due to forest clearing, the population of these large mammals has declined. The status of this wildlife is presented in the table below.

Table 4.17: The response of respondents on current status of wildlife.

	Frequency	Percent
Increasing	7	4.7
Decreasing	127	84.7
No change	16	10.7
Total	150	100.0

As shown in the above table, 84.7% of respondents answered that wildlife was currently decreasing in the area because of forest changes. 4.7% of respondents replied that the currently wildlife was increased and 10.7% of them answered that there was no change in wildlife in the study area. Depending on table 4.16, the response of respondents to the current status of wildlife was shown graphically in the figure below..

Table 4.18: Problems faced by wildlife due to loss of habitat/forest change.

No	Items	Frequency	Percent
1	Killed by farmers	71	47.3
2	Death because of starvation	19	12.7
3	Conflict with humans	37	24.7
4	Migration to others area	23	15.3
	Total	150	100.0

Table 4.17 shows that 47.3% of the respondents replied that wildlife was killed by local people/farmers, 24.7% of them replied that some were conflicted with humans, 15.3% of them answered that some wildlife was migrating to other areas, and 12.7% answered that some of them died because of starvation.Therefore, deforestation in the study area causes a series of problems for wildlife living in the area. Because the forest is a place where animals live; find their food sources, breed, and care for their young, most wildlife has emigrated from the study area because of forest loss and habitat disturbance. As evidenced by the responses, there was a direct relationship between the forest and wildlife. This means forests provide wildlife with food, a nesting place, cover (shelter), shade, and oxygen.

As table 4.18 shows, the problem faced by wildlife is being killed by farmers or local people. Conflict with humans manifests itself in the form of migration to other areas and deaths due to starvation. From these, the second problem faced by wildlife in the study area was a conflict with humans (24.7%). These problems happened because forest cover was greatly changed and wildlife lost their habitat, and there was a conflict with humans. Due to habitat loss in the study area, different wildlife was in conflict with humans. See the following table.

Table 4.19: The large mammal more conflict with humans

Items	Frequency	Percent
Ethiopian wolf	20	13.3
Mountain nyala	19	12.7
Leopard	17	11.3
Wart hog	51	34
common jackal	20	13.3
hyena	19	12.7
Red jackal	4	2.7
Total		100

As the above table indicates, 34% of the respondents answered that warthog had more conflict with humans, 13.3% of them answered that Ethiopian wolf and common jackal had conflicted with humans, 2.7% of them answered that red jackal conflicted with humans, and 12.7% of the respondents replied that mountain nyala and hyena were conflicted with humans. From this result, it can be concluded that warthogs are more commonly attacked by humans. Because of the deforestation of the high-density and dense forest. Additionally, leopards are also killed by local society. Because a person who killed a leopard would have good recognition in the local society. .

In addition to these wildlife conflicts with humans, some of wildlife was hunting in the study area. This shows in the table below.

Table4.20: The most Wildlife hunting in study area

No	Items	Frequency	Percent
1	Menelik's bush buck	120	80
2	Mountain nyala	28	18.7
3	No hunting	2	1.3
4	Total	150	100.0

Source: frequency analysis in SPSS software

As shown in table 4.20, 80% of respondents replied that Menelik's bushbuck was hunted by hunters, 18.7% of them answered that mountain nyala was hunting, and 1.3% of respondents answered no hunting in the study area. Based on this, the above wildlife is under threat due to forest change. In agreement,(Girma et al., 2018) stated that livestock encroachment and forest clearing/tree removal have a great impact on the populations of Menelik's bushbuck and Mountain nyala in the study area. And from the results shown in the table above, the percentage of respondents on wildlife hunting in the study area was shown in the figure below

Due the forest decline in the area, wildlife conflict with humans and decreased in the number. This was shown in the following table.

Table 4.21: The most wildlife currently decreased in a number/population in the study area.

No	Items	Frequency	Percent
1	Mountain nyala	28	18.7
2	Menelik bush back	52	34.7
3	leopard	23	15.3
4	common jackal	23	15.3
5	Wart hog	24	16

From result of frequency analysis, 18.7% of respondent answered mountain nyala was decreased, 34.7%, 15.3%, 15.3% and 16% of respondent replied that Menelik bush back, leopard, common jackal and Wart hog were decreased from the study area. As shown in table above table, the most wildlife currently decreasing in the study were; Menelik bush back, Mountain nyala, Warthog, leopard and common jackal respectively. Because of forest cover change, problems have occurred with this wildlife forest change (conflict with humans and hunting by hunters). Not only this, due to the change of high density and dense forest, some wildlife migrate from the area and do not currently appear in the study area,are shown in the table below.

Table 4.22: the wild life that currently not appear in study area

No	Items	Frequency	Percent
1	Ethiopia wolf	82	54.7
2	Red jackal	68	45.3

Source: frequency analysis in SPSS software

There was different wildlife that lived in the study area. However, some wildlife is currently not appearing in the area due to the loss of high-density and dense forest. From table 4.21, 54.7% of respondents replied that the Ethiopia wolf did not currently appear in the study. In addition to this, 45.3% of respondents answered that red jackal does not appear in the area.

4.1.11 Future predictions of forest cover change for 2044

A cellular automaton (CA) is a relatively simple modeling approach, which is compatible with Geographical Information Systems (GIS), and it has been applied to reproduce the evolution of some natural phenomena, This modeling approach is also commonly used for simulating the lLULC and forest change (Zheng et al., 2017).

The MOLUSCE Plugin is used to obtain a land cover change map and to establish the trend of change for the study area between 2022 and 2044. The plugin measures the percent of area change in a given year and provides a transition matrix that shows the proportions of pixels changing from one LULC to another. The plugin carried out the area change map, which presents the change in the land from 2022 to 2044 in all 5 classes. The transition matrix from 2022 to 2044 is shown in the figure below.

Table 4.23: Transition probability matrix of LU/LC classes from 2022 to 2044

Land use classes	Highdensity forest	Dense forest	Sparse	Grassland	Farmland
High density forest	0.247846	0.035113	0.546367	0.110740	0.059936
Dense forest	0.000373	0.103027	0.811689	0.074474	0.010437
Sparse	0.000021	0.000167	0.935976	0.055822	0.008015
Grassland	0.002449	0.000079	0.151486	0.645689	0.200296
Farmland	0.002744	0.000517	0.058697	0.114889	0.823153

This table shows that for 22 years starting from 2022, we expect, 24.746% of high-density forest to persist and 3.5113 % change to the dense forest, 54.6367% to the sparse forest, 11.0740% to grassland with no reversion back to the high-density forest, and 5.9936% to farmland with no reversion back to the forest. 10.3027% of dense forest, 81.1689% of sparse forest, 7.44744% of grassland, and 1.0437% of farmland remain. Sparse persists at 93.5976%, with 5.5822% and 0.8015% changing to grassland and farmland, respectively. Whereas 64.5689% of grassland remains and 20.0296% of farmland has been converted, finally, 82.3153% of farmland persists and 11.4889% has changed to grassland. From the transition probability matrix, the persistence value of high density and dense forest are less than that of other classes, which means that both forest areas have a high probability to be changed. When compared to high-density and dense forest, other classes have a high percentage of persistence.A high percent of persistence means less change in class and the low percent of persistence means a high change in class.

4.1.11.1 Validation

.The validation models are calculated for the LULC map of predicted 2022 with a reference map of 2022 and for the predicted LULC map for 2044. These validation modules are kappa (histogram), kappa (overall), kappa (location), and % of correctness. Therefore, the first LU/LC map of 2022 and the predicted map of the 2044 Kappa index of the agreement were shown in the table below.

Table 4.24: kappa index of validation (simulated map 2022 with reference map 2022).

No	Kappa validation	Value
1	% of correctness	94.69469
2	Kappa(overall)	0.91897
3	Kappa(histogram)	0.93699
4	Kappa(location)	0.98076

Table4.23 shows the result of the validated module to check the agreement between the real classified image of 2022 and the predicted map of 2022. The result of the kappa value was: kappa (histogram) is 0.93699, kappa(location) is 0.98076, kappa (overall) is 0.91897, and % of correctness is 94.69469, which shows the consistency between the predicted 2022 LULC and the real 2022 LULC situation is good and the model is reliable. Therefore, the prediction of the 2044 LULC raster is carried out, which is shown in Figure 4.30, and the validation statistics of the predicted 2044 raster are given in the Table below.

Table 4.25: kappa index of validation for predicted map for 2044.

No	Kappa validation	Value
1	% of correctness	91.22585
2	Kappa(overall)	0.85089
3	Kappa(histogram)	0.90100
4	Kappa(location)	0.93328

The above table indicates that, the estimation Kappa (histogram) is 0.90100, Kappa (location) is 0.93328, Kappa (overall) is 0.84089 and % of correctness is 91.22585. Thus, predicted map of LU/LC for 2044 years was shown in the figure below.

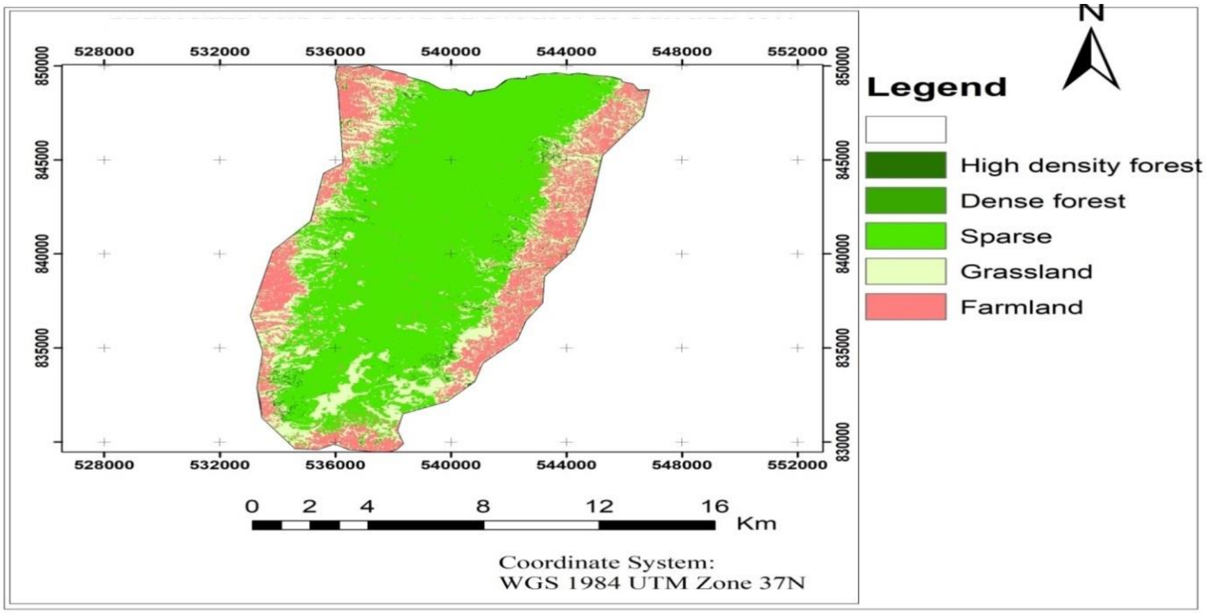


Figure4.22: Predicted LU/LC map of Galema forest for 2044

From the predicted LULC map of 2044, each land class covers high-density forest 191.43ha, dense forest 151.92ha, sparse 9328.27ha, grassland 4802ha; and farmland 2899.35ha. Furthermore, their percentage coverage of the total area was as follows: 1.1% for high-density forests, 0.9% for dense forests, 53.7% for sparse forests, and 27.6% and 16.7% for grassland and farmland, respectively. Here, the coverage of high-density and dense forest was decreasing as compared with other classes. See the following table showing the area coverage of each land class in hectares and percent.

Table 4.26: Area covered by land classes of predicted map for2044

No	**Land classes**	**Year**	
		2044	
		ha	**%**
1	High density forest	191.43	1.1
2	Dense forest	151.92	0.9
3	Sparse	9310.45	53.7
4	Grassland	4802	27.6
5	Farmland	2899.35	16.7
	Total	17355.15	100

From the predicted LULC map of 2044, each land class covers high-density forest 191.43ha, dense forest 151.92ha; sparse 9328.27ha, grassland 4802ha; and farmland 2899.35ha. Furthermore, their percentage coverage of the total area was as follows: 1.1% for high-density forests, 0.9% for dense forests, 53.7% for sparse forests, and 27.6% and 16.7% for grassland and farmland, respectively. Here, the coverage of high-density and dense forest was decreasing as compared with other classes. See the following table showing the area coverage of each land class in hectares and percent.

Table 4. 27: Area change between LU/LC map of 2022 and 2044

No	**Land classes**	**Year**				**Change between 2022-2044**	
		2022		**2044(predicted)**			
		ha	**%**	**ha**	**%**	**ha**	**%**
1	High density forest	679.45	3.9	191.43	1.1	-488.02	-2.8
2	Dense forest	1166.56	6.7	151.92	0.9	-1014.64	-5.8
3	Sparse	8733.2	50.3	9328.27	53.69	595.07	3.39
4	Grassland	4526.24	26.1	4802	27.74	275.76	1.64
5	Farmland	2249.7	13	2899.35	16.7	649.65	3.7
	Total		100		100		

Source; from ArcGIS attribute table of the classifications map and prediction map

The table illustrates the area coverage of each land use class in hectares and percent as well as the change between two periods of time(2022 and the predicted year 2044). This change shows both positive and negative values. A positive value shows there was an area increment of land use class between the two periods. Conversely, the negative shows there was an area decrement of land use class between the two years. The land coverage of land classes in 2022 and predicted for the year 2044 in ha were high-density forest 679.45, 191.43, dense forest 1166.56, 151.92, sparse forest 8733.2, 9328.27, grassland 4526.24, 4802, and farmland 2249.7, 2899.35. High density and dense forest were significantly altered as a result of these. See the predicted forest map in the figure below, which is extracted from the predictedLULC.

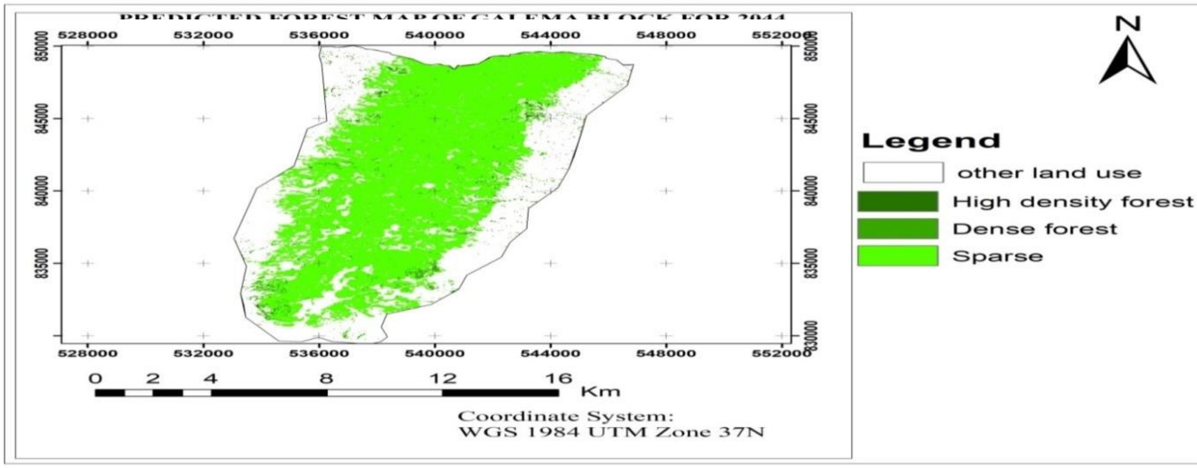
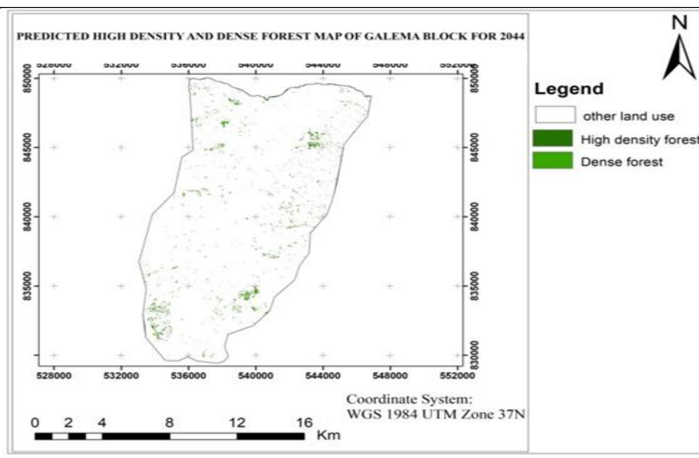


Figure 4.28: predicted high density, dense and spares forest map for study area

As shown in table 4.26 and figure 4.33, sparse forest covers a large area (9328.27) as compared with high density (19.43) and dense forest (151.92). This translates to a change in the sparse forest from 8733.2 to 9328.27, a change in high-density forest from 679.45 ha to 191.43, and a change in dense forest from 1166.56 to 151.92. These show that high density and dense forest were changed into the sparse forest and other land use classes. For more information about high density and dense forest, see the following predicted map and pie chart, which show the coverage of both forests in percent.



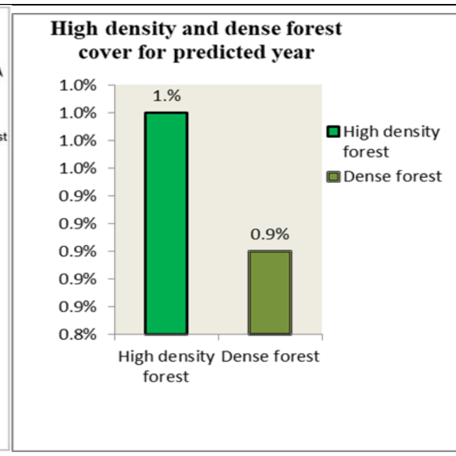


Figure4.23: predicted high density and dense forest map

Figure4.24: Bar graph of predicted forest

As shown in pie chart 4.34 the coverage of high density and dense forest were highly decreasing. There were change of forest cover from a map 2022 up to 2044.see the table below which shows, area loss in hectare and percent.

Table 4.28: forest covers and loss in hectare and percent between Lu/Lc map of 2022 and 2044

No		**year**			**Rate of change**	
		Land Cover classes	**Forest cover in hectare 2022**	**2044**	**Area Loss in ha**	**Area Loss in %**
1	Forest cover and loss in	High density forest	679.45	191.43	-488.02	-2.8
2	ha and percent	Dense forest	1166.56	151.92	-1014.64	-5.8
	Total loss in ha and %				-1502.66	-8.6

In the above Table the loss of high density forest is -488.02ha and dense forest is -1014.64ha.atotal loss in hectare and percent for both forest are -1502.66ha and -8.6% respectively.

4.2 Discussion

The results to be discussed are :LULC change detection, including forest cover change between the selected three years based on the classified map and NDVI value; statistical analysis to determine the influencing factors for forest change and the problems that occurred on wildlife as a result of forest change; and future prediction of forest cover change for the study.Thus, the listed results are discussed as follows.

4.2.1. Discussion on LULC and Forest Change Result

In this section, the extent, trend, change rate, and accuracy of each classified land cover class, as well as the change of high density, dense, and sparse forest are discussed for selected three years (2000, 2011 and 2022). The total area covered by LULC for the study area is 17355.15ha, and each land cover class covered a different area. The study area is classified into five land cover classes. In 2000, high-density forest covered 2846.28ha, dense forest covered 6882.30ha, sparse forest covered 5130.87ha, grassland and farmland covered 477.37 ha and 2018.33 ha, respectively, and in 2011, each land use class covered 1902.83 ha, 3265.24ha, 7807.24ha, 2260.06ha, and 2119.78ha.

However, the area covered by each land cover class in 2022 was as follows: 679.45ha (high-density forest), 1166.56ha (dense forest), 8733.2ha (sparse forest), 4526.24 ha (grassland), and 2249.7ha (farmland).There was an area change between each land cover class in selected years. High-density forest was changed by 943.45ha (this was converted to any other land use class) for the first eleven years and by 1223.38ha in the second eleven years (2011-2022). In addition to this, dense forest was changed by 3617.06ha in the first eleven years (2000-2011) and 2098.68ha (converted to any other land use class) in the second eleven years.

Both these forests showed a decrement. But sparse forest coverage increased by 2676.46ha in the first eleven years and 925.96ha in the second one. These show that there was area conversion between land use classes. When compared to grassland and farmland, high density and dense forest were highly converted to sparse. In contrast, sparse forest was converted to grassland and farmland rather than dense forest and high-density forest (based on the transition matrix). But the amount of conversion was different for each land use class. According to(Reusing M. 2001), Ethiopia's high forest cover decreased from 4.75% to 3.93% of the total land area between 1973 and 1990. Because the study was conducted in Ethiopia, high-density forest decreased from 16.4% to 3.9%, and dense forest decreased from 39.7% to 6.7%. but sparse, changing from 29.5% to 50.3%.Totally, the three classified forests covered 85.6% of the initial year (2000) and changed to 60.9% in the final year (2022). This shows that the forest decreased by 24.7%.In the case of grassland, the area covered was 477.37 ha during the year 2000, it was 2260.06ha in the year 2011, and 4526.24ha in the year 2022. This shows that the area increased by 1782.69 ha and 2266.18 ha in the first and second eleven years. As shown in the transition matrix, high-density forest, dense forest and sparse forest were directly converted to grassland. Moreover, the sparse was changed into grassland. The farmland area also increased by 101.45ha and 129.92ha in the first eleven years and the second eleven years. There was a conversion of land use classes into farmland as shown in the transition matrix. All land use classes like high-density forest, dense forest, sparse and grassland were converted to farmland. Moreover, sparse and grassland were converted into this class. In agreement with this result(Abera, 2019), in Ethiopia, farmland has increased from 9.44 million to 15.4 million hectares in 2001 and 2009, respectively.

Thus, the study area is a part of Ethiopia, and the forest cover has continuously decreased. The study has positive implications for the mentioned scholar and the conversion of forest land to farmland decreases forest coverage. This study also improves the idea of the scholar because the forest was changed into farmland in the selected three years (for a total of 22 years). The area of forest change for 22 years was 24.8%, which included the conversion of forest into farmland and other land use classes.

4.2.2. Discussion on change detection based on NDVI result

The NDVI value is used to identify the vegetation cover in the study area and its result provides evidence for LULC change. The major change in NDVI shows the loss of forest cover for twenty-two years in the study area. Thus, the discovered NDVI value indicates a decrease from 0.69214 in 2000 to 0.612899 in 2011, and from 0.612899 to 0.526901 in 2011 and 2022, respectively. The total change in NDVI value over the last twenty-two years was 0.16523, from 0.69214 in 2000 to 0.526901 in 2022. difference shows that vegetation cover was decreasing between the initial and final years. Simultaneously, NDVI value decrements show that forest coverage has decreased from 2000 to 2022.

4.2.3. Discussion on factors for forest change and problem observed

From the findings based on frequency analysis of a number of respondents on the factor of forest change, they answered different causes of deforestation in the study area. The findings of this section show that there were a number of factors that caused a change in the forest. These factors were obtained from the community of the selected six kebele. 150 respondents participated in this factor. These factors identified in the study area were farmland expansion, firewood collection, charcoal production, timber production, population growth, and wildfire. Based on the number of respondents, the ranks of factors were identified. Wildfires, expansion of farmland, firewood collection, making charcoal, timber production, and population growth were factors that were put in order. When compared to other factors, wildfire, farmland expansion, and firewood collection play a larger role in the change of the forest over time. In addition to this, making charcoal, timber production, and population growth have their own negative effects on forest change. As discussed by (Netsanet, 2007) the causes of forest cover change were: agricultural land expansion, infrastructure expansion, wood extraction, and others that changed the physical state of the land.

Furthermore, as stated by(Girma, H. M., & Hassan, 2014), human-induced environmental impact has also increased to fulfill the increased requirement of land resources, and it directly affects the forest land cover.

As a result, frequency analysis of respondents shows that due to forest change, there were four problems observed. These were: climate change, loss of the habitat of mammals, soil erosion low agricultural production, and losing wildlife. From these problems, losing habitat for mammals, losing wildlife, and climate change were more visible in this study area. Moreover, in this study area, as the forest was changed due to the above factors, different wildlife were losing their habitat and migrating from the area, which is discussed in the next section

4.2.4 Discussion on problems occurred on wildlife due to forest change

In this section, the results obtained in frequency analysis from the community were discussed. According to information gathered from the local community and the Lemu - Bilbilo environmental protection authorities, this forest was home to a variety of wildlife, including mountain nyala, Menelik's bush buck, Ethiopian wolf, mountain nyala, Warthog, common jackal, hyena, and red jackal. However, a result of frequency analysis from respondents shows, that due to forest change, this wildlife was; killed by farmers, and died because of starvation, conflict with humans, and migration to other areas. The Ethiopian wolf, mountain nyala, leopard, warthog, common jackal, hyena, and red jackal had the most conflicts with humans. Some of them were hunted in the study, including Mountain nyala and Menelik's bushbuck, and the number of these (Mountain nyala, Menelik's bushbuck, common jackal, leopard, and Warthog) wildlife decreased in the area, but Ethiopia wolf and red jackal were not currently appearing in the area(source: from local community).

This entire problem occurred due to a change in high-density and dense forest from 16.8% to 4% and 39.2% to 7%, respectively. There was high deforestation due to the factors that were identified in the above section. When both forests were greatly changed, the wildlife lost their habitat and there was a conflict with humans. The sparse forest was not used as a habitat for large mammals because sometimes it serves as grassland (source community elders). In agreement with this study (Girma et al., 2018) stated that the removal of trees and livestock encroachment have a great impact on mountain nyala and Menelik's bushbuck in this area.

4.2.4. Discussion on the future prediction for 2044 result of forest cover

From the findings shown in table 4.29, the change between the previous (2022) and predicted (2044) land classes indicates that high-density forests and dense forest decreased by 2.8% and 5.8%. Grassland and farmland increased by 3.39%, 1.64%, and 3.7%, respectively. 2.8 % and 5.8% of both forests were converted to other land classes. These were converted into sparse farmland and grassland, as indicated by the transition matrix. In agreement with this finding, as discussed by (D'Annunzio et al., 2015) it is predicted that forest areas are projected to continue to decline at alarming rates in some regions. Evidently, the integrated effects of forest cover changes in the study area can lead to the highly variable response of rainfall and temperature over time. The prediction result of the map for 2044 shows that there will be a great loss of high-density and dense forest, which will lead to a high rate of problems if the same trend is continued up to the predicted date. Furthermore, high-density and dense forests were used as homes (habitats) for wildlife when these forests were continuously changed up to the year 2044, and the wildlife lost their habitats, clashed with local society, and was killed as a result of the loss of habitats. The population of each wildlife species in the area decreased. Thus, these findings have great importance for environmental managers and wildlife conservation managers to make a plan to control the loss of these forests, to ensure a stable climate, and minimize the problem occurring to wildlife in the study area.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion.

The study area contained different LULC classes. From this, forest cover is the one that is classified into high-density forest, dense forest, and sparse forest. High-density and dense forest are used as habitats for large mammals, and the sometimes sparse forest is used as grassland for livestock. But this forest cover has changed due to different human activities in the area. And different problems have happened to wildlife and the environment over the last 22 years. Remote sensing data and interviews with local community members and experts were used to analyze forest change and driving factors.

Analysis of the results from the classified image shows that the magnitude of LULC in general and forest cover change, in particular, drastically changed between 2000 and 2022. In particular, the expansion of farmland, grassland, sparse forest cover, and decline of forest cover were observed. In relation to this, currently, the overall condition of the forest cover land of Galema forest is strongly disturbed. Besides, the areal extent of forest cover land is reduced from time to time. From the total area, about 2846.28ha and 6882.30ha of land were covered with high-density and dense forest in 2000. But, this forest declined from 679.45ha to 1166.56ha in the year 2022. On top of this, considering the annual rate of forest cover change between 2000 and 2022, the computed result indicated that about 2166.83 ha and 5715.74 ha of both forest lands are changed into other land use land cover. Totally, 24.7% of both high-density and dense forests were changed into other land use classes.

The result from frequency analysis revealed that forest cover was changed in the study area due to the expansion of farmland, firewood collection, making charcoal, timber production, population growth, and wildfire. In particular, high-density and dense forest areas have been converted into sparse grassland, and a few of them have been changed to farmland. Areas that were covered by high-density and dense forest lands in the early 2000s are now completely changed into sparse and other land classes. Due to high density and dense forest decline in the study area, some problems like climate change, losing habitat for mammals, soil erosion, low agricultural production, and losing wildlife were observed. Furthermore, many wildlife were killed by farmers as a result of starvation, conflict with humans, and migration to other areas.

Different wildlife conflicts with humans have occurred as a result of forest change, including the Ethiopian wolf, Mountain nyala, Leopard, Wart hog, Common Jackal, Hyena, and red jackal.Some of them were hunting in the study. Include Mountain nyala and Menelik's bush buck. As a result, five wildlife species have vanished from the area, and Ethiopian wolves and red jackals are no longer seen in the Galema forest (source: local community).

The probability matrix tells us that the transition from high-density forest to high-density forest, dense forest to dense forest, and sparse to spare was 24.7846%, 10.3027%, and 93.5976%, respectively, based on the prediction result. This means that more than half of the high-density and dense forest were converted into other land classes, whereas sparse forest remained almost unchanged. Deforestation in the study area increased as a result of both forest conversions starting from the selected three years up to the predicted year. Conversely, 64.5689% of farmland and 2.3153% of grassland were unchanged, and more than half of both land classes were persistent. Finally, of the five classified land classes, high-density, and dense forest cover 2% of the total. which shows that both forests decreased by 8.6% due to human activity, and if the same trend continues up to the predicted year, these forests will be finished. In addition, the problem occurring due to forest change in the study area is increasing, and the wildlife is losing their habitat and conflicting with local people. Unless necessary measures are taken to reverse the problem, the decline of both forests and wildlife could lead to a total loss of wildlife.

5.2 Recommendations

The final result of this study shows that; the decrement of high density and dense forest with some increment of the sparse forest, the driving factors for forest change like the expansion of farmland, firewood collection, charcoal making, timber production, population growth, wildfire, and the loss of wildlife in the study area. Therefore, to protect the natural and plantation forests from further depletion and use these precious resources on a sustainable basis to minimize the loss of wildlife, the following feasible suggestions are forwarded based on the findings, and the conclusions are drawn.

- As a result, as shown in the classified image between selected years and the information from the respondent, the high density and dense forests were changed and wildlife lost their habitat.

A large area of forest was removed by fire for the expansion of farmland, and wildlife was burned by fire. As a result, lemu- Bilbilo and sirka environmental protection authority offices are developing a new mechanism to control fires that occur unexpectedly in the area.

- Both Lemu - Bilbilo and Sirka district micro and small enterprise offices should create other job opportunities for local people who engaged their life on the clearing of forests and earning money selling forest products like charcoal, fuel wood, and timber.
- The governmental bodies and private sectors in these two districts must participate in Local communities on different natural forest conservation mechanisms like reforestation, afforestation, and agro-forestry programs, and also the management of planted trees by understanding the forest is used as the home of wildlife.
- One of the most devastating factors for wildlife and habitat destruction is the change of forest from time to time for charcoal production. Thus, the responsible bodies give attention to minimize the use of fuel wood and charcoal consumption in urban and rural areas by producing a new electric system and distributing it to rural areas.
- Above all, there is a need for the design of policies and strategies to protect the destruction of forest resources. This requires well-organized institutions to take responsibility for the conservation of forest resources at a district level.
- In this study, population map is not considered as an input variable for future prediction and outdated data about wildlife was used because there was no new settlement in the study area.As well as there is no recorded updated data about wildlife. Therefore, the concerned body or another researcher will use population growth as an input variable for future prediction and updated data of wildlife to obtain more useful information and results.

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APPENDICES

Appendix1 Survey Questioner for cause of Forest covers Changes and impact on wildlife.

This questionnaires is collect for obtaining of information about the study that attempt to investigate the current status and causing factors of forest cover in the study area .as well as the problem face in the study area due to forest cover change .Thus, general purpose of the study was to investigate the impact of forest cover change and future prediction for forest change by using geospatial technology in Galema forest, Arsi zone, Oromia, Ethiopia. This study will try to describe the way and the rate at which forest cover is change in past 22 years and for the future 22 years. Not only this also describe problem occurs on wildlife. Thus, the success of the study depends on your genuine responses to each question. Your response will be used only for the intended purpose. Therefore, please read and respond to each item in the questionnaires and indicate your answer by selecting letter and ticking in the provided box for close ended questionnaires and indicate your answer by Writing on the provided space for open ended questions. I appreciate your willingness to answer each question and help me.

General description: I need your name so writing in space provided.

Full Name____

Job____ Sign__________

Part I: Respondent’s background.

1. Sex: A) Male B) Female

2. Age:

A .40-45 year B. 45-50 year C. 50-55 year D. 55-60 year E. 60-65 year

3. Educational Status:

A. unlettered B. Elementary C. Secondary school D. Preparatory E. above grade12

4. For how long do you live around this forest?

A.10-20 year B.20-30 year C.30-40 year D. above 40

Part II: Community participation on the awareness of forest and wildlife protection

5. According information you have, what are the major uses of forests in the area. List down?

A ______________________________ D __________________________

B______________________________ E __________________________

6. Is there settlement or translocation of people around study (galema forest) area?

A. Yes B. No

7. If your answer is yes, what was the forest coverage of the area before and after settlement?

A. Declined (thinned) B. Increased C. No change

8. How is today's coverage of the forest when compared to the conditions before 2022?

A. Declined (thinned) B. Increased C. No change

9. What are the major Driving forces of forest cover change? (Put in order)

A. Farmland expansion ______ E. Cutting of trees for house and fens construction_____

B. Cutting trees for fire wood _____ f. Population growth __________

C. For charcoal production________ G. For timber production._______

D. wild fire__________________

10. is there wildlife lived in Galema forest? Use this sign

A yes B No

11. If your answer is yes list the major wildlife currently lived in this area?

A.____
B.____
C. ____
D. ____

12. What do you think about forest and wildlife? What important they have in ecosystem?
____
____
____

13. Depending on current situation, what are the major impacts of forest cover change, on wildlife especially on large mammals, and List down?

A.____
B.____
C. ____
D. ____

14. Which types of mammals were affected more by the loss of habitat in the area and decreasing their population?

A.____
B.____
C. ____
D. ____

15. Depending on the answer of question 11, which wildlife was more conflict with society?

A.____
B.____

C. ____
D. ____

16. Is there hunting of wildlife at your living area?

A. yes B. No

17. If your answer is yes, when they undergone hunting of wildlife? Which wildlife is commonly hunted?

A.____
B.____
C. ____
D. ____

18. Which wildlife had completely migrated/disappeared from the area?

A.____
B.____
C. ____

19. What do you think the attitude of the peoples lived around Galema on forest and wildlife?

____
____
____

20. Who were the responsible body for the cleaning of forests and the problem faced by wildlife in your area?

A.____
B.____
C. ____
D. ____

Appendix2. A numbers of wildlife living in the study area.

number	Scientific name	Common name of wildlife(large mammals)	Location
1	Canis simensis	Ethiopia wolf	galema forest
2	Tragelaphus buxtoni	Mountain nyala	galema forest
3	Tragelaphus scriptus	Menelik's bushback	galema forest
4	Panther pardus	Leopard	galema forest
5	Canis aureus	Common Jackal	galema forest
6	Lepus stark	Ethiopian highland hare	galema forest
7	Potamochoerus africanus	warthog	galema forest
8	Beira	antelope	galema forest
9	Crocuta crocuta	hyena	galema forest
10	Canis aureus	Red jackal	galema forest

Source: Lemu - Bilbilo environmental protection authority

Appendix3 .Accuracy Assessment

.For image of 2000

classes	High density forest	Dense forest	Sparse	Farm land	Grassland	user	Percent (%)
high density forest	57	3	0	0	0	60	95
Dense forest	1	69	9	0	0	79	87.34
sparse	0	0	57	1	5	63	90.48
Farm land	0	0	0	40	4	44	90.91
grassland	0	0	5	2	46	53	86.79
producer	58	72	71	43	55	299	
Producer accuracy (%)	98.28	95.83	80.28	93.02	88.46		

$$\text{User accuracy} = \frac{number\ of\ correctly\ classified\ pixels\ in\ each\ class}{total\ number\ of\ pixels\ in\ each\ catagory} * 100$$

1	High density forest	User accuracy(%)	57/60=95
2	Dense forest		69/79 = 87.34
3	Sparse		57/63 = 90.48
4	Farmland		40/44 = 90.91
5	Grassland		46/53 =86.79

$$\text{Over all accuracy} = \frac{\text{Total number of correctly classified diagonal pixel}}{\text{total number of referance pixe}} * 100$$

$$= \frac{57+69+57+40+46}{299} * 100 \quad = \mathbf{89.97}\%$$

$$\text{Kappa coefficient} \quad = \frac{(\text{Ts xTcs}) - \sum(\text{column total x row total})}{\text{Ts} - \sum(\text{column total x row total})} * 100$$

$$= \frac{(299\text{x}269) - \sum(60\text{x}58+79\text{x}72+63\text{x}71+44\text{x}43+53\text{x}55)}{299\text{x}299 - \sum(60\text{x}58+79\text{x}72+63\text{x}71+44\text{x}43+53\text{x}55)} * 100$$

= 80431- (3480+5688+4473+1892+2915)/89401-18448=87.34% its was ok

.For image of 2011

classes	High density forest	Dense forest	sparse	Farm land	grassland	user	Percent (%)
high density forest	45	2	0	0	0	47	95.75
Dense forest	1	67	2	0	0	70	95.71
sparse	0	1	60	0	1	62	96.77
Farm land	0	0	0	67	5	72	93.06
grassland	0	0	2	10	38	50	76
producer	46	70	64	77	44	301	
Producer accuracy (%)	97.83	95.71	93.75	87.01	86.36		

$$\text{User accuracy} = \frac{number\ of\ correctly\ classified\ pixels\ in\ each\ class}{total\ number\ of\ pixels\ in\ each\ catagory} * 100$$

1	High density forest	User accuracy(%)	45/47=95.75
2	Dense forest		67/70 = 95.71
3	Sparse		67/70 = 96.77
4	Farmland		67/72= 93.06
5	Grassland		38/50 =76

$$\text{Over all accuracy} = \frac{\text{Total number of correctly classified diagonal pixel}}{\text{total number of referance pixel}} * 100$$

$$= \frac{45+67+60+67+38}{301} * 100 \quad = \mathbf{92.035}\%$$

$$\text{Kappa coefficient} \quad = \frac{(\text{Ts xTcs})-\sum(\text{column total x row total})}{\text{Ts}-\sum(\text{column total x row total})} * 100$$

$$\frac{(301 * 277) - \sum(46 * 47 + 70 * 70 + 64 * 62 + 77 * 72 + 44 * 50\ )}{301 * 301 - \sum(46 * 47 + 70 * 70 + 64 * 62 + 77 * 72 + 44 * 50)} * 100$$

83377-(2162+4900+3968+5544+2200)/90601-18774

64603/71827 =89.95%~ 90% Classification accuracy was ok

.For image 2022

	High density forest	Dense forest	Sparse	Farm land	grassland	user	Percent (%)
high density forest	53	2	0	0	0	55	96.36
Dense forest	0	31	0	0	0	31	100
sparse	0	3	80	0	0	83	90.36
Farm land	0	0	0	62	4	66	93.94
grassland	0	0	0	5	61	66	92.42
producer	53	36	80	67	65	301	
Produceraccuracy (%)	100	86.11	100	92.54	93.85		

$$\text{User accuracy} = \frac{number\ of\ correctly\ classified\ pixels\ in\ each\ class}{total\ number\ of\ pixels\ in\ each\ catagory} * 100$$

1	High density forest	User accuracy(%)	53/55=96.36
2	Dense forest		31/31= 100
3	Sparse		80/83 = 90.36
4	Farmland		62/66 = 93.94
5	Grassland		61/66 =92.42

$$\text{Over all accuracy} = \frac{\text{Total number of correctly classified diagonal pixel}}{\text{total number of referance pixe}} * 100$$

$$= \frac{53+31+80+62+61}{301} * 100 \quad = \mathbf{95.35}\%$$

$$\text{Kappa coefficient} \quad = \frac{(\text{Ts xTcs})-\sum(\text{column total x row total})}{\text{Ts}*\text{Ts}-\sum(\text{column total x row total})} * 100$$

$$= \frac{(301\text{x}287) - \sum(53*55+31*36+80*83+66*67+66*65)}{301*301-\sum(53*55+31*36+80*83+66*67+66*65)} * 100$$

= 86387-(2915+1116+6640+4422+4290)/90601-19383

= 86387-19383/71218 =94.08% Classification accuracy was ok

Appendix4: GCP points for ground truth (from field survey)

Nothing	Easting	Description
831567.30	534729.39	High density forest
831911.70	534836.29	High density forest
832096.83	533905.38	High density forest
835889.87	539382.10	High density forest
845287.11	538220.65	High density forest
834374.84	539516.45	Dense forest
844472.14	539669.81	Dense forest
845656.45	541898.18	Dense forest
847326.90	540837.31	Dense forest
845202.12	539030.10	Dense forest
831757.63	535071.42	Sparse
834137.86	537351.60	Sparse
838765.77	539257.50	Sparse
847211.60	543584.99	Sparse
842197.08	542460.34	Sparse
831433.53	535331.56	Grassland
832907.35	536404.40	Grassland
837118.93	538239.36	Grassland
835338.51	540668.24	Grassland
845036.98	536453.75	Grassland
843131.25	535654.92	Farmland
847574.95	545348.14	Farmland
831263.56	536337.00	Farmland
834610.59	533850.63	Farmland
844155.51	543740.04	Farmland

Appendix6: Some samples of photo taken during field study.