MODELING OF CHILLIMO PROTECTED FOREST COVER DYNAMICS USING GEOSPATIAL TECHNOLOGIES: DENDI WOREDA, OROMIA REGIONAL STATE, ETHIOPIA

Gadisa Diribsa

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 Master's in Geo-informatics

Office of Graduate Studies

Adama Science and Technology University

January, 2023

Adama, Ethiopia

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APPROVAL SHEET

We, the advisors of the thesis entitled “Modeling of chillimo protected forest cover dynamics using geospatial technologies: Dendi woreda, Oromia regional state, Ethiopia” and developed by Tolesa Chala, 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)		
Major Advisor	Signature	Date
Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Gadisa Diribsa have read and evaluated the thesis entitled “Modeling of chillimo protected forest cover dynamics using geospatial technologies: Dendi woreda, Oromia regional state, Ethiopia” and Examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted in partial fulfillment of the requirement of the degree of Master of Science in Geo-informatics.

Chairperson	Signature	Date
Internal Examiner	Signature	Date
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Final 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).

Department Head	Signature	Date
School Dean	Signature	Date
Office of Postgraduate Studies, Dean	Signature	Date

DECLARATION

I Gadisa diribsa hereby declare that this Master Thesis entitled "Modeling of chillimo protected forest cover dynamics using geospatial technologies: Dendi woreda, Oromia regional state, Ethiopia" is my original work. That is, it has not been summited for the award of any academic degree, diploma or sources certificate in any other university. All sources of materials that are used for this thesis have been dully acknowledged through citation.

Gadisa diribsa ________________________ ________________

Name of student Signature Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that We have read the revised version of the thesis entitled “Modeling of chillimo protected forest cover dynamics using geospatial technologies: Dendi woreda, Oromia regional state, Ethiopia” prepared under our guidance by Gadisa Diribsa submitted in partial fulfillment of the requirements for the degree of Master's of Science in Geo-informatics.

Therefore we recommend the submission of the revised version of the thesis to the department following the applicable procedure.

Roba Gemechu (PhD)		
Major Advisor	Signature	Date
Co-advisor	Signature	Date

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LIST OF ACRONYMS AND ABBRIVATIONS

CAD: Computer Aided Design

CSA: Central Statistical Agency

DEM: Digital Elevation Model

ERDAS: Earth Resource Data Analysis System

ETM: Enhanced Thematic Mapper

FAO: Food and Agriculture Organization

FAP : Forest Action Program

FCC: Forest cover change

GCP: Ground Control Point

GIS: Geographic Information System

GPS: Global Positioning System

LULC: Land Use/Land Cover

MoA: Minister of Agriculture

NIR: Near Infra-Red

NFPA: National Forest Program Actions

RS : Remote Sensing

SPSS: Statistical Package for Social science

TIFF: Tagged Image File Format

USGS: United state geological survey

ABSTRACT

Forests constitute one of the world's most valuable natural resources and play a key role in global ecological balance. 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 assessment of forest cover change of chilimo and make future predictions for forest change by using geospatial technology. Furthermore, a 17-year forecast was made using QGIS to suggest how the forest might change in the future. The study used two spot images from 2006, 2016 and a Sentinel-2A image from 2023 to analyze forest change. These satellite images revealed four major land cover classes: dense forest, sparse forest, built-up, and farmland. Therefore, as a result of change detection, dense and sparse forests were decreased by 983.4ha and 166.5ha while, agricultural land and built-up area where increase from 1135.5 to 14.14ha from 2006 to 2023 respectively. The frequency analyzed driving factors of forest change were cultivated land expansion, firewood collection, grazing, population growth and charcoal production. Because of these factors, the forest was degraded, and some problems occurred in study area like, loss of wild life, climate change and soil erosion. As the prediction result shows, dense and sparse forest forests were decreased by 159.2ha and 214.5ha on other hand farm land and built-up where increased by 375.4ha and 18.2ha from 2023 to 2040 respectively. If this trend continues, great impact on climate change, soil erosion and loss of wild life. 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, chilimo, modelling.***

CHAPTER I: INTRODUCTION

1.1. Background of the study

Forest is a major natural resource that helps to keep ecological balances (Suryabhagavan, 2019). Forest is one of the most essential types of resources that humans and other animals rely on, it helps to regulate environmental and biological change by ensuring that soil, water, climate, and rainfall are all in excellent working order and can be sustained (Mideksa, 2009).

Forest cover change frequency is increasing globally. Wildfires have major environmental and ecological issues; threaten human lives, causing massive losses of lives and properties (Parajuli et al., 2020). Wildfires contribute considerably to environmental deterioration, especially global warming, on a worldwide scale (Tan et al., 2007). Forest fires are also a major source of damage to forest resources, and they occur regularly in varying degrees of severity (Ghorbanzadeh et al., 2019). Fire plays an important role in decreasing both the quality and quantity of forest resources. Between 1990 and 2000, Africa lost about 52 million hectare of forest, accounting for about 56% of the global reduction in forest cover. Southern Africa (including Tanzania) accounted for about 31% of the forest loss on the continent (Saklani, 2008).

Almost 6.8 million square kilometers of African land were originally forested. Africa is one of the most severally deforested continents. Forests in Africa are believed to have been cleared 29 times faster than they were being planted in early 1980s compared to 10.5 in Tropical America and 4.5 in Tropical Asia (Heltberg, 2002). The depletion of forests is of great concern for environmental and development in developing contents in general Africa in particular. Unsustainable use of forests has resulted in severe environmental problems.
According to FAO, 2011, from 1995 to 2010, Ethiopia lost about 141,000 hector 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).

Currently, satellite images are used to evaluation of the forest cover change using remote sensing and GIS techniques: the case of chilimo protected forest dandi woreda. As stated by Kumar et al., 2014, remote sensing datasets are very useful and very important for forest cover mapping and monitoring. Many researchers explore the study of forest change analysis by using remote sensing data. But the previous researchers is use landsat image with having 30 m spatial resolution however current study use remote sensing data like spot image by having 10m spatial resolution to get high accuracy result. So, spot image better than landsat image to acquire image quality interpreted. Therefore, this study aimed to fill the existing research gap by using remote sensing and GIS techniques to evaluate forest cover change of chilimo forest.

1.2. Statement of the Problem

Forest change have become a major concern for several environmental experts, on a global scale, forest cover change is the most effective means of transforming tropical forests into agricultural areas, and it has severe impacts on the global atmosphere (Yakubu et al., 2015). When forest fire burns in an uncontrolled manner, fire has been a cause of ecosystem disruption. According to Vicente-Serrano et al., (2020) loss of forest, loss of bio-diversity, loss of wildlife habitat, global warming, soil degradation, loss of biophysical wood and fodder, damage to water and other natural resources, and loss of natural regeneration are among the ecological and socio-economic effects of wild land fires.

In Ethiopia, decentralized forest resource management was initiated in the mid of 1990s with the support of international non-governmental organizations (NGOs) to mitigate natural resource degradation and its effects on the livelihoods of people (Kassa et al., 2009). Participatory Forest Management (PFMPs) is a new paradigm of forest management which is adopted and implemented in order to fulfill the interests, respecting of traditional users and hence such a bottom-up approach may encourage a sense of ownership to the rural people to conserve forest resources. The participatory forest management plan has been going on in Chilimo dry afro-montane forest which is one of the oldest remnant forests found in the central highlands of Ethiopia since 1996 (Lemenih et al., 2015). Nevertheless, several studies show that initiatives that use some kinds of participatory approach to conservation of natural resources often fail to achieve their goals in terms of power devolution for decision making and promoting conservation (Wells & McShane, 2004).

Due to forest cover change from time to time the number of wildlife decreased. As a result, the natural environment as well as ecological balance of the area is under a serious of threat due to the Persistent disturbance of the forest resources by the local community. If the use of forest and deforestation are continuously increasing the problem are increasing on; the wildlife habitat and environmental change. The aim of this study is to Evaluation of chilimo forest cover change using geospatial technologies. Also GIS and remote sensing are used to detect forest cover change in chillimo forest over last 34 years between 2006 and 2023 also, modelling for 2040. Finally, this research will intend to raise awareness for stakeholders and indicate appropriate measures.

1.3 Objective of the study

1.3.1 General objective

The general objective of this study is to Modeling of chillimo protected forest cover dynamics from 2006 to 2023 using geospatial technologies: Dendi woreda, Oromia regional state, Ethiopia

1.3.2 Specific objectives

The specific objective of this study will to:

- ✓ Identify driving forces for forest cover change and consequences.
- ✓ Evaluate the trends land use/land cover dynamics on forest cover change between selected years.
- ✓ Detect the spatial change of forest cover for the study area between 20o6-2023 years.
- ✓ Forecast for future prediction forest cover change of study area from 2023-2040.

1.4 Research question

- ✓ How to identify factor that influence forest cover change and consequences in the study area?
- ✓ What are the impact of land use/ land cover dynamics of the study area?
- ✓ What are the spatial changes in forest cover between the selected three years?
- ✓ How to forecast future prediction forest cover change of the study area?

1.5. Significance of the study

Despite a growing awareness among scholars and practitioners regarding the role of local people’s to determine the success or failure of natural resource management schemes a lot less attention is given to their roles in the overall process of forest reserve design and implementation. Well managed forest that contributes for ecotourism to provide local communities with motivation to maintain and protect forest and wildlife when local people get income and employment from ecotourism; they are far less likely to destroy the natural resources through unsustainable exploitation.

The findings of the study are expected to contribute towards an understanding of the dynamics of deforestation in Chilimo forest; the community in the local area can make use of the findings of the study so, improved the forest coverage management practices, it gives some guide line to the causes of climatic change, global warming and environmental protection agencies about the existing situations on deforestation of Chilimo forest besides to these the finding of this study will hopefully be of scientific contributions for those who are interested to make further studies in similar issues at different geographical settings and it will also help to inform policy makers on how to involve the local communities in forest management activities.

1.6 Expected outcome of the study

This study will give how much forest cover of chillimo is changed in the last 18 years using GIS and Remote Sensing. Forest cover change detection maps of the study area will prepare to analysis changes. Therefore, we will expect from the finding of this study to identify forest cover change of the chillimo within different time interval and it will contribute information for decision-makers, resource management and planners for sustainable development and management of the natural resource.

1.7 Scope of the study

This study will focused on the evaluation of the forest cover change using geospatial technology: the case of chillimo forest dandi woreda. The study will be conducted in Chilimo forest. Chilimo forest is cover around 7148.6 hectors. In order to investigate the problem attempt will be made to look in-to the dynamics of forest cover that focuses in dendi woreda in chilimo forest. In this study to analyze the spatio-temporal dynamics of forest cover hange and its prediction was carried out in three comparison years.

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CHAPTER II: LITERATURE REVIEW

2.1. Forest cover and deforestation

Forest is one of the great inherited resources of the earth. It includes natural forests and forest plantations. The term is used to refer to land with a tree canopy cover of more than 10 percent and area of more than 0.5 hec (FAO, 2000). (WBISPP, 1992) also defines forest as “a relatively continuous cover of trees, which are ever green or semi-deciduous only being leafless for a short period, and then not simultaneously for all species”. Forests are determined both by the presence of trees and the absence of other predominant land-uses. The trees should be able to reach a minimum height of 5 m. Young stands that have not yet reached, but are expected to reach, a crown density of 10 percent and tree height of 5 m are included under forest, as are temporarily unstocked areas (FAO, 2000).

Some define deforestation as the area that no longer remains in primary forest (Pichon,et al., 2001). Others use strict sense of land-use conversion and define deforestation as the complete clearing of tree formations and their replacement by non-forest land-use (Thwin, 2003). Forest degradation is a temporary or permanent deterioration in the density or structure of vegetation cover or its species composition. This encompasses the effect of selective logging, which causes change in canopy cover. It is also useful in accounting for the effects of short-rotation shifting cultivation, in which secondary forest (forest fallow) grow on abandoned plots but never reaches the same biomass or overall quality as mature forest as it is cleared again for cropping after a few years. The difference in the definition not only affects the measurement of the forest resources but also of annual deforestation.

2. 2. Global overviews of forest cover change

Based on Earth observing satellite image 1990, there were some 1150 million hectare of tropical rain forest with the area of the humid tropics deforested annually estimated at 5.8 million ha. A further 2.3 million hectare of humid forest is apparently degraded annually through fragmentation, logging and/or fires. In the sub-humid and dry tropics, annual deforestation of tropical moist deciduous and tropical dry forests comes to 2.2 and 0.7million ha, respectively. Southeast Asia is the region where forests are under the highest pressure with an annual change rate of 0.8 to 0.9%. The annual area deforested in Latin America is large, but the relative rate (0.4 to 0.5%) is lower, owing to the vast area of the Amazonian forests. The humid forests of Africa are being converted at a similar rate to those of Latin America 0.4 to 0.5% per year (Mayaux et al., 2005).

2.3. Trend of forest covers change in Ethiopia

The forest cover of Ethiopia estimates made from 1940s to early 1960s ranged between 2.6 million hectare and 12.2 million hectare. Apparently, estimates given by different authors show variation and this has been attributed to the differences in defining the forest by the authors (Melaku, 1992). The general truth, however, is that the forest cover has been diminishing through time.

More recent work on forest monitoring of Ethiopia (Reusing, 1998) clearly indicated the high rate of forests clearing in the country during the last three decades. The study was conducted using the Geographic Information System (GIS), and analysis from the satellite images of 1973-1976 showed that the forest cover in the country was 4.75% , while it declined to 3.93% between 1986 and 1990 (Reusing, 1998). Accordingly, deforestation between 1973 and 1990 was around 24,543 Km2 (2.14%) of the country. Reusing, (1998) has also showed the change detected in the natural forest cover between 1973 and 1990 in Ethiopia.

2.4 Causes and Consequence of forest cover change in Ethiopia

Forest decline in Ethiopia is highlighted by several authors, (Gessesse, Demel, Reusing). Regardless of the disagreement exists about the cause and consequences of deforestation, the need for more space for cultivation is mentioned as the major and underlining factor of the problem. As the result of the growing demand of agricultural land, more trees being increasingly removed (Gessesse, & Christianson, 2007). (EFAP, 1994) claims that the population increase plays a major role. Similarly, (Demel, 2000) stated that the major reasons for deforestation are the clearing of forests and woodlands for cultivating crops and the cutting of trees and shrubs for various purposes, notably for fuel wood, charcoal, construction materials, etc.

However, others linked the underlying causes of deforestation with the vicious cycle of mutually reinforcing factors, namely poverty, population growth, poor economic growth, and the state of the environment (MNRCDEP, 1994). With population increasing faster than the economy, the per capita income declined. These factors adversely affected natural resources, particularly forests and woodlands. Deforestation is one of the major factors contributing to land degradation by exposing the soil to various agents of erosion. With high-intensity rainstorms and extensive steep slopes, Ethiopia is highly susceptible to soil erosion, especially in the highlands. The organic content of soils is often low due to the widespread use of dung and crop residues for energy (Demel, 2000).

Land degradation in turn greatly affects agricultural productivity and production. In 1990 alone, for instance, reduced soil depth caused by erosion resulted in a grain production loss of 57,000 (at 3.5 mm soil loss) to 128,000 tons (at 8 mm soil depth). It has been estimated that the grain production lost due to land degradation in 1990 would have been sufficient to feed more than four million people. The availability of land suitable for agriculture is shrinking, while at the same time the amount of land required to feed the growing population is steadily increasing (Demel, 2000). Hence, deforestation results in environmental degradation in the form of land and water resources degradation as well as loss of biodiversity (Demel, 2000).

2.5. Major forest conservation management practices

2.5.1. Traditional methods to conserve forestry

Traditional Forest Management practices this study has got experience of the religious institutions as the major contributor for traditional forest conservation. The only areas where one can observe trees in central Ethiopia are the surrounding of churches. These patches of natural forest have survived as the result of the traditions conservation effort (Yeraswork, 1995). These forests are still sanctuaries of many plant and animal species that have almost disappeared in most parts of northern Ethiopia (Alemayhu, 2002).

2.5.2.1. Geda system traditional forestry conservation practice

Indigenous knowledge, as the knowledge obtained through protracted interaction humanity with its environment, cannot be seen apart from the indignity of people adoption to the indigenous culture. Enforcement of Geda Laws on indigenous knowledge of forest conservation the one who do not obey the law of conserving forests, grass and waters decreed at Geda assembly stated that “those who fail to respect Gada laws are make to slaughter their bulls for their wrong doings and in certain cases chased out of the forests. In related to this noted that the Guji people seem to have good knowledge of the advantage of trees. Because of this, they have law which for bides the felling of big trees. The Abba Geda, the Quuallu as well as elders in the village often proclaim that trees should not be cut down. If a person cut down a tree without the consent of the Quuallu or Abba Geda he/she undergoes corporal punishment in the form of beating in public or a payment in cattle. Thus they perceive that cutting down of trees is compared to killing of a person. It is possible to learn such active laws of people from the proverb presented below. “Mukti lubbuu dha, luubbuu hin huban” (Trees are life; one does not harm life) (Negessa, 2011). Forests serve as shades for animals, humans and the under growths like coffee. They “shade the land and serve as a shelter for the cattle during dry season.

2.5.1.2. The tradition of the sacred grove conservation practices of forestry

Traditional forests reserves are protected natural forest established by ancestors to perform many socio- cultural functions and are protected in accordance to customary laws, not based on government legislation. These reserves generally have a long history with well preserved forests that could demonstrate what the surrounding environment could have looked liked, if humans had not altered it. Therefore, the traditional forest reserves might have significant ecological value and a potential high biodiversity (Alemayhu, 2002).

Many tree specious surrounding religious areas have relationship with the term sacred groves in most literature. The tradition of the sacred grove is well in Ethiopia tradition in experience of traditional religion as the oromo sacred Adbar or in the clump of trees that customarily envelope the Debre (Bahru, 1997)**.** Sacred groves are smaller or larger ecosystems, set aside for a religious purpose. The origin of sacred groves can be attributed to the slash and burn system of agriculture, where several forests patches was left standing around farm lands. These groves came to be institutionalized as centers for culture and religious life. Taboos and social sanctions protect the sacred groves from deterioration due to human interference. This habitat at patches may be the only primarily forests reaming locally. Several endemic and endangered species have been recorded from sacred groves (Alemayehu, 2002). Sacred groves which form conservation sites and act as a refuge for specious are becoming ecologically important in the light of the current rates of deforestation and species loss.

2.5.1.3. Traditional knowledge of forestry conservation

Medicinal properties of plants have been recognized and practiced by traditional communities as a traditional for thousands of years. Knowledge on some common medicinal plants of their locality is valuable with all the members of the community (Ravishankar, 1995). However, the elderly members possess a great deal of knowledge of medicinal plants as well as on medicines for curing certain life treating diseases traditional knowledge forest conservation forests for their medicinal purpose.

2.5.1.4. Traditional forestry conservation practices strategies of EOTC

EOTC (Ethiopia Orthodox Twehido Church) apply two traditionally conservation strategies, namely religious holiness and legal protection. Religious Holiness the main mode of protection is achieved through creating religious commitment and respect among the followers. As the church is believed the house of God, everything in the compound is sacred and respect. Every follower is expected to respect and protect the house of God together with the forest involving. Cutting a tree in the church compound is considered as denying the presence of God unless it is for spiritual purpose of the church (Alemayehu, 2002). It is believed that cutting in and smuggling of trees from the church compound would bring a misery and the one who did it is considered as the person who has violated the kingdom of God and would be isolated from the church community. A person that cut a tree or even a dead branch for personal use would be presented to the church community. He or she would be alienated from the church community which is said to be ‘Gizit’.

Hence, Orthodox Christian fear such conditions and tradition was protects the tree in church forests. Legal Protection Method monastery forest resources are found around people of different attitudes and perspectives which force to use guards and civil law to conserve and protect their forest resources. At present the demand forest products increasing the encroachers and outlaws destruct the forest (Alemayehy, 2002). Therefore, EOTC assign guards to prevent such conditions before it happens and to bring to the civil courts for the appropriate measures.

2.5.2. Modern Forest Management methods to conserve forestry

2.5.2.1. Community based forest management

Natural resource management have different dimension, but participation is not always beneficial for conservation of forest because of types of participation, who participate, when they participate and under what circumstance (Zelalem, 2005).Community based forest Management through organized forest user group as a concept and a philosophy was considered by the former bureau of agricultural and rural development, where in all the forest dependent villagers of a village organize themselves into small cohesive group with the objective of protecting, regenerating and managing the forests in the vicinity of their village (Zelalem and Mulugeta 2012. community based natural resource management has been the key and also the most criticized aspects of most participatory approaches. In most cases a unified, homogenous and community in locally evolved rules and norms for equitable and sustainable management of resource is visualized. On the other hand, it is argued that social identities such as gender, wealth, age and origins divided cross cut community boundaries can be over looked (Agrwal, ,2000).

2.5.2.1 Participatory forest management

The arrangements for managements that are negotiated by multiple stakeholders and are based on set of rights and privileges recognized by the government and widely accepted by resource users; and the process for sharing power among stakeholders to make decisions and exercise control over resource use.

2.5.2.2 Social forest management

The term social forestry is difficult to define precisely, but is generally understood to mean treegrowing (including associated products, for example, Bamboo, grasses, legumes) for the purpose of rural development (Castern, 2005) for the purpose of rural development. As social forestry has a rural development focus and is heavy dependent on the active participation of people, it is also known as “forestry for local community development” or “participatory forestry”. Social forestry has grown in importance and now constitutes a major element over all progress of rural development. From modest beginnings over a decade ago, there has been an almost exponential growth in the human and financial resources devoted to social forestry.

Social forestry progress usually includes one or more of this component like farm forestry, community forestry, reforestation or rehabilitation of degraded forest areas. The objectives of social forestry necessarily differ by component while all social forestry aims to increase production and reduce environmental degradation (Chomitz, 2007), the nature of the product, the type of management and the distribution of benefits depend on the type of social forestry involved.

2.6. Remote Sensing and GIS

2.6.1. Remote Sensing

Remote Sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation (Lillesand and Kiefer, 2000). The focus of remote sensing in scope of this study is the measurement of emitted or reflected electromagnetic radiation, or spectral characteristics, from a target object by a multispectral satellite sensor. Remote sensing satellite images are immensely used in natural resources monitoring and management, study the time to time changes due to its repetitive coverage especially in forest resources estimation and monitoring.

2.6.2. Geographic Information System (GIS)

Different authors defined GIS from different perspectives. (Borrough and Mc Donnel, 1986) define "GIS is a Powerful tool for collecting, storing, retrieving, as well, transforming and displaying spatial data from the real world for a particular set of purpose". On the other hand, (EFAP, 1994) define "GIS is a specific information system applied to geographic data and is mainly referred to as a system of hardware, software and procedures designed to support the capture, management, manipulation, analysis, modelling and display of spatially-referenced data for solving complex planning and management problems". Most of the definitions given to GIS are relay on the computer based. This is because; it is a computer technology that realized the digital data. By now, GIS is popular as a result of the rapid access to data, flexibility, easy update opportunity and other features that enable to analyze different databases. In addition, the popularity of GIS has become more pronounced as a result of parallel development with satellite technology and computer science (Borrough and Mc Donnel, 1986).

GIS is an information system that is designed to work with data referenced to spatial or geographic coordinates. GIS is both a database system with specific capabilities for spatially referenced data, as well as a set of operation for working with data. The functions of GIS include data entry, data display, data management, information retrieval and analysis. The applications of GIS include mapping locations, quantities and densities, finding distances and mapping and monitoring change.

2.7. Application of Remote Sensing and GIS to monitor forest cover change

Remote Sensing is a powerful technique for surveying, mapping and monitoring earth resources. This technology combined with GIS which outshine in storage, manipulation and analysis for Geographic information and Socio-economic data to provide a wider application. Land resource and environmental decision makers require quantitative information on the spatial distribution of land use types and their conditions as well as temporal changes. The potential of remote sensing and GIS in the field of forestry become established over many years through the use of aerial photos and satellite image interpretations in forest cover change detection analysis, for the generation of cover map and inventory analysis. Remote sensing brings together a multitude of tools to better analyze the scope and rate of deforestation.

Multi-temporal data provides for change detection analyses. Images of earlier years are compared to recent scenes, to tangibly measure the differences in the sizes and extents of forest cover change. Data from a variety of sources are used to provide complementary information. Satellite image data can be used to efficiently monitor the status of existing clear cuts or emergence of new ones, and even assess regeneration condition. In countries where cutting is controlled and regulated, remote sensing serves as a monitoring tool to ensure companies are following cut guidelines and specifications.

2.8 Empirical review

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 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 has been known to be the major driving forces. 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 forest conservation management practice, which was not included in the previous study (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 conservation management practice. But the present study will include all parts of the chilimo forest and identify the impact of forest change 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.

CHAPTER III: MATERIALS AND METHODS

3.0 Description of study Area

Chilimo forest is in Western Shoa Zone close to Ghinchi town, Capital of Dendi District, and 70 km west of Addis Ababa. It is one of Government's Forest priority area surrounded by 7 kebeles engaged in traditional agricultural activities such as animal raising and crop cultivation. The district has a total area of 109,729 m2 with an altitudinal range from 2000-3200 m.a.s.l (Mohammed and Inoue, 2012)

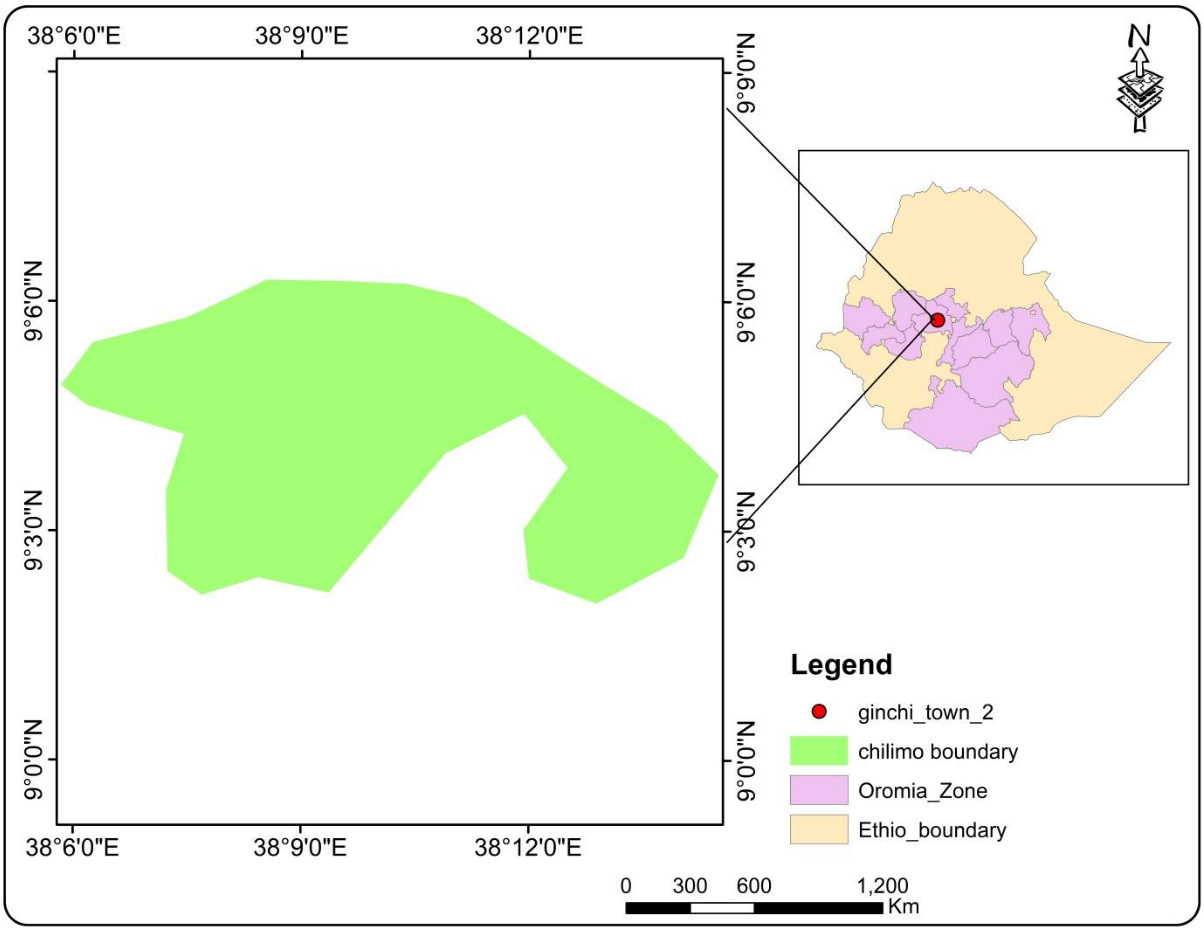

Figure 3.1Location map of study area

3.1. Demography

Based on figures published by the Central Statistical Agency in 2005, this woreda has an estimated total population of 255,896, of whom 129,226 are men and 126,670 are women; 29,602 or 11.57% of its population are urban dwellers, which is less than the Zone average of 12.3%. With an estimated area of 1,549.07 square kilometers, Dendi has an estimated population density of 165.2 people per square kilometer, which is greater than the Zone average of 152.8.

3.2 Climate

The Chilimo Gaji forest area and the surrounding peasant associations are made up of two major agro-ecologies, namely: (i) Dega temperate like climate which is characterized by cold temperature, (ii) the Weyina Dega which is warm compared to Dega. The type and range of crops grown in these two agro-ecological zones are different and in most cases the agronomic practices are not the same. Because of cold temperature in the Dega zone the range of crops grown and potential tree species are fewer compared to the Woina Dega agro ecological zone. The climatic data for 27 years was obtained from Holleta research center and analysed. June-Augest is season when highest rainfall is recorded and during this time almost all variety of crops is sown from the beginning up to the end of this period, though maize is sown starting from the end of March.

3.2.1 Rain fall

The season June-July represents one of the main cropping season of the district. From the 27 years data analysed the highest rain is recorded in the year (2005)1431.5 mm/yr. followed by 1996 (1410.9 mm/year). The Chilimo Gaji forest and the surrounding area receives rain for 5 months (May–September), with the highest peak is in July (Fig 2). The average yearly rainfall for the last 27 years is approximately 1091.51 mm in the study area (Holeta research center, 2014). The 5.31 ºC was the minimum temprature recorded in 2006, where as 25.1 ºC was the maximum temperature recorded in 2009.

3.3. Materials and software

In this research various software‘s and materials were used for different purposes in order to achieve the proposed objective. There are a number of different kinds of methods, strategies and techniques to process input data to generate the required output with desired quality. The methodology integrates remote sensing and GIS tools.

3.1 Materials and software used

Table 3.1 Materials and software used

Name of software	Purpose
ArcGIS 10.8.1	For thematic map preparation, accuracy assessment and Resample pixel size of sentinel and spot image.
ERDAS Imagine 2015	Digital image preprocessing, layer stacking, radiometric correction and delineation of area of interest (AOI) or subset.
Google Earth Pro	Visualization and verification of classification and point data collection for accuracy assessment of 2006, 2016 & 2023 maps.
Microsoft Word and Excel	Integrating attribute data and writing final thesis report. Chart preparing, graphs and statistical analysis.
Envi	For Image and forest cover classification,
Handled GPS	To collect sample coordinate to verify ground truth.
SPSS	Statically analysis for factors that influence forest cover change.

3.4. Data Types and sources

Table 3.2 Data source

Data	Spatial Resolution (m)	format	Purpose
Spot	10	raster	For image classification
Spot	10	raster	For image classification
Sentinel 2A,2022	10	raster	For image classification
GPS point	-	point	To verify the base map
master plan		Shape file	To identify boundary of study area

Land use/ land cover classification scheme

Table 3.3: Major land use /land cover class for Chilimo forest and its description.

Land use classes	Descriptions
Dense forest	Area covered by highly natural forest and tree plantation.
Sparse forest	Area covered by scattered natural tree.
Agricultural land	a large area of land used or suited for farming
Built-up	Area cover by building and infrastructure

3.5 methods of data analysis

In order to fulfill my objective the researcher uses the following procedures

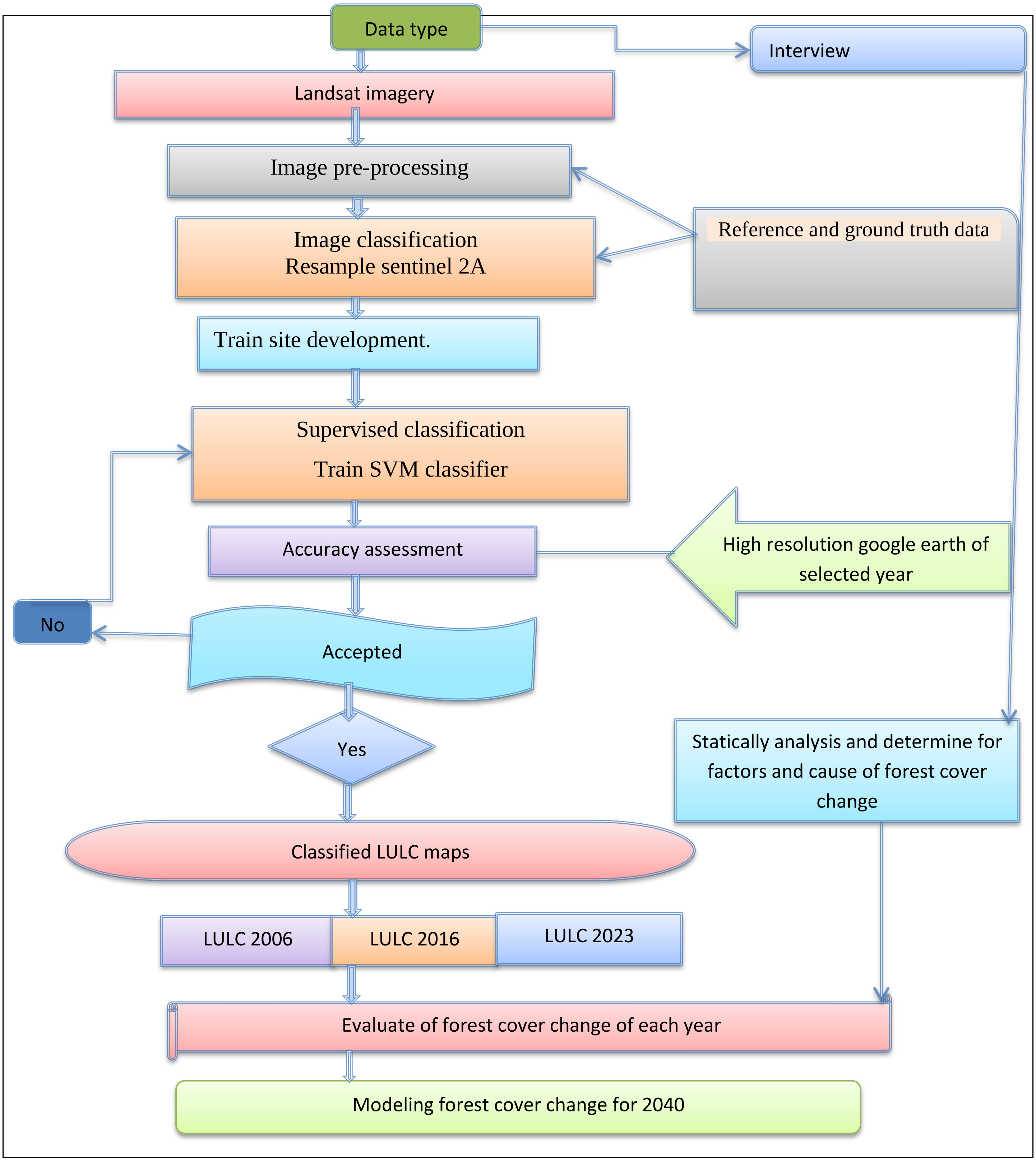

Figure 3.2 Work flow chart

3.6. Methodology of the study.

3.6.1 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. After layer stacking and band combination, radiometric corrections were made for the images of 2006, 2016, and 2023, 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 (2006, 2016, and 2023) by using shape file

3.6.2 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 the 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 will be done 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.

3.6.3 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 (2006, 2016, and 2023). 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=$Q2-Q1t$………………………..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 final year -Area initial year.........................equation 3.2

Percentage of LULC change = (Area final year -Area initial year)*100…… 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 2006.2016 and 2023.

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 (2006, 2016 and 2023) NDVI value are Calculated by using the equation below.

-For spot image of 2006 and 2016

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

-For Sentinel 2A image of 2023

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

3.6.4 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, 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 2006, 2016, and 2023 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, 2014), kappa value is calculated by using equation 3.6

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

Overall accuracy= $\frac{\text{Total number of correctly classified diagonal}}{\text{pixelTotal number of referance pixecatagory}}$ *100…………..equation 3.5

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

CHAPTER IV RESULT AND DISCUSSION

4.1 Introduction

This section describes the results obtained through data processing and analysis methods and it encompass in the following major parts. In the first part, the land use/ land cover map of 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 were described.

4.2 Statistical Analysis for identify factors that influence forest cover change.

Statistics are applied in this study to become more scientific about decisions for identifying the factor that influence forest cover change in chilimo forest. The sample data collected from four kebeles and municipality employers. The total number of sample were 79 from this Ten (10) were female and sixty nine (69) are males. The gender based frequency analysis of total respondents on both cause of forest cover change factors and the problems due to the forest change was represented as follows**.**

Table 4.1 Gender based frequency analysis of respondents

sex	Respondents	%
female	10	12.7
Male	69	87.3
Total	79	100.0

Source: SPSS frequency analysis.

The frequency analysis on above table shows the total numbers of respondents for the study to determine, which factors highly affecting the forest cover change to be analyzed and what was the happened problems due the change of the forest in study area. To attain the required goal

87.3% of males and 12.7% of female are participated to respond the prepared questions properly

Table 4.2 Age based frequency analysis for forest cover change of chilimo forest

	Age of respondent		
	Characteristics	Frequency	Percent
	30-35 years	28	35.4
	35-40 years	18	22.8
	40-45 years	14	17.7
	45-50 years	3	3.8
years	50-55 years	5	6.3
	55-60 years	4	5.1
	60 years above	7	8.9
	Total	79	100.0

From these respondents, 28 (35.4%) were 30-35 years old, 18 (22.8%) were 35-40 years, 14 (17.7%)40-45 years, 3 (3.8%) 45-50 years, 5 (6.3%) 50-55 years, 4(5.1%) 55-60 and7(8.9%) above 65 years old .This indicates that the average age of respondents was 45–50 and 50–55 years old.

Table 4.3 community stay at the study area

Duration around the study area		
	Frequency	Percent
10-20 Years	39	49.4
20-30 Years	23	29.1
30-40 Years	17	21.5
Total	79	100.0

The community stay the duration of each respondent in the study area was 39(49.4%) for 10-20 years, 23(29.1%) for 20-30 years and 17(21.5%) for 30-40 years. Therefore, based on respondent responses key factors for forest change, the problem happened due to forest change 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, a problem that occurred due to forest change, the responsible bodies, you can see from the appendix.

4.3.1 The key drivers/factors for forest cover change

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. 4 Current status of the forest.

Response	Frequency	Percent
increasing	3	3.8
decreasing	73	92.4
No change	3	3.8
Total	79	100.0

Before chillimo forest covered was 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 cultivated land, production of 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(3.8%) answered that forest cover had increased, and 3(3.8%) answered there were no changes in the forest. However, around 73(92.4%) of respondents answered that the coverage of forests had greatly changed due to different factors, which are illustrated in the table below.

Table 4. 5. Numbers of respondents in percent on driving factors for forest change

cause of forest cover change	Response	Percent
Expansion for cultivated land	38	48.1
Cutting tree for firewood	13	16.5
charcoal production	11	13.9
grazing	7	8.9
population growth	10	12.7
Total	79	100.0

Source: community based interview data

Result shows in above table, there are several reasons for the forest cover change. Some of them are Expansion of farmland, Fire wood collection, making charcoal, Grazing, Population Growth. From the result, 48.1% of the respondents replied that cultivated land was cause forest loss; 16.5%, 13.9%, 12.7%, and 8.9% of the total respondents answered that Expansion for cultivated land, firewood collection, making charcoal, population growth, and Grazing production were other factors for forest change, respectively. From this result, the expansion of cultivated land and firewood collection were the major factors for forest change.

Due to the forest cover change the amount of LULC change will lead to some problems. Based on frequency analysis of respondents' number in SPSS, due forest cover change the problems occurred in the study area were shown in table below.

Table 4. 6 Respondents number on problem due to forest change.

Problem occurred due to forest change	respondents	Percent
loss of wild life	43	54.4
climate change	27	34.2
soil erosion	9	11.4
Total	79	100.0

Source: from community based interview data.

As indicated in table 4.6, 43(54.4%) of the respondents said that the wildlife was decreased or lost immediately due to forest cover change, and 27 (34.2%) and 9 (11.4%), respondents replied that climate change, high soil erosion, can occur in the study area. This implies that forest loss is linked to wildlife loss, climate change, and soil erosion.

4.4 Trained of land use /land cover change

4.4.1 Land use/land covers classification

Land use/land cover map of the image the study area were categorized in to four major types; these are: Density forest, sparse, Agricultural land and Built up.

4.4.2 Land use /land cover map

Based on the results extracted from the Spot image of 2006, the LULC of the study area was classified into four major classes. This area has Dense forests, Sparse forests, Agricultural land and Built up. Therefore, the results of these classes are shown in the following figure.

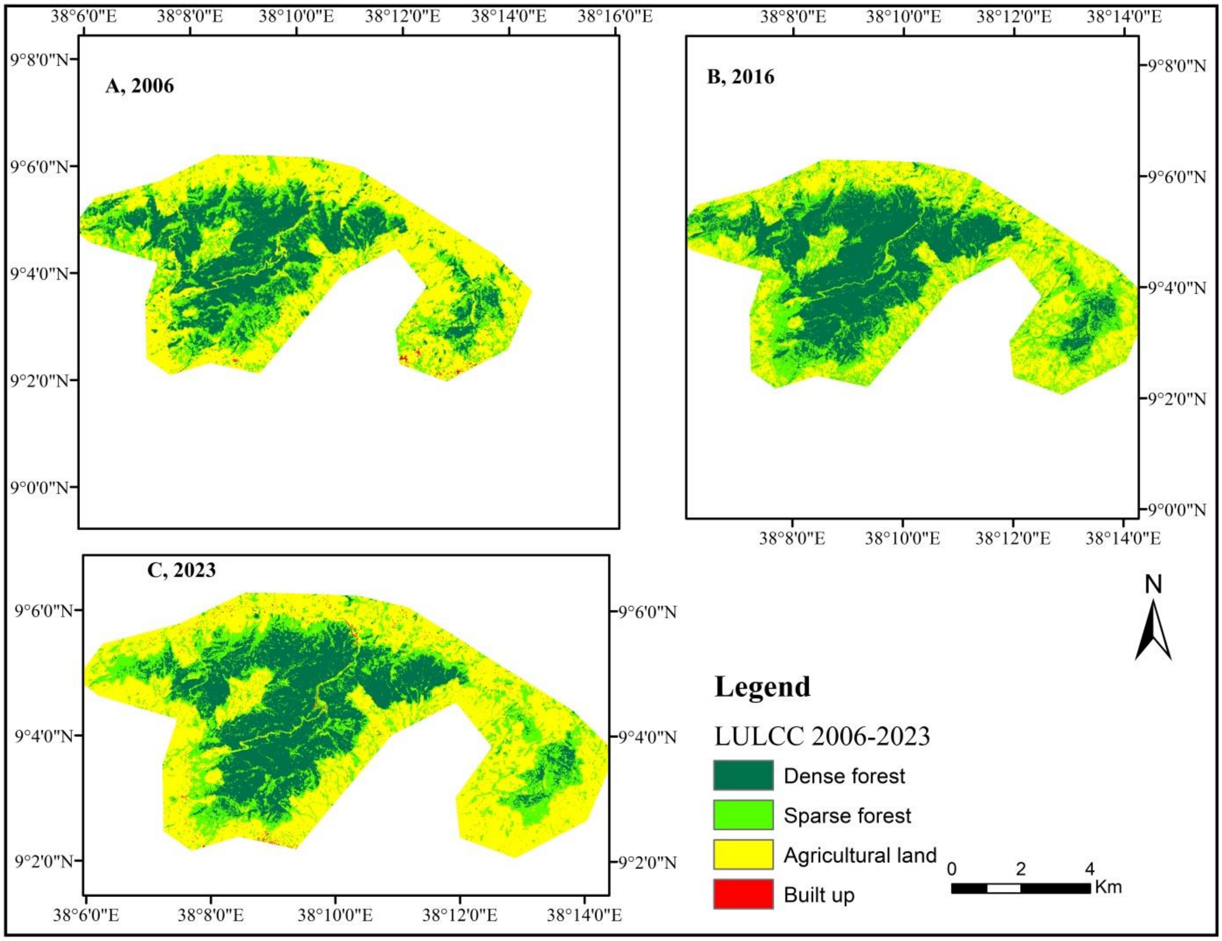

Figure 4.1 land use/land cover change of chilimo forest from 2006 to 2023 years.

4.4.3 Accuracy Assessment of the image

A map using remotely sensed or other spatial data cannot be regarded as the final product without taking necessary steps towards assessing accuracy or validity of that map (Congalton, 1991). Assessing accuracy for each category as well as for the whole image is essential to compare the results of various classification techniques and quality and reliability of the results obtained. Sampling size is an important consideration for accuracy assessment and sufficient number of samples was taken which ranges between 34 and 112 pixel samples for each classes. Moreover, for accuracy assessment of the classified images ground truth (physical survey) and google earth were used for further validity of the data. To compute accuracy, an error matrix is created to show the difference between classified categorical maps and their conforming actual reference maps. The error matrix or confusion metrics is an array of values allocated to a specific category in the reference data and the classified map to be assessed in the table. The rows in the table represent the categories of reference image or data while columns represent for the categories of classified image or map in the error matrix. The values along the diagonal represent the number of correctly classified points or true sample pixels. All non-zero values off the diagonal show discrepancy of the classified image and reference image which is error of omission (processing error) and commission (command error). Commission errors are incorrect inclusions and specify number of points whose pixels incorrectly included to column categories but omission errors are incorrectly excluded pixels from row categories. Next calculation for producer's accuracy, user's accuracy, overall accuracy and kappa statistics were discussed in detail.

i. Producer's Accuracy

The producer's accuracy informs the image analyst of the number of pixels correctly classified in a particular category as a percentage of the total number of pixels actually belonging to that category in the image and calculated by using (Equation 1). Accordingly, the results showed the minimum producer's accuracy result for the study was showed that 91.9%, 93% and 92% for the year 2006, 2016, and 2023 classification maps or results respectively. The producer's accuracy for other categories varies between 91.9% and 100% for all years which indicates that the classification performances were reliable and the results are acceptable.

ii. User's Accuracy

The user's accuracy is computed using the number of correctly classified pixels to the total number of pixels assigned to a particular category. It is the probability that a pixel classified on the image actually represents that category on the ground and calculated by using (Equation 2). Accordingly, the results showed that user's accuracy varies between 80% and 100% for the year 2006, 91.2% and 100% for the year 2016, 93% and 100% for the year 2023.Therefore, the results in both producer's and user's accuracy indicated that the performance of image and its classification was achieved very well and the error margins are within acceptable accuracy.

Table 4. 7Accuracy assessment table of 2006

	Dense forest	Sparse forest	Agricultural land	Built-up	Total (user)	UA(%)
Dense forest	84	0	0	0	84	100
Sparse forest	0	91	6	0	97	93.8
Agricultural land	0	13	98	0	111	88.3
Built up	0	0	3	12	15	80
Total	84	104	107	12	285	

PA(%)	100	91.9	97.3	100	
Over all accuracy					92.8%

Table 4. 8 Accuracy assessment table of 2016

	Dense forest	Sparse forest	Agricultural land	Built-up	Total user	UA(%)
Dense forest	60	1	0	0	61	98.4
Sparse forest	0	108	4	0	112	96.4
Agricultural land	0	0	92	0	92	100
Built-up	0	0	3	31	34	91.2
Total producer	60	109	99	31	299	
PA(%)	100	99	93	100		
Over all accuracy(%)					97.3	

Table 4. 9 Accuracy assessment table of 2023

	Dense forest	Sparse forest	Agricultural land	Built-up	Total	UA(%)
Dense forest	35	0	0	0	35	100
Sparse forest	3	46	0	0	49	94
Agricultural land	0	0	63	0	63	100
Built-up	0	0	3	38	41	93
Total	38	46	66	38	188	
PA(%)	92	100	95	100		
Over all accuracy(%)					96.8	

iii. Overall Accuracy

The combined accuracy of map for all the classes can be described using overall accuracy, which calculates the proportion of pixels correctly classified (Anupam, 2017). Accordingly, an overall accuracy was calculated using (Equation 3) and the results showed that 92.8%%, 97.3% and 98.6% for the year 2006, 2018, and 2023 classified maps respectively.

iv. Kappa Analysis

Kappa analysis generates a kappa coefficient or statistics. It is a measure of the agreement between two maps taking into account all elements of error matrix. The values are varies between 0 and 1 and thus the results converging to 1 show excellent conformation between the classified map and reference image. Accordingly, It was calculated using (Equation 4), an overall kappa statistics results indicated 0.89, 0.94 and 0.96 for the year 2006, 2016, and 2023 classification maps respectively. Therefore, Kappa coefficient of 0.89, 0.94 and 0.96 implies that the classification process was avoiding 89%, 94% and 96% of the error that a completely random classification would generate.

4.5 Land use Land covers (LULC) Analysis

4.5.1.Land use Land cover (LULC) in 2006

As presented in (Table 4.4) and (Figure 4.1), land use/land cover (LULC) of chillimo forest in quantity and map respectively. In this year (2006) Dense forest cover was the highest coverage 3037ha (42.5%) of the total area in the boundary. Also, a relatively considerable amount of the area was covered by Agricultural land was 2205.4ha (30.9%) followed by Sparse forest 1896.4ha (26.5%), Built up area 9.2 (0.1 %).

Table 4.10Area and percentage coverage land use land cover (LULC) of 2006

Year	2006	
LULCC	Area(ha)	%
Agricultural land	2205.4	30.9
Built up	9.2	0.1
Dense forest	3037.5	42.5
Sparse forest	1896.4	26.5
Grand Total	7148.6	100.0

(Source: Satellite image analysis of 2006)

4.5.2 Land use Land cover (LULC) in 2016

In this year (2006), Built-up and agricultural land was slowly expanded but,dense and sparse forest was decline during this period. Similar to the year 2006 the land use land cover classes that covered the highest share of total area were dense forest which was about 2516.0 ha (35.2%) of the total area. Likewise, a relatively considerable amount of the area was covered by Agricultural land 2430.3ha (34.0%) followed by Sparse land 2190.9ha (30.6%), and Built-up area 11.4ha (0.2%) see also (Table 4.10 and Figure 4.2).

Table 4. 11Area and percentage coverage land use land cover (LULC) of 2016

year	2016	
LULCC	Area (ha)	%
Agricultural land	2430.3	34.0

Built up	11.4	0.2
Dense forest	2516.0	35.2
Sparse forest	2191.1	30.6
Grand Total	7148.6	100.0

4.5.3. Land use Land cover (LULC) in 2023

After 10 years in 2023 the land use land cover (LULC) of the study area was intensely changed. Agricultural laand during this period covered the highest share of total area which was about 3340.9ha (46.7%), followed by dense forest and sparse forest which was 1577.14ha (28.7%) and 1727.7ha (24.2%) respectively. Others, built-up area constitute the smallest portion of the total area in the chilimo boundary which was 23.6ha (0.3%) respectively.

Table 4. 12 Area and percentage coverage (LULC) of 2023

Year	2023	
LULCC	area (ha)	%
Agricultural land	3340.9	46.7
Built up	23.6	0.3
Dense forest	2054.3	28.7
Sparse forest	1727.7	24.2
Grand Total	7148.6	100.0

Table 4.13Over all change from 2006 to 2023

Year	2006		2016		2023	
LULCC	Area(ha)	%	Area (ha)	%	area (ha)	%
Agricultural land	2205.4	30.9	2430.3	34.0	3340.9	46.7
Built up	9.2	0.1	11.4	0.2	23.6	0.3
Dense forest	3037.5	42.5	2516.0	35.2	2054.3	28.7
Sparse forest	1896.4	26.5	2191.1	30.6	1727.7	24.2
Grand Total	7148.6	100.0	7148.6	100.0	7148.6	100.0

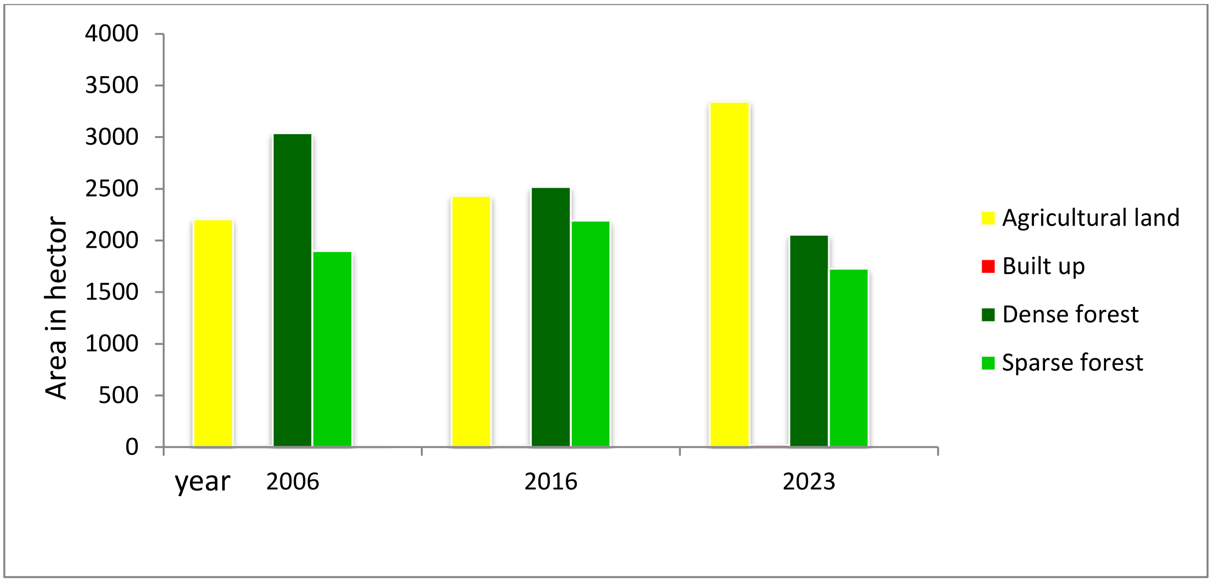

Figure 4 2 historical land use/land cover results in 2006, 2016, and 2023

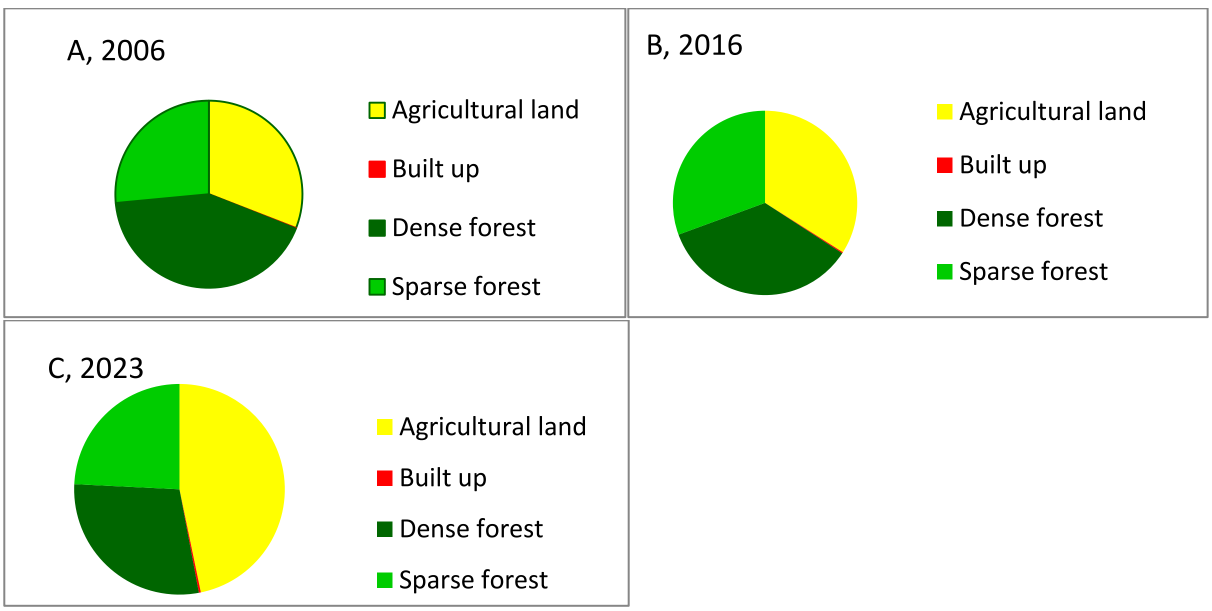

Figure 4 3Pie charts of land use/land cover maps in percentage for 2006, 2016 &2023

From the change map shown in Figure 4.2, there is a conversion of one class into another class between the years 2006 and 2016. These conversions were between the same class and different classes. Dense forest to dense forest, Sparse forest to sparse forest, built-up to built-up, and Agricultural land to Agricultural land (i.e., between the same land use/land cover 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.

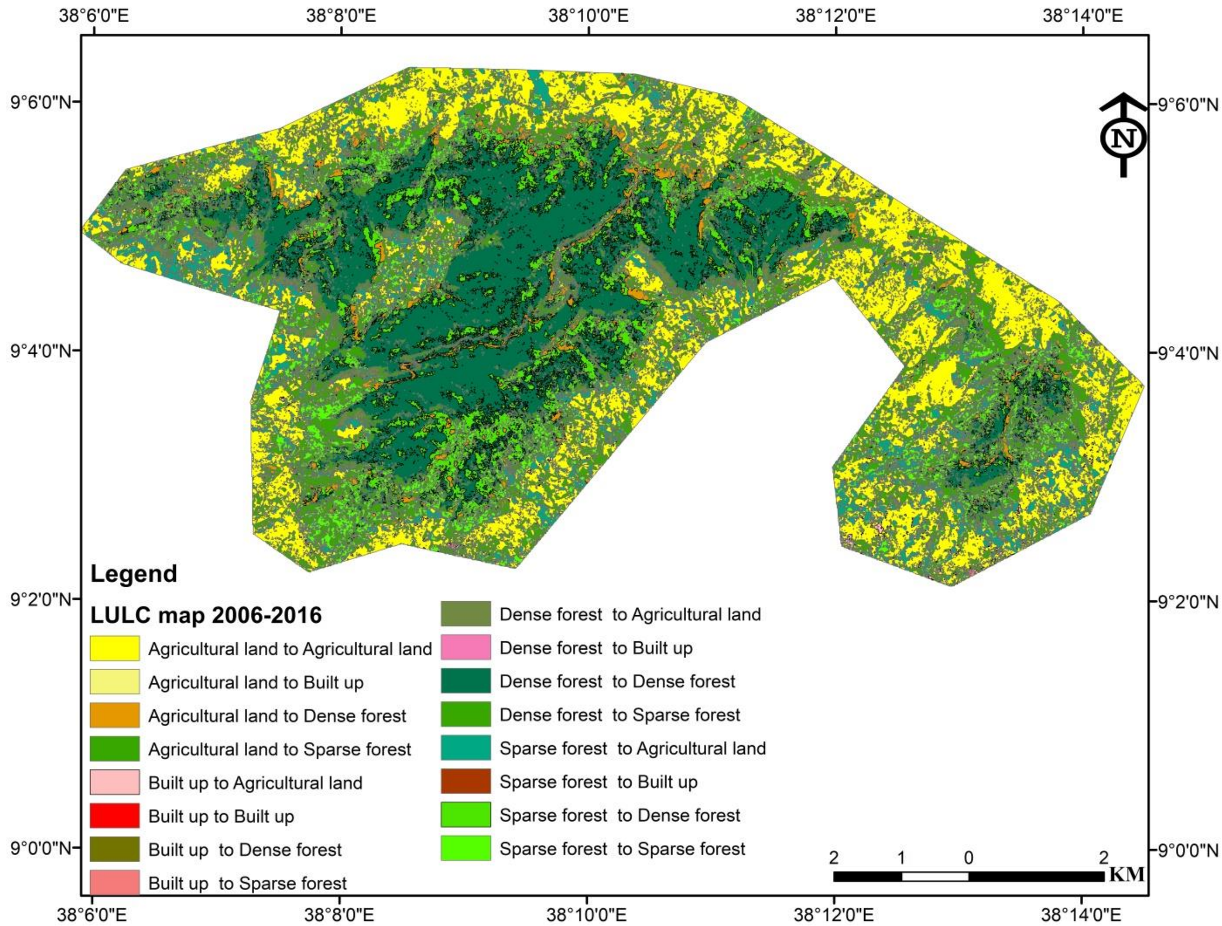

Figure 4.4 Change map of between 2006 and 2016

Table 4.14 Change matrix of land uses between 2006- 2016

	LULC class	Area of Land use class (ha) in 2016 (final)				
		Agricultural land	Built up	Dense forest	Sparse forest	Grand Total
Area of Land use class (ha) in 2006 (initial)	Agricultural land	1106.8	3.3	220.8	874.5	2205.4
	Built up	0.1	7.1	1.6	0.4	9.2
	Dense forest	875.2	0.3	1760.7	401.3	3037.5
	Sparse forest	448.2	0.7	532.9	914.9	1896.7

	Grand Total	2430.3	11.4	2516.0	2191.1	7148.8
	Change	224.9	2.2	-521.5	294.4	

According to the transition matrices between 2006 and 2016, Agricultural land to Agricultural land were 1106.8, Built-up to Built-up 7.1, dense to dense forest 1760.7, sparse to sparse 914.9 hectare respectively. This means the diagonal number indicates an unchanged area. However, in another word the conversion from one class to another class indicates the area convergence of the classes between selected years. Area of land use/land cover change from the final to initial in 2006 to 2016, agricultural land, built-up, and sparse were increased by 224.9, 2.2, and 294.4 hectors Respectively but, dense forest decreased by 521.5 hector.

4.5.4 Change detection between 2016 and 2023

This period shows a similar trend to the previous period in some land use/land cover classes. The total areas covered by agricultural land and built-up where increased while the area covered by dense and sparse were decrease. From the below LULC matrix table agricultural land and built-up were increased by 910.6 and 12.2 and -223.4 in hectare. In another ways dense and sparse were decreased by 461.7, 461.1hector respectively.   The diagonal matrix indicates that there is no change between the periods unless and otherwise there is a change.

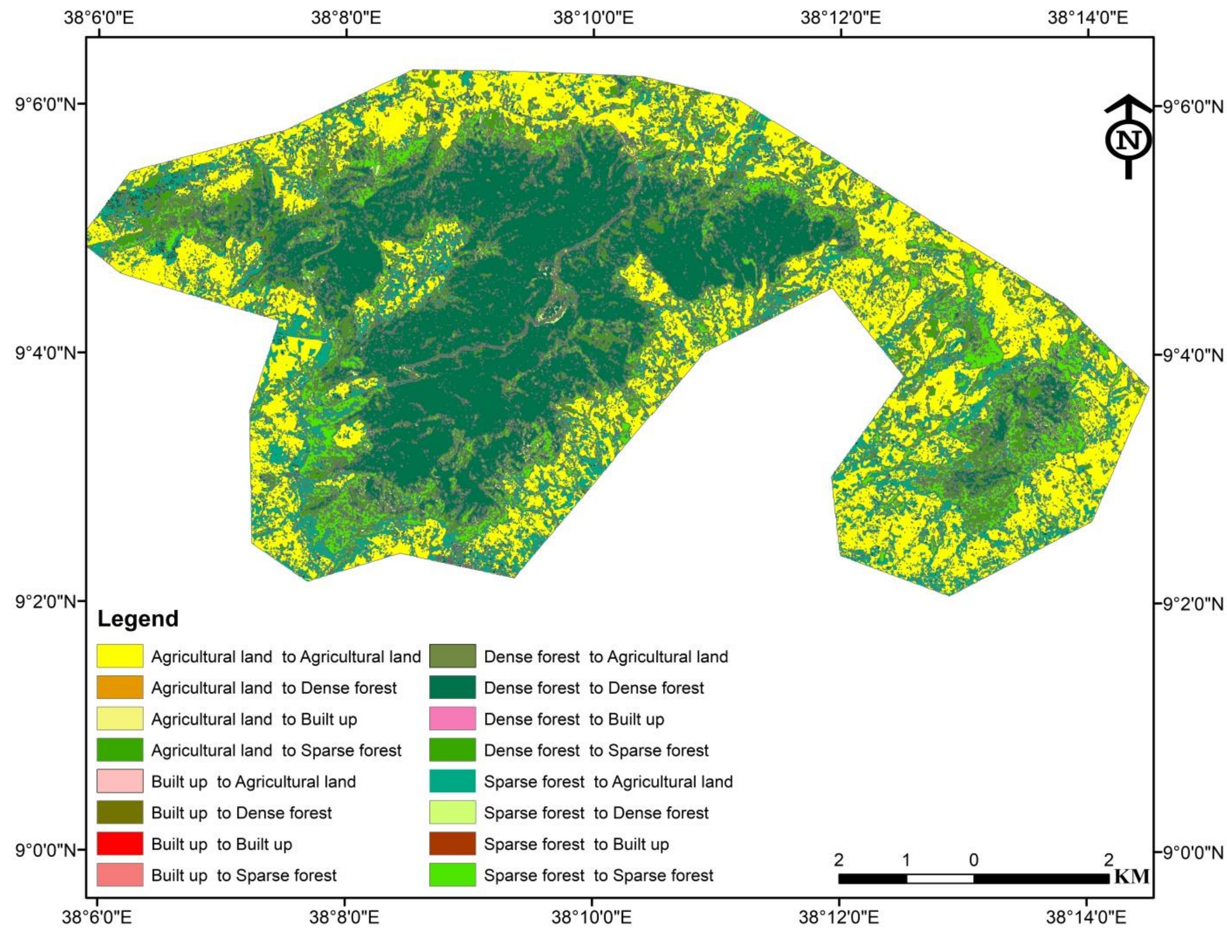

Figure 4.5 Change map of between 2016 and 2023

Table 4.15 Change matrix from 2016 to2023

Area of Land use class (ha) in 2016 (initial)	LULC classes	Area of Land use class (ha) in 2023 (final)				
		Agricultural land	Built up	Dense forest	Sparse forest	Grand Total
	Agricultural land	2324.5	3.0	6.6	96.2	2430.3
	Built up	1.1	9.5	0.2	0.6	11.4
	Dense forest	21.2	5.2	1991.4	498.2	2516
	Sparse forest	994.1	5.9	56.1	1135	2191.1
	Grand Total	3340.9	23.6	2054.3	1730	
	Change	910.6	12.2	-461.7	-461.1	7148.8

4.5.6 Over all Change detection between 2006 and 2023

The change between these years shows the overall change between the initial period (2006) and the final period (2023). During the initial period most of the area was covered by dense forest and at final year Agricultural land covered large area, the least coverage in initial period was built-up. The dense forest decreased from 3037.7ha in 2006 to 2054.3ha in 2023 with a decrement of 983.4ha between the years. Conversely, farm land and built –up area shows an increment of 2205.4ha to 3340.9ha and 9.2 to 23.6 from 2006-2023 and the change is 1135.5ha and 14.4 respectively.

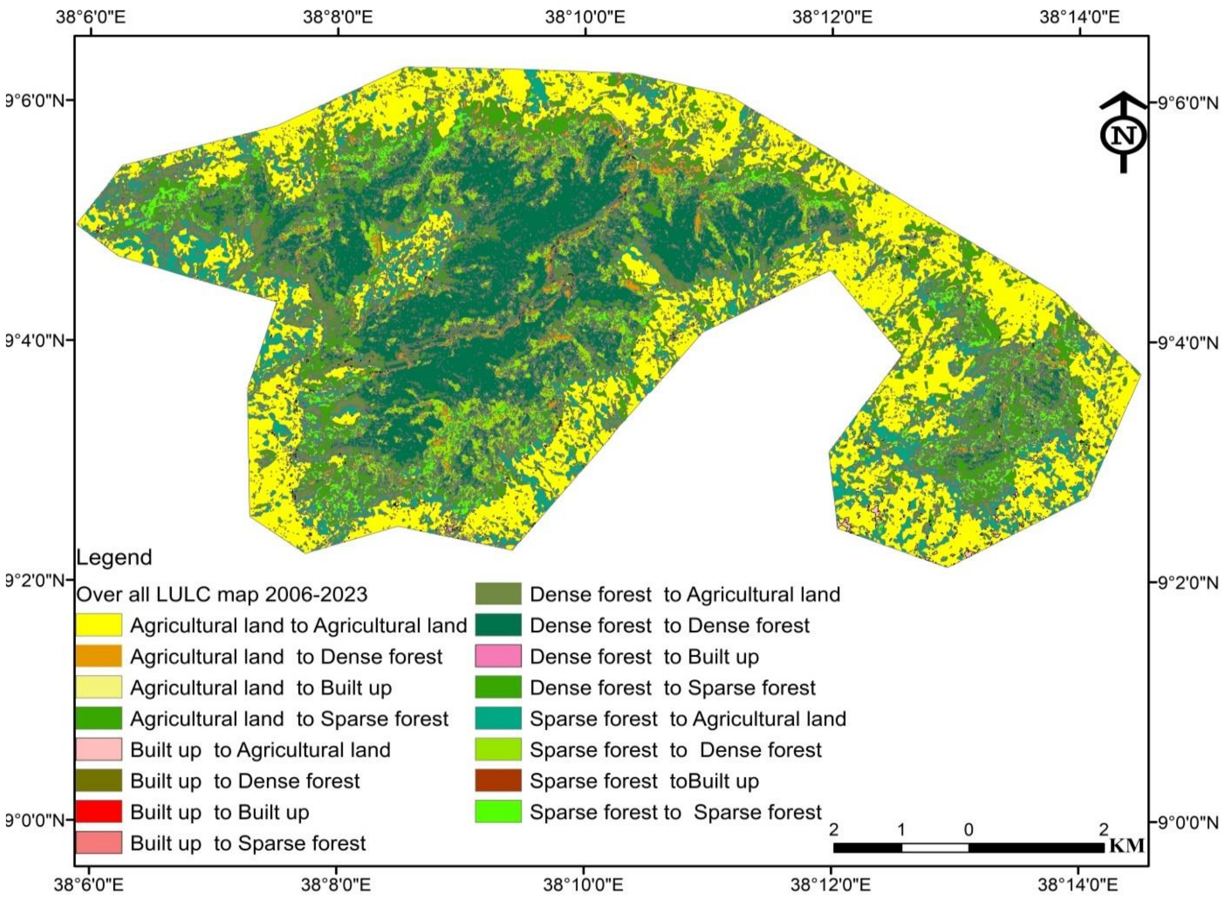

Figure 4 6 Over all change from 2006 to 2023

Table 4. 16 Change matrix of land use/land cover from 2006 to 2023

Area of Land use/land cover class (ha) in 2006 (initial)	LULC classes	Area of Land use class (ha) in 2023 (final)				
		Agricultural land	Built up	Dense forest	Sparse forest	
	Agricultural land	1392.6	6.9	294.7	511.2	2205.4
	Built up	0.3	7	0.9	1.0	9.2
	Dense forest	1152.1	4.3	1245.8	635.5	3037.7
	Sparse forest	795.9	5.4	512.9	582.3	1896.5
	Grand Total	3340.9	23.6	2054.3	1730.0	7148.8
	Change	1135.5	14.4	-983.4	-166.5	

4.6 Area gain and loss between selected years.

year	Agricultural land(ha)	Built up(ha)	Dense forest(ha)	Sparse forest(ha
2006-2016	224.9	2.2	-512.5	-294.4
2016-2023	910.6	12.2	-461.7	461.1
2006-2023	1135.5	14.4	-983.4	-166.5

In above table indicate the area loss and gain in hectares between selected years (2006 and 2016, 20016 and 2023, 2006 and 2023). Negative signs show that area's loss and positive signs show that area's gain. The area lost for dense forest and sparse forest between 2006 and 2016 is 512.5ha and 294.4ha, respectively. The areas gained for agricultural land and built-up are 224.9 and 2.2ha respectively. The area lost for dense forest between 2016 and 2023 was 461.7ha, and the another land cover classes were gained like agricultural land, built-up and sparse forest was 910.6ha and 12.2ha respectively. From 2006 to 2023, the total area lost for dense and sparse was 983.4ha and 166.5ha, while agricultural land and built-up was gained by 1135.5ha and 14.4ha.

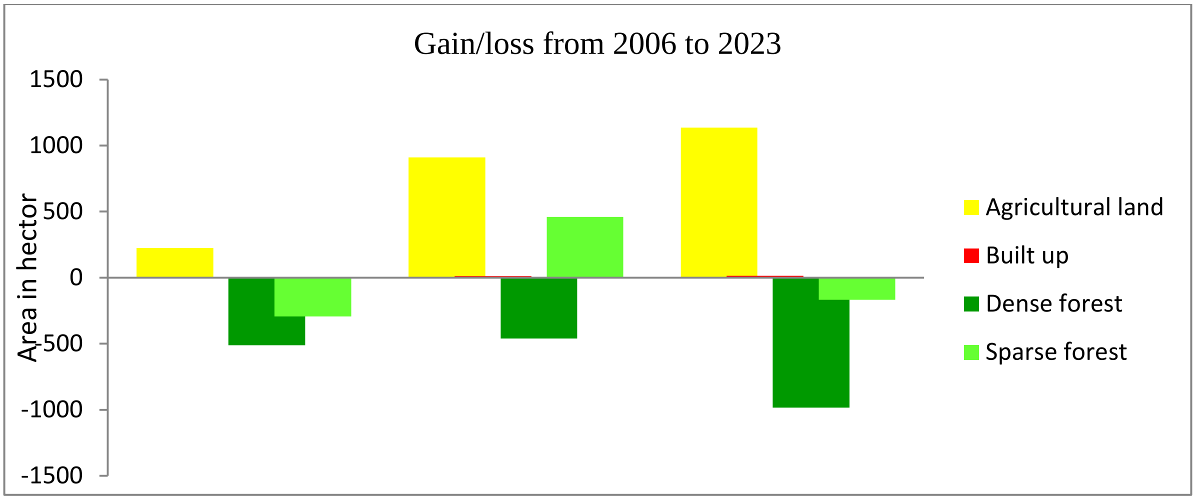

Figure 4.7 gain and loss of land use/land cover for 2006 to 2023

4.7 Predicting forest cover change for 2040

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 LULC 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 2023 and 2040. 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 2023 to 2040 in all 4 classes.

Table 4. 17 Predicted LULC for chilimo forest 2040

Year	20240	
LULCC	area (ha)	%
Agricultural land	3698.5	51.7
Built up	41.8	0.6
Dense forest	1895.1	26.5
Sparse forest	1513.2	21.2
Grand Total	7148.6	100.0

Cellular Automata-ANN, based on the change in LULC between 2006 and 2023, was used transitional potential modeling to forecast future changes. The result indicates that the probabilities of the increasing area will be covered by the agricultural land and built-up areas. The reasons for these changes are that the method is based on the previous change in pixels according to 2006 and 2023. The below map show the change in each land cover, its predicted that, Dense and sparse will decrease more and it will cover about 26.5% and 21.2% of the study area in 2040, while agricultural land and built-up will increase in 51.7% and 0.6% respectively.

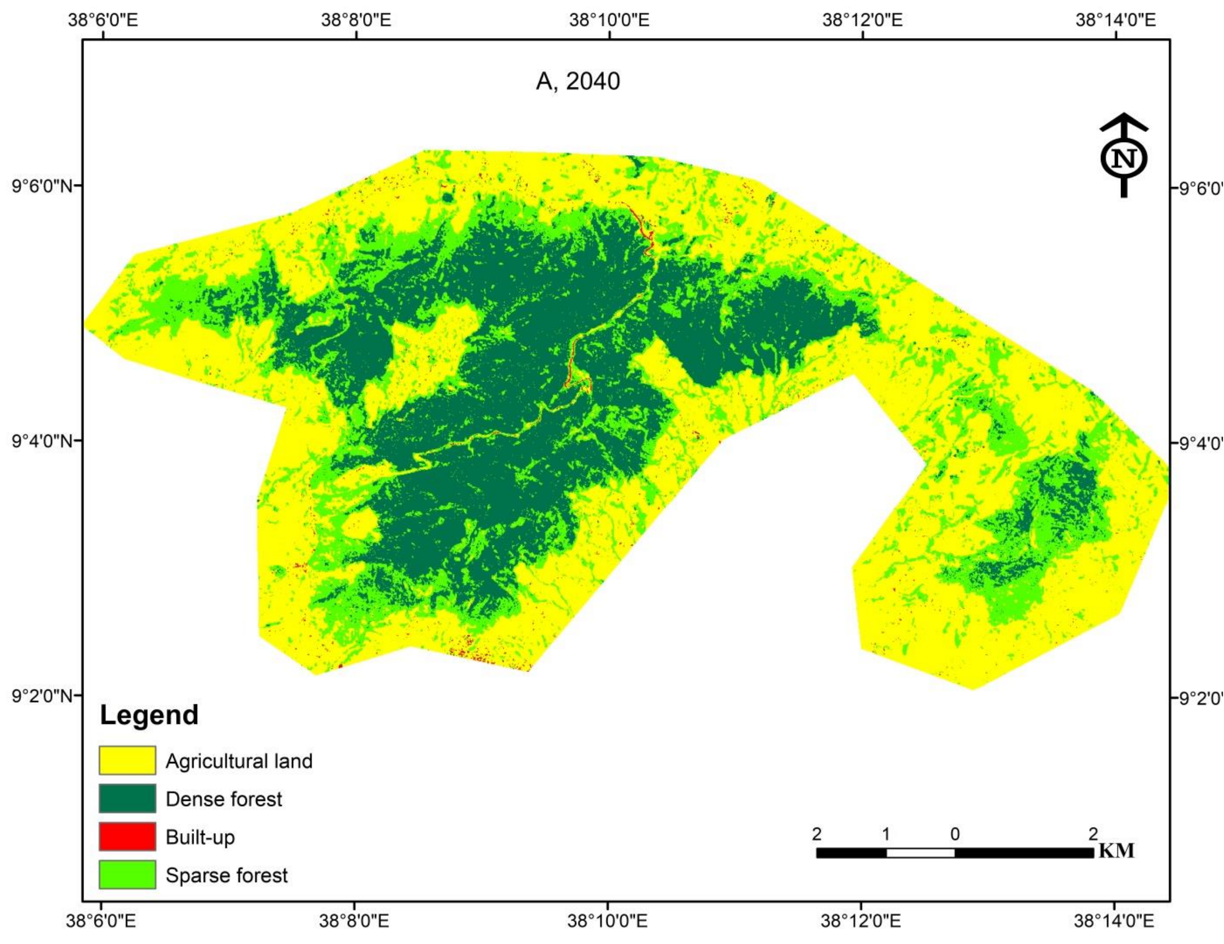

Figure 4.8 Predicted forest cover change for 2040

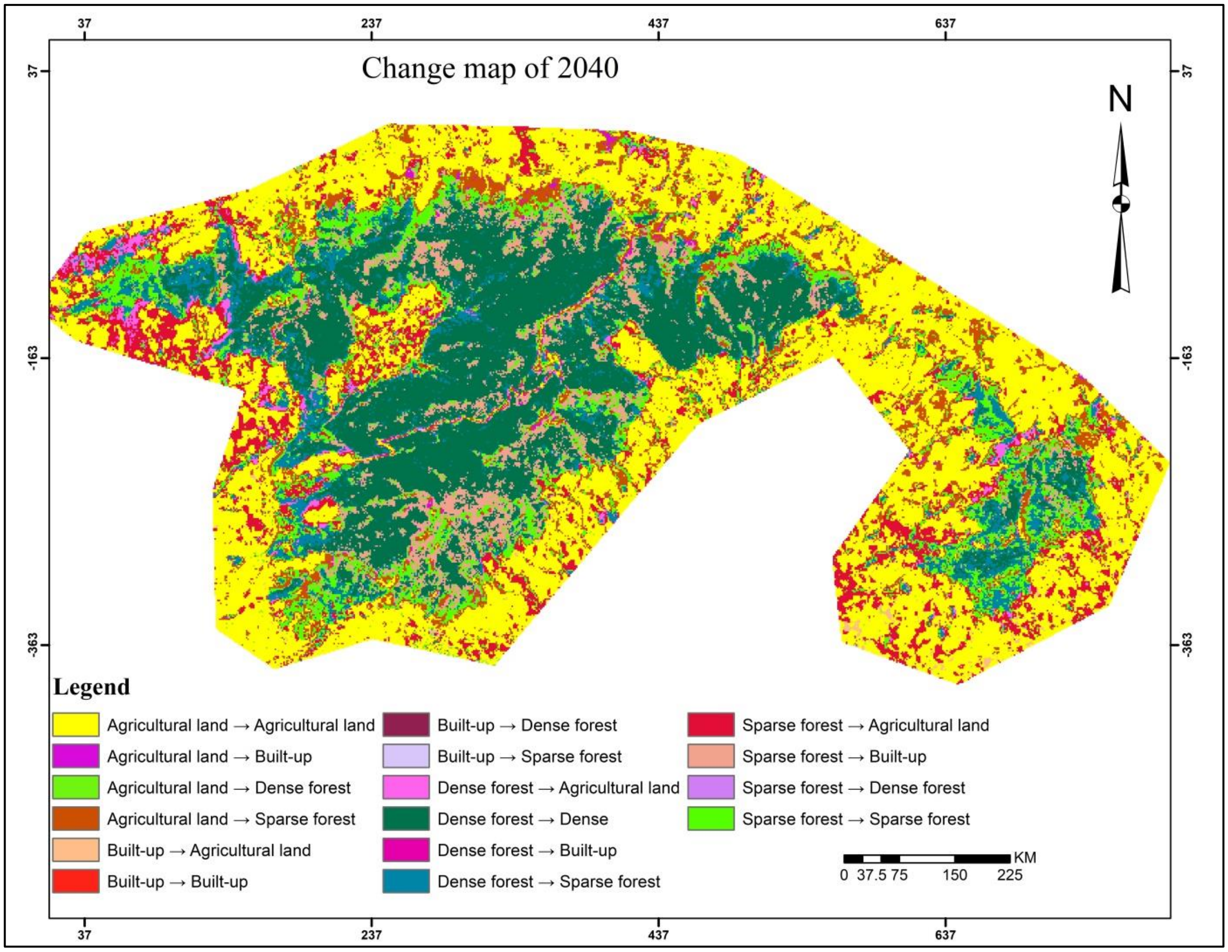

Figure 4 9 Change matrix from 2023 to 2040

Improving the use of accurate data in studies of land change by Utilizing stratified estimation, estimating precision and characterizing uncertainty. Validation computes kappa statistics. Input accuracy is typically evaluated using the kappa statistic. The degree to which the data gathered for the study are accurate representations of the variables measured is what gives rater reliability its significance. The MOLUSCE plugin integrates some well-known algorithms for transition potential modeling, such as the ANN (multilayer perceptron), weights of evidence, multi-criteria evaluation, logistic regression, and CA algorithm, for future simulation. The spatial variables for model calibration were chosen based on their relatively strong association with LULCC. In this study used the CA-ANN approach for transition potential modeling and prediction. Employed LULC data from 2006–2023 along with spatial variables to project LULC for 2031 and obtained a validation kappa value of 0.96. After obtaining the projected LULC, compared the actual LULC of 2023 with the projected data and obtained an overall accuracy of 98.45% and an overall kappa value of 0.97. Tables 4.18 show the actual and forecasted maps and statistics for 2023 to 2040.

Table 4. 18Predicted forest cover change 2023-2040

Year	2023		2040		Accuracy	Kappa value	
LULC classes	Area (ha)	Area (%)	Area (ha)	Area (%)		ANN	Validation
Agricultural land	3340.9	46.7	3698.5	51.7			
Built-up	23.6	0.3	41.8	0.6	98.45%	0.97	0.96
Dense forest	2054.3	28.7	1895.1	26.5			
Sparse forest	1727.7	24.2	1513.2	21.2			
Total area (ha)	7148.6	100	7148.6	100			

4.8 discussion

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

4.8.1 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 dense and sparse forest are discussed for selected three years (2006, 2016 and 2023). The total area covered by LULC for the study area is 7148.6ha, and each land cover class covered a different area. The study area is classified into four land cover classes. In 2006, dense forest was covered 3037.5ha, sparse forest cover by 1896.4ha, Agricultural land were 2205.4ha and built-up also covered by 9.2ha In this year (2006), Built-up and agricultural land was slowly expanded but, dense and sparse forest was decline during this period. Similar to the year 2006 the land use land cover classes that covered the highest share of total area were dense forest which was about 2516.0 ha (35.2%) of the total area. Likewise, a relatively considerable amount of the area was covered by Agricultural land 2430.3ha

(34.0%) followed by Sparse land 2190.9ha (30.6%), and Built-up area 11.4ha (0.2). In 2023 the land use land cover (LULC) of the study area was intensely changed. Agricultural land during this period covered the highest share of total area which was about 3340.9ha (46.7%), followed by dense forest and sparse forest which was 1577.14ha (28.7%) and 1727.7ha (24.2%) respectively. Others, built-up area constitute the smallest portion of the total area in the chilimo boundary which was 23.6ha (0.3%) respectively.

There was a conversion of land use classes into farmland as shown in the transition matrix. The change between these years shows the overall change between the initial period (2006) and the final period (2023). During the initial period most of the area was covered by dense forest and at final year Agricultural land covered large area, the least coverage in initial period was built-up. The dense forest decreased from 3037.7ha in 2006 to 2054.3ha in 2023 with a decrement of 983.4ha between the years. Conversely, farm land and built –up area shows an increment of 2205.4ha to 3340.9ha and 9.2 to 23.6 from 2006-2023 and the change is 1135.5ha and 14.4ha respectively. All land use classes like dense forest, sparse and built-up 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 34 years). The area of forest change for 34 years was 52.9ha%, which included the conversion of forest into farmland and other land use classes.

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 density forest and sparse forest. Dense forests 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. Remote sensing data and interviews with local community members and experts were used to analyze forest change and driving factors of the study area.

Analysis of the results from the classified image shows that the magnitude of land use/land cover change and forest cover change, in particular, dramatically changed between 2006 and 2023. In particular, the expansion of cultivated land, grassland, Cutting tree for firewood and charcoal production are factors for decline of forest cover in chilimo forest. In relation to this, currently, the overall condition of the forest cover land of chilimo forest is strongly disturbed. Besides, the areal extent of forest cover land is reduced from time to time. The total area of chilimo forest was 7148.6ha, from this about 3037.5ha and 1896.4ha of land were covered with Dense and sparse forest in 2006. But, this forest declined from 2054.3ha to 1727.7ha in the year 2023. On other hand, agricultural land and built-up area where increase from 2205.4ha and 9.2ha in 2006 to 3340.9 ha and 23.6ha in 2023 respectively.

The result from frequency analysis revealed that forest cover was changed in the study area due to the expansion of cultivated land, firewood collection, making charcoal, grazing, and population growth. In particular, dense forest areas have been converted into sparse grassland, and a few of them have been changed to farmland. Areas that were covered by Sparse forest more changed to farm land and built-up area. Due to dense and sparse forest decline in the study area, some problems like climate change, soil erosion, and losing wildlife were observed.

Deforestation in the study area increased as a result of both forest conversions starting from the selected three years up to the predicted year. The spatial variables for model calibration were chosen based on their relatively strong association with LULCC. In this study used the CA-ANN approach for transition potential modeling and prediction. Employed LULC data from 2006–2023 along with spatial variables to project LULC for 2031 and obtained a validation kappa value of 0.96. After obtaining the projected LULC, compared the actual LULC of 2023 with the projected data and obtained an overall accuracy of 98.45% and an overall kappa value of 0.97 for 2040. In addition, the problem occurring due to forest change in the study area is increasing, and the wildlife is losing their habitat, and other factor on study area. Unless necessary measures are taken to reverse the problem, the decline of forests and problem occur due to forest change.

5.2 Recommendations

The final result of this study shows that; the decrement of dense and sparse forest with some increment of the sparse forest in 2016, the driving factors for forest change like the expansion of cultivated land, firewood collection, charcoal making, grazing, and population growth, 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 given.

- ✓ As a result, as shown in the classified image between selected years and the information from the respondent, the dense and sparse forests were changed and wildlife lost their habitat.
- ✓ The governmental bodies and private sectors 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.
- ✓ 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.

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Appindex A

Artificial neural network curve