NATURAL FOREST CHANGE DETECTION USING GEOSPATIAL TECHNOLOGIES CASE OF MARI MANSA DISTRICT, DAWRO ZONE SOUTH ETHIOPIA

By

Tariku Kebede Tofu

A Thesis Submitted to the Department of Geomatics Engineering,
School of Civil Engineering and Architecture

Presented in Partial Fulfillment of Requirement for Degree of Master's of Science in Geo- Informatics Engineering

Office of Graduate Studies
Adama Science and Technology University

July, 2021

Adama, Ethiopia.

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Major Advisor: Dr Roba Gemechu (PhD.)

Co-advisor: Dr Keredin Temam (PhD.)

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APPROVAL SHEET.

We, the advisors of the thesis entitled "**Natural Forest Change Detection Using Geospatial Technologies: Case of Mari Mansa District, Dawro Zone, South Ethiopia**" and developed by Tariku Kebede Tofu, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Tariku Kebede Tofu** have read and evaluated the thesis entitled **"Natural Forest Change Detection Using Geospatial Technologies Case of Mari Mansa District, Dawro Zone, South 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 Geoinformatics 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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DECLARATION.

I hereby declare that this Master Thesis entitled "**Natural Forest Change Detection Using Geospatial Technologies Case of Mari Mansa District, Dawro Zone South 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.

Tariku Kebede Tofu ________________________ ________________

Signature Date

RECOMMENDATION

We, the advisor(s) of this thesis, hereby certify that we have read the revised version of the thesis entitled **"Natural Forest Change Detection Using Geospatial Technologies Case of Mari Mansa District, Dawro Zone, South Ethiopia"** prepared under our guidance by **Tariku Kebede Tofu** submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Geoinformatics Engineering.

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

Dr.Roba Gemechu (PhD.)	______________	______________
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Dr. Keredin Temam (PhD.)	________________	______________
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LIST OF ACRONYMS AND ABBREVIATIONS

CP: Control point

CSA: Central Statistical Authority

EGII Ethiopia Geospatial information institute

ETM: Enhanced Thematic Mapper

ERDAS Earth resource data analysis system

FAO: Food and Agriculture Organization of the United Nations

GCP: Ground Control Point

GIS: Geographic Information System

GPS: Global Positioning System

IFMP: International Forest Management Project

ITTO International Tropical Timber Organization

KIA Kappa Index of Agreement

MoA; Ministry of Agriculture

NDVI: Normalized Difference Vegetation Index

NIR: Near Infra-Red

NTFP: Non-timber forest product

OLI Operational Land Imager.

PFM: Participatory Forest Management

SFM: Sustainable Forest Management

SRTM: Shuttle Radar Topographic Mission

SPSS Statistical Package for Social science

TM: Thematic Mapper

TIRS Thermal Infrared Sensor

UN: United Nation

USGS United States Geological Survey.

WBISPP Woody Biomass Inventory and Strategic Planning Project

ABSTRACT

Currently, natural forest cover decline problems due to anthropogenic activities and natural factors are very common. Hence, the increasing population wants to fulfill their demand by converting the natural forest ecosystem into different types of land use. This resulting loss of biodiversity and climate change. Thus, this study was aimed at identifying causing factors for natural forest change and examining the spatio temporal change of natural forest and other land use dynamics for the last 20 years (2000-2020) by using change analysis in ArcGIS 10.8 and ERDAS 2014. Furthermore, future prediction for 2030 by using CA-Markovi in Terrset software was carried out to suggest the change of forest for the future. From the community the factors like, agricultural land expansion, charcoal making, fuel wood , timber production and overgrazing were identified as causes of spatiotemporal natural forest cover dynamics of the study area. Three Landsat images, 2000 ETM, 2010 ETM, and 2020 OLI-TIRS were used for the study. Four major land uses namely; natural forest, farmland, plantation, and settlement were clearly identified for the study from those satellite images. Therefore, the result of change detection of classified land use reveals that, in the entire study period, farmland increased by 2.5% between the years 2000-2010, and also show an increment by 12% between the years 2010-2020. Similarly, Settlement land, increased by 8% during the first ten years (2000-2010). Furthermore, it shows the increment in the second ten years (2010-2020) by 6.29%. Moreover, plantations show an increment of 0.4% during the first ten years and declined by 0.33% in the second ten years. On the other hand, natural forest land, declined by 12% between the periods 200 -2010. In addition, it shows decrement by 14% during 2010-2020. The prediction for 2030 indicates that natural forest declined by 4.7% and plantation was declined by 2.5% between 2020 and the predicted year. On the other hand, farmland will expand by 3.55% while settlement increasing by 3.63 % between 2020 and the predicted year. So, to alleviate the fast natural forest cover dynamics of the study area, concern bodies work together to conserve and protect the natural forest of the study area.

Keywords: *Geospatial technologies, Mari mansa and natural forest monitoring*

CHAPTER I: INTRODUCTION

1.1. Background of the Study

Natural forest is both an ecological unit and a resource unit. In place of an ecological unit, it integrates diverse fauna, flora, and the physical environment; as a resource unit, it has various economic, ecological, and social values. However, regardless these significances the natural forest cover decline is serious problem throughout the world. According to (Keenan et al., 2015), at the worldwide level, natural forest area declined by 3%, from 4128 million hectares in 1990 to 3999 million hectares in 2015 by anthropogenic and natural factors. Consistent with this, the findings of (Brambilla et al., 2010;FAO & JRC, 2012) stated that, the forests cover accounted for a loss of 5.2 million hectares between the time periods 2000-2010. Thus, the changes like deforestation, degradation, and fragmentation threaten the integrity of natural forests. Hence, the natural forest cover loss resulted the loss of biodiversity, and climate change (Contreras-Hermosilla, 2000). Moreover, Changes in forest can alter the supply of ecosystem services and affect the well-being of humanity (Rimal et al., 2019; Dong et al., 2019).

As reported by (World Bank, 2017),between 1990 and 2015, East Africa's forest cover decreased annually by 1% due to anthropogenic pressures . Agricultural expansion into the forest land, timber logging, charcoal production, and firewood harvesting are the major drivers of deforestation in Africa (Negassa et al., 2020). consistent to this, factors like Smallholder farmers collect fuel wood, construction materials, and other forest products for subsistence were causes the natural forest change (Nerfa et al., 2020).These lead to unabated deforestation, which has been recognized together of the main drivers of biodiversity loss also as a threat to the existence of the global ecology.

In Ethiopia natural forest resources have declined by factors like, conversion to agriculture, timber production, and overgrazing and fuel wood consumption (Million, 2011). Consistent with (Abera et al., 2019), in Ethiopia, the cultivated area has increased from 9 million hectares in 2001 to 15 million hectares in 2009 alone (i.e., 6 million ha in 8 years) and resulted with forest decline. Moreover, in view of forest resource degradation, (Dessie & Christiansson, 2008) argued that Ethiopians face rapid deforestation and land degradation that has been driven by an increasing population demand which successively resulted in extensive forest clearing for agriculture, overgrazing, exploitation of prevailing forests for fuel wood, fodder, and construction materials and expansion of settlements. Natural forest was a resource for local communities as a source of fuel wood and construction wood. Additionally, it's used for the commercialization of non-timber products in some local markets. Moreover, they represent pasture for domestic grazers. Ecologically, forests are essential for the entire Ethiopian ecosystem, because they prevent the loss of top layers of fertile soil. Damages are already visible in deforested parts where the poor soil has considerably reduced agricultural performance and hinder reforestation possibility for the longer term as stated by (Tadesse et al., 2015).

Particularly, the natural forest coverage decline is serious problem in the study area (source, Mari Mansa natural resource management office). This natural forest decline was mainly by the factors like charcoal extraction, timber production, agricultural land expansion and overgrazing. Consistent to this the forest change driving factor like clearance for subsistence agriculture is the forest reduction in Ethiopia was discussed by (Lemenih et al., 2008; Teketay et al., 2010) . The forest cover decrement in study area resulted with the problems like, climate changes, decrement of honey production and losing habitat for wildlife ,loss of wildlife like lions and deer and also made dread of desertification in study area.

Therefore, the information gap on the trend of natural forest change and it causing factors affects the choice of intervention to reverse the worsening situation of natural forest loss within the district. Thus, understanding forest patterns, changes, and interactions between anthropogenic activities and phenomenon are essential for correct forest management and decision improvement.

Today, data from satellites are very applicable and useful for forest cover change detection studies and future prediction. Furthermore, the community-based interview data were wont to determine the more affecting factors for natural forest change in study area. Remote sensing datasets are very useful and very important for forest cover mapping and monitoring (Lu et al., 2004).Therefore, this study was intended to assess the status of forest cover change and to predict for future 2030 by using geospatial technologies and the study was intended to find out highly affecting factors of natural forest cover decrement within the study area. Thus, addressing the trend of forest cover change up to present and for future prediction also determining the driving factors for natural forest change within the study area helps to reinforce the natural forest management and ecosystem services.

1.2. Statement of problem

The natural forest cover decline is commonly known problem in Ethiopia (Dessie & Christiansson, 2008). Thus, the change in trend of natural forest is a dynamic, widespread and accelerating process mainly driven by natural factors and anthropogenic pressures, which in turn drives changes that would impact natural ecosystem. According to (IFMP, 2000), in Ethiopia the current rate of deforestation is estimated at 160,000 to 200,000 hectares (ha) per year. The decline of natural forest was due population pressures like, clearing for agricultural use, overgrazing, and exploitation of existing forests for fuel wood and cutting for construction materials.

Mainly, the natural forest in study area was very important for the local communities like, for fire wood, as construction materials for house, for timber product, charcoal as well as it was as habitat for wild life and maintain good climatic condition. Nevertheless, the best conservation and protection for this resource is not given well. Thus, the natural forest decline is serious problem in the study area (source, Mari Mansa natural resource management office).This was resulted with, loss of wildlife, agricultural unproductivity and climate change are seriously affect the environment. Thus, to reduce the increasing deforestation, consistent, versatile, accurate, cost-effective and up to date information very essential tools (Hayes & Sader, 2001).

Reliable information on the status and trends of forest resources helps decision-makers for orienting forestry policies and programs. Natural forest change maps provide the basis for discussions with local users and stakeholders on improving forest management practices to achieve sustainability. Unfortunately, the forest is notorious for changing rapidly, and consequently, the existing maps are quickly outdated (Kleinn et al., 2002). Therefore, in most cases the stakeholders have to prepare new forest maps or update the existing ones to show the decreasing forest cover using geospatial technologies.

Hence, lack of cost-effective and updated information about the spatial change of natural forest change and its causative factors is the gap observed in the study area. Therefore, this study can fill the gap and helpful for the decision-makers by providing updated information on the forest change and indication of its change for the future. Moreover, the study suggests some way to overcome the more affecting factors of forest change that observed during field survey.

Finally, the critical issue stated in this study was the nature of the Mari Mansa natural forest cover change. Thus, it important to assess the status of forest resource cover change and predicting its change for the future through geospatial technologies like, GIS, RS, ERDAS and Terrset geospatial modeling and monitoring software. Additionally, the community-based interview data mainly on forest change driving factors are analyzed in SPSS to suggest conservation measures to protect and use the valuable forest resources in a sustainable manner.

1.3. Objectives

1.3.1 General objectives

- ☞ The general objective of this study was aimed to assess change of natural forest in study area using geospatial technologies.

1.3.2 .Specific objectives

The specific objectives of the study was aimed to;-

- ☞ Identify driving factors/forces for natural forest change in study area.
- ☞ Quantify the spatial change of natural forest of study area between the years 2000, 2010 and 2020.
- ☞ Predict the pattern of natural forest change of study area for future 2030

1.4. Research questions.

- ☞ What are the major causes for natural forest changes in study area?
- ☞ What are the spatial change of natural forest of the study area between the year, 2000, 2010 and 2020?
- ☞ What will be the pattern of natural forest of study area for future 2030?

1.5. Significance of study

To challenge the alarming rate of deforestation experienced in many parts of the country, Ethiopia has been launched huge reforestation program since 2000 E.C. But, the rates and extent of the problem are still debatable due to limitations of reliable data. Thus, this study provide reliable data regarding to the natural forest in Mari Mansa district. Specially, the result of this study plays important contributions for forestry, policy maker, researcher and stakeholder of the district. Therefore, the contribution of the study for listed beneficiaries are as follows;-

- ☞ For Forestry: - Provide an important information towards the spatio temporal change of natural forest for its change study.
- ☞ For Policy Makers: - Provide achievable way to solutions for those who are responsible and interested for taking measures to mitigate the natural forest reduction problem.
- ☞ For Researcher: - Generate first-hand information on the problem of natural forest cover change and its future prediction in the study area for those who are interested to conduct further research on the issue.

1.6 .Scope of the study.

The spatial scope of study was in Mari mansa district located in Dawro Zone, Southern Ethiopia. For the study landsat images obtained during clean sky is used to monitor and predict the natural forest coverage change by using geospatial technologies like, GIS, RS, Terrset and ERDAS. In addition, community based interview data was used to determine the driving forces for the natural forest change in study area.

1.7. Limitation of Study

Regarding to limitation of the study, the study constrained by some limitations like, convincing household head to give response during household survey on forest changing factors and its impact on the environment have taken more time from proposed time. But, in collaboration with the Kebele agricultural experts we convinced them to respond. Moreover, lack of transport access in rural area to collect primary data types like, interview data and GCP data for ground truthing was the observed challenge during the study. Thus, to overcome this challenge motorcycles are used and which taken high cost during the travel for data collection.

1.8 Organization of the study

In generally, this study consists of four main chapters and conclusion and recommendation section. Each chapter of the study portrays the required points of the study. Thus, chapter one includes the contents like, background, statement of problem, objective research question, significance, scope and limitation. Chapter two is literature review section, which contain the general concepts, methods used the causes of deforestation, impact of deforestation. Chapter three is methods and materials used .which includes, the description of study area, data types and sources, methods. Chapter four is data analysis, result and discussion. In addition conclusion and recommendation are included as sub-section of the study after chapter four. Lastly the study includes the references section and appendix section.

CHAPTER II: LITERATURE REVIEW

In this chapter the definition of terms, global forest change, the forest change and its factors in Ethiopia, the suggested points to reduce the forest change, use of geospatial technologies like GIS and RS to monitor forest change, methods used if forest change and prediction area reviewed and gap are presented as follows.

2. General concepts

During the past millennium, humans have taken an increasingly large role within the modification of the worldwide environment. With increasing numbers and developing technologies, man has emerged because the major, most powerful, and universal instrument of environmental change within the biosphere today. Universally, land cover now a day is altered primarily by direct human use. Any conception of global change must include the pervasive influence of human activity on land surface conditions and processes (Yang, 2001).

(Bruzzone & Cossu, 2003), defined change detection as the process of identifying differences in the state of an object or phenomenon by observing it at different times. According to ((Lambin & Strahler, 1994) there were five categories of causes influenced land-cover change: a) long-term natural changes in climate conditions, b) geomorphological and ecological processes such as soil erosion and vegetation succession, c) human-induced alterations of vegetation cover and landscapes such as deforestation and land degradation, d) inter-annual climate variability and e) the greenhouse effect caused by human activities. (Boakye et al., 2008), found that vegetation changes are often the result of anthropogenic pressure (e.g. population growth) and natural factors like variability in climate. They reported that tropical forests are exploited for various purposes like timber, slash-and-burn cultivation, and pasture development. They further explained that degradation of forest or woodland has an impact on catchment processes and biochemical cycles and leads to soil erosion and water shortage not only in the regions immediately suffering from deforestation but also in reasonably distant areas.

There are increasing rates of conversion of forest and woodlands in developing economies everywhere on the planet, mainly for the slash-and-burn farming practice (Groten et al., 1999).The Sustainable Forest Management (SFM) concept has been initiated to address many problems The Sustainable Forest Management (SFM) concept has been initiated to deal with many problems concerning deforestation, especially those in developing countries. International

Tropical Timber Organization (ITT O) pioneered in defining criteria and indicators of natural tropical forest for sustainable forest management within the early 1990‟s. ITTO remains aiming at achieving SFM by reviewing, assessing, and monitoring forest lands (McDonald & Lane, 2004).Many studies are performed to spot factors that cause deforestation in developing countries. One among those factors is inappropriate agricultural technology utilized in farmland located around the forest area (Angelsen & Kaimowitz, 2001).

The misuse of forest resources thanks to the centralization of forest management policy is taken into account as another factor for deforestation (Rosyadi, 2003). Moreover, (Boltz et al., 2003), declared that conventional logging operation with unplanned-selective logging method also becomes one factor of deforestation. However, the foremost important factor that causes deforestation comes from Illegal logging and trade (Atmopawiro, 2004). Consistent with, (Casson & Obidzinski, 2002), illegal logging is defined because of the harvesting of woods in contravention of laws and regulations that were designed to stop the overexploitation of forest resources and to market sustainable forest management.

Modern technologies like GIS and RS, provide a number of the foremost accurate means of measuring the extent and pattern of changes in landscape conditions over a period of time. (Miller & Rogan, 2007; Damizadeh,2000) used satellite images, as an efficient technique to review how changes in vegetation cover are growing. Satellite data became a serious application in change detection due to the repetitive coverage of the satellites at short intervals (Mas, 1999).

2.1. Land-use and land-cover (LULC) change

Land-use and land-cover (LULC) change also known as land change, is a general term for the human modification of Earth's terrestrial surface. Though 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 (Ellis, 2007)

2.1.1. Land Cover

Land cover denotes the physical and biological cover over the surface of the land, including water, vegetation, bare soil, and/or artificial structures (Ellis, 2007).Land cover denotes the surface cover over land, including vegetation, rock, and human-modified surfaces such as buildings (Ellis et al., 2010).Land cover may be a characteristic of the land which will be observed physically, as by remote sensing. This is different from land use because a single land-cover type can be used in various ways by humans (Ellis. et al., 2010).

2.1.2. Land use

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. Social scientists and land managers define land use more broadly to incorporate the social and economic purposes and contexts for and within which lands are managed (or left unmanaged), such as subsistence versus commercial agriculture, rented vs. owned, or private vs. public land (Ellis, 2007).

2.2 Natural and semi natural forest.

2.2.1 Natural Forest

Forest naturalness is characterized by elements such as a complex spatial structure, composition and distribution of climax species, a wide range of ages in tree species, and the presence of coarse woody debris. All of the following loosely defined terms, that is natural forest, old-growth forest, ancient forest, primary forest have been used interchangeably in literature (FAO, 1997). Natural forests have unique features that distinguish them from other forest types. A more natural forest is one that is only slightly modified, contains primarily native species, and requires less human input to maintain system functions (Peck, 1998).

2.2.2. Semi-natural Forest

Semi-natural forests are defined as those forests, which have been modified by humans through use and management. A stand that is composed predominantly of native trees and shrub species that have not been planted. Also, a forest that has developed gradually or accidentally, like its location or site quality wasn't fitted to intensive exploitation or production-oriented management (e.g. mountainous regions) (FAO, 1997).

2.3. Status and Trends of Forest Area Global context.

According to (FAO, 2020) forests currently cover 30.8 percent of the global land area .The total forest area is 4.06 billion hectares, or approximately 0.5 ha per person, but forests are not equally distributed around the globe. More than half of the world’s forests are found in only five countries (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 2.1).

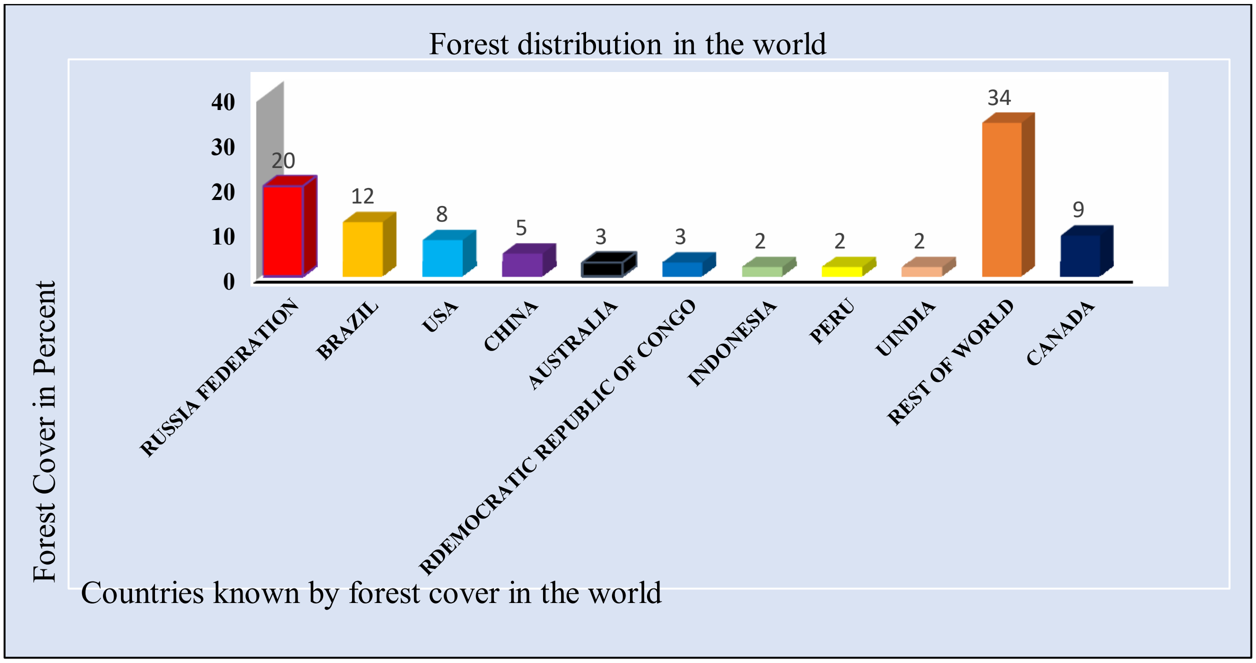


Figure 2. 1 Global distribution of forests in 2020.

Source: FAO, 2020.

2.4. The causes and impact of deforestation

2.4.1. The causes of deforestation

The causes for deforestation accompanied by the loss of biodiversity can be explained on two different levels: the local level and the global one. The local level includes the destruction of forests caused by local inhabitants. 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. The global level of deforestation is formed by the worldwide demand for natural resources (e.g. timber, soil, gas, oil). In this context mining and industrial digging cause high damage to forests. Another aspect that has a negative impact on the ecological value of forests is conventional tourism (Sánchez-Cordero et al., 2009).

As the human population increased, the demand for arable land was inevitable and, gradually, agricultural activity started to dominate vast areas from gentle slope to the steeper slopes of the high mountains. The conversion of land to agriculture had also extended into the flat swampy plains of the plateau. Hence, through several millennia, vast areas of forest land were converted to agricultural lands. Moreover, through the influence of humans, most of the high forests in the country, particularly the dry evergreen montane forests and highland grassland as well as most of the moist evergreen montane forests, had been changed to farmlands and grasslands (Hurni, 1993). These findings, (Bekure.w, 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 Woldemariam, 1991).

2.4.2. Impact of deforestation

The loss of forests and biodiversity has manifold negative consequences. Particularly due to the unique significance of forests for CO_2 conversion and storage, deforestation of forests entails an intensification of the greenhouse effect which contributes to global warming. But biodiversity loss also disrupts the natural functions of an ecosystem which makes it more vulnerable to shocks and disturbance and less able to supply humans with its diverse services.

As a result of deforestation, unimaginable difficulties would arise. The most and direct effect of deforestation is land degradation and desertification. According to (Gebremichael, 2014),thirty four percent of the land of Africa is now under the threat of desertification and more than 80 percent of Africa's dry lands are moderately or severely decertified. A 1984 survey of desertification trends estimated that as much as 742 million hectares in Africa 26 of total land area and more than 85 percent of the dry land area was undergoing moderate to severe desertification.

A total of 108 million individuals been in the affected zones in 1983 with 61 million people in areas undergoing severe desertification. This process has been speeded the poor management of semiarid zones, population pressures, and adverse human impact, and severe widespread poverty conditions. To make problems worse, prolonged and extended drought has become a recurrent phenomenon with devastating impact on lives, agriculture, and land; sediments in many Africa river are increasing roughly one and a half times as fast as the population in their catchment areas; the utilization of marginal land and soil erosion and degradation (Gebremichael, 2014).

In the case of Ethiopia, the most challenging situation for the country as a whole, particularly, highland areas are land degradation or loss of land fertility due to soil erosion as a result of deforestation. Most of the economic activity directly or indirectly depends on agriculture. The productivity of land that satisfies the demand for food and necessary produce for industry and export is depending on the fertility of the land.

Land degradation and the occurrence of drought are the two major challenges to the country's production and productivity. According to (Teferi, R., 1999).The major cause of land degradation in Ethiopia is soil erosion, which nearly one billion tons per year in the country's highlands. This is primarily due to human activities, particularly overgrazing, over-cultivation and deforestation.

2.5. Extents of forest cover in Ethiopia

Ethiopia owns diverse vegetation resources, from tropical rain and cloud forests in the southwest and on the mountains to the desert scrubs in the east and northeast and parkland agroforestry on the central plateau (Demel Teketay.,2010)

The vast terrestrial land surface with biologically productive climate and soil indicates the country has a huge forestry development potential. The forest resources are an important gift of the country. They contribute production, protection, and conservation functions.

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 (Bekele, 2011).

In 2005, the forest cover had further declined and was projected to cover 13.0 million ha. In other words, our country lost over 2 million ha of her 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 natural 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 Gambella region account for 95% of the total high forest area (Takano et al., 2010).

2.6. The causes of forest cover change in Ethiopia

The causes for forest cover change accompanied by the loss of biodiversity can be explained on two different levels: the local level and the global one. The local level includes the destruction of forests caused by local inhabitants. 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 highly affect the natural forest. The global level of deforestation is formed by the worldwide demand for natural resources (e.g., timber, soil, gas, oil). Another aspect that has a negative impact on the ecological value of forests is conventional tourism. In Ethiopia, forests, woodlands, and mixed-use landscapes are often targeted for agricultural expansion as a means to maximize benefits from land-based investments while avoiding the displacement of cropland. Increased investment is welcomed by host country governments for its opportunity to stimulate rural economies while fostering national economic development (Dangel, 2016).

The major issue is the annual destruction of the natural forest for agricultural expansion. According to (Madan et al., 2019)The extent of destruction of natural forests was estimated to currently total about 59,000 ha per annum in the three main forested regional states of Oromia, Southern Nations, nationalities, and Gambella only. The finding of (Guillozet & Bliss, 2011), also illustrates that the absence of clear institutional authority and communication between concerned agencies further retarded transparency in forest management and leads to unwise use of forest resources in Ethiopia..

2.7. Possible Conservation Measures

The problem of deforestation can be mitigated through the application of different forest conservation actions. These measures include reforestation, afforestation, agroforestry, social forestry, family planning, and area enclosure (FAO,2010).

2.8 GIS and RS in forest cover change detection.

Remote Sensing may be a process of acquiring information about the surface without actually being in touch with it. This is often done by sensing and recording reflected or emitted energy and processing, analyzing and applying that information (Canada center for remote sensing, 2008.). RS technique for forest cover change detection and monitoring has been wont to assess the dissimilarities in forest cover over two or longer periods caused by environmental conditions and human actions. GIS and RS are practical tools in estimating and validating ecosystem changes arising from forest use and forest management interventions. Quantitative knowledge about LULC changes enables the economic comparison of various ecosystem services within and across different countries (Kreuter et al., 2001).

Another unique quality of RS data is that it provides a way of quickly identifying and delineating various forest types, a task that might be difficult and time-consuming using traditional ground surveys. Data is out there at various scales and resolutions to satisfy local or regional demands. Species identification are often performed with multispectral, hyper-spectral, or air photo data interpretation. Both imagery and therefore the extracted information are often incorporated into a GIS to further analyze as slopes, ownership boundaries, or roads (Canada Centre for Remote Sensing Tutorials, 2008). Satellite RS may be a widely used technique to supply LULC maps and to review vegetation cover (Fung & Chan, 1994).

Normally, data about the earth's features are acquired either from the air (aerial photography) or from space (satellite imagery). Aerial photographs are in analogue form while images are basically in digital form. Remote sensing is predicated on the measurement of electromagnetic energy. The remote sensing sensor measures the energy that is reflected or backscattered by the earth's surface. The measured energy is converted and stored as a digital number (DN) value, which ranges from 0-255. Each pixel (picture element or unit area or ground cell) features a single DN value. Most sensors measure reflected sunlight (passive remote sensing) however, some sensors detect energy emitted by the earth itself or provide their own source of energy (active remote sensing) (Lillesand, T., and Kiefer,.2000)

The reflective characteristics of vegetation are different from those of bare soil or water and are dependent on the properties of the leaves including the orientation and the structure of the leaf canopy (Mather, 1999).The proportion of the radiation which is reflected in the different parts of the spectrum depends on leaf pigmentation, leaf thickness and composition (cell structure) and on the amount of free water in the leaf tissue.

The reflectance is low in both the blue and red regions of the spectrum, due to absorption by chlorophyll for photosynthesis; however, it is high in the green region. In the near-infrared (NIR) region, the reflectance is far above that within the visible band thanks to the cellular structure within the leaves. Hence, vegetation are often identified by the high NIR but generally low visible reflectances. This property has been used in primarily for reconnaissance missions during war times for "camouflage detection". The reflectance of bare soil mostly depends on its composition. However, the reflectance of clear water is generally low.

Digital (computer based) or visual image-interpretation techniques are applied to extract information from the satellite image data. For an accurate image classification, data collected from ground truthing or ground survey is linked to image data. In this way a map showing various land cover types of the area is produced. This study uses satellite imagery to detect and map areas of forest cover by taking advantage of unique reflective characteristics of forest vegetation.

2.9. Image Classification

Image classification is that the process of 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, T., and Kiefer, 2000). Remotely sensed data of the world could also be analyzed to extract useful thematic information for various purposes. The overall objective of image classification procedures is to automatically categorize all pixels in an image into land use/land cover classes or themes (Lillesand, T., and Kiefer,2000).

2.10. Accuracy assessment

The general acceptance of the error matrix because the standard descriptive reporting tool for accuracy assessment of remotely sensed data has significantly improved the utilization of such data. An error matrix is a square array of numbers structured in rows and columns which expresses the number of sample units (i.e. pixels and clusters of pixels) 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, 2002).

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). It's widely used because all elements within the classification error matrix, and not just the most diagonal, contribute to its calculation and since it compensates for change agreement (Rosenfield & Fitzpatrick-Lins, 1986).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).

The Kappa coefficient lies normally on a scale between 0 (no reduction in error) and 1 (complete reduction of error). The latter indicates complete agreement and is usually multiplied by 100 to offer a percentage measure of classification accuracy. 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 and (Congalton, 1991).According to (Jensen, 1996),Kappa is computed as,

$$K=\frac{N\sum_{i=1}^{r} xii-\sum_{i=1}^{r}(x_{i+x_{x+i}})}{N^2-\sum_{i=1}^{r}(x_{i+x_{x+i}})} \ldots\ldots\text{eq 2.1}$$

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

2.11. Change detection

Change detection is that the process of identifying differences within the state of an object or phenomenon by observing it at different times. Essentially, it involves the power to quantify temporal effects using multi-temporal data (Singh, 1989).Remote sensing provides a viable source of data from which updated land-cover information can be extracted efficiently and cheaply to inventory and monitor changes effectively. Thus change detection has become a significant application of remotely sensed data because of repetitive coverage at short intervals and consistent image quality (Mas, 1999).

2.12. Normalized Difference Vegetation Index (NDVI)

NDVI may be a simple numerical indicator that will be wont to analyze remote sensing measurements, typically but not necessarily from an area platform, and assess whether the target being observed contains green vegetation or not.

Since early instruments of Earth observation, such as NASA's ERTS and NOAA's AVHRR, acquired data in the red (R) and near-infrared (NIR), it was natural to exploit the strong differences in plant reflectance to work out their spatial distribution in these satellite images. These spectral reflectances are themselves ratios of the reflected over the incoming radiation in each spectral band individually. Subsequent work has shown that the NDVI is 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).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 (Bannari et al., 1995)

Theoretically, NDVI value ranges between -1 to +1. Measured value range from -0.35 (water) through zero (soil) to +0.6 (dense green vegetation). Vegetation cover can be compared between different soil types at NDVI values of 0.05 or higher (Groten et al., 1999). This corresponds to DN value of 135 or higher after the NDVI image has been re-scaled to the image domain (0-255). It can be concluded that the more positive the NDVI the more green vegetation there is within a pixel. Mathematical formulae for calculating NDVI is as follows;-

$$\text{NDVI} = \frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}} \qquad 2.2$$

Where; *NIR* = the spectral reflectance measurements acquired in the near-infrared region (band) R = the spectral reflectance measurements acquired in the red region (band) In the case of

2.13. Markov Chain Modelling

The Markov chain model may be a unique and commonly used tool in land use modeling which demonstrates the LULC changes as a model (Weng, 2002).Within the Markovian system, the longer term state of a land-use system is modeled on the idea of the immediate proceeding state (Araya, 2009).The Markov chain analysis describes the probability of LULC changes from one period to a different by constructing a transition probability matrix between period-one and period-two.

A Markovian process is one during which the longer term state of a system are often modeled purely supported the immediately preceding state. Markovian chain analysis will describe the land-use change from one period to a different and use this because the basis to project future changes. Modeling help to supply a far better understanding of the factors that drive forest changes and generate future forest cover scenarios to support the planning of policy responses. Markov chain helps to work out exactly what proportion land would be expected to transit from the later date to the anticipated date supported a projection of the transition potentials into the longer term and creates a transition probabilities file. this is often achieved by developing a transition probability matrix of land use change from the time one to time two, which shows the character of change while still serving because the basis for projecting to a later period of time . The Markov chain projection model was implemented on two classified LULC maps of various times.

The model according to (Salah, 2016), is based on the assumption that a future state (t_2 can be determined by its current state (t_1). In LULC modelling, the process determines the t_1 to t_2 LULC distribution using a transition matrix.

It is expressed as: $vt_2 = M \times vt_1$……………………………………2.4

Where; vt_1 is the Lu/Lc proportion vector input, vt_2 is the Lu/Lc proportional vector output and M is the m × m transition matrix for the time difference $\Delta t = t_2 - t_1$.

CA-Markovi model is the most commonly used model among many LU /LC modeling tools and techniques which models both spatial and temporal changes (Weng. Q, 2002) . It consist cellular automata and Markovi chain to predict/LC trend over the time (Nouri. J, 2014).

Finally, from the reviewed literatures related to the study, the methods used, the results attained were reviewed and the identified some gap. Thus, from the review of literature the unsupervised classification used and the kappa value for accuracy validation to proceed post classification was less than 80%. These may result the miss location of land use classes and may have less agreement to say the classification is accurately represent the ground land use classes. Therefore, this study tried to consider the above points and used the supervised classification techniques to categorize the land use classes and proceeded to post classification when the level of kappa is greater than 85%. Finally, in this study the community based data about natural forest changing factors are identified to recommend.

CHAPTER III: MATERIALS AND METHODS

3.1. Study Area Description

3.1.1. Location of study area

Mari mansa district is located in Dawro Zone, Southern Nation, Nationalities and People's Regional State (SNNPRS).The capital town of the district called Mari. Based on UTM WGS 1984 it found between 6°54′00" up to 7°05′15" north and 37°00′59.2" up to 37°8′01" east. The district is bounded to the west by Tocha Woreda of Dawro zone, to the south by Gofa zone, to the North West by Tocha Woreda of Dawro Zone to the east by mareka woreda of Dawro zone. Source (Mari mansa district administrative Office).See the map of study are was as show fig 3.1 below.

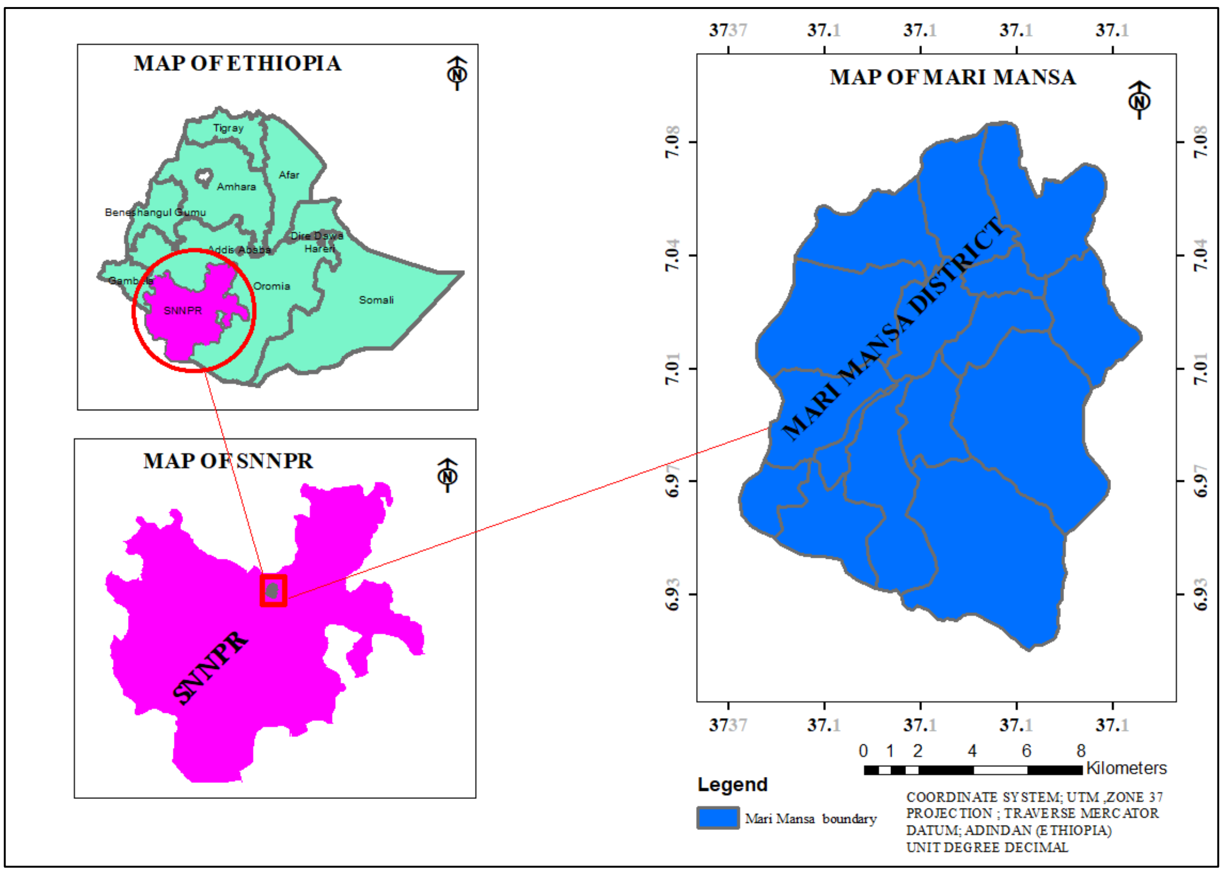


Figure 3. 1 Map of Study Area

3.1.2. Population

Mari mansa district is one of the district in Dawro Zone. Dawro zone has 10 districts namely: Mareka, Loma, Gena, Disa, Tocha, and Issera, kachi, Mari mansa, Tercha zuriya, and in addition one city-administration (i, e, Tercha City Administration). Based on the Census conducted by the Central Statistical Agency of Ethiopia (CSA), this Zone has a total population of 492,742, of whom 457,711 (93%) live in rural area whereas only 35,031 (7%) live in urban area. Concerning the population number of the study area, it is about 73,158 and from this 37,409 are males and 35,749 are females.

3.1.3. Economic Source

According to the agricultural office of Mari mansa woreda/district, the economy of Mari mansa district is largely dominated by subsistence agriculture and livestock farming practices. Mixed farming dominated the areas, with crop and livestock farming practiced in the study area. Crops such as barely, wheat, beans, and pea are grown in the higher altitudes, while sorghum, teff and maize are the principal crops in the mid and low altitudes. Various vegetables, fruits and groundnuts are extensively cultivated in the area. In addition to the above listed Inset is also mostly used in Mari mansa district. Source (Mari Mansa district agricultural office).

3.2. Data Collection and Data Sources

Data used for this study are field survey data, literature review, satellite images and topographical maps. The field survey was conducted to have general overview of the physical condition of the study area, including topography, vegetation and land use type. From field survey photograph of the needed area and GPS points for ground truthing were taken, detailed information on previous forest cover and general management practice was observed during field survey. Moreover, Information on forest change causing factors, the impact of forest change on the area, the essence of forest resource for the area and conservation measures underway was gathered using research tools known as formal interviews. Furthermore, during field survey focus group discussions on the interview data with the community and field observations about the study area were done.

From the USGS and Ethiopia geospatial information institute (EGII) Landsat 7-ETM" for the year 2000, landsat 7-ETM" for the year 2010 and Landsat 8-OLI-TIRS for the year 2020 images were acquired for this study. As they provide an appropriate and cost-effective source of information for a wide range of applications, including land change mapping. Images (data sets) were obtained from the United States Geological Survey (USGS) (http://glovis.usgs.gov). For this study both primary and secondary data types are used to achieve the required goal of the study as described below.

3.2.1. Primary data

This type of data are the raw data which is used in this study to meet the required aim of study by processing the in selected analysis types. This type of data used in this study were photographic image of the necessary area, community based interview data and forty four GPS points were collected for ground truthing. Thus, at sampling site mentioned numbers of reference points were randomly identified during February 23-28/2021 using Garmin76 GPS receiver for the selected areas of farm land, forest ,plantation and settlement for accuracy assessment.

3.2.2. Secondary Data

Secondary data were collected from different sources. Some of this data used in this study were books, published and unpublished works on this area, useful documents, records of offices regarding the issue and any reports that could contribute to the study were reviewed. Any helpful information sources from CSA (Central Statistical Authority), Agricultural Offices, natural resources management office of Mari mansa woreda, Ethiopia geospatial institute (EGII).

3.2.3 Data Sources and Its purpose

The satellite image and its source were illustrated in table 3.1, below**.**

No.	Sources	Resolution	Data and sensors used with its ID	Path /row	Acquisition date	Cloud cover	Used for
1	USGS	30*30	Landsat-7-ETM" Image	169/ 055	27/02/2000	<18%	Forest change analysis
2	USGS	30*30	Landsat-7-ETM" Image	169/ 055	13/12/2010	<5%	
3	USGS	30*30	Landsat-8-OLI-TIRS Image	169/ 055	27/12/2020	0.00	

Table 3. 1 satellite image used, and its sources

For other data used for this study and its source were illustrated in table 3.2 below

No.	Source	Data used	Purpose
1	From my friend	Ethio boundary	For Map of study area
2	Community	Interview data	For SPSS analysis
3	Field survey	44 GCP points	For ground truthing
4	EGII (Ethiopia geospatial information institute.)	Shape file of study area	For Clipping
5		Topographic map of study area	For georeferncing

Table 3. 2 Other data type used and its sources.

No.	Software	Version	Used in the study for
1	Erdas imagine	2014	Land sat pre-processing a
2	ARCGIS	10.8	Classification, Mapping of LULC and for predicted forest cover mapping
3	Terrset	-	Prediction
4	SPSS	-	Statistical analysis of interview data
5	Microsoft office	2013	Document preparation
6	Mendeley desktop	1.19	For referencing

Table 3. 3 Softwares used for the study.

3.3. Methods

The methods were techniques/procedures followed in this study to come up with the required result. Furthermore, it shows the technical steps followed to answer the research questions. Thus, based on the research objectives the methods used to attain the research goal are below.

3.3.1. Community Data Sampling Method.

For statistical analysis the community based data were obtained by using stratified sampling method. In this method the 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 sub populations of sizes $\mathrm{N1};\ \mathrm{N2};\ \ldots;\ \mathrm{Nn}$ respectively. From set of sizes $n1;\ n2;\ \ldots\ ;\ nn$ will be taken from each stratum (kebele) by treating each stratum as a separate population. This method of sampling was selected because the selected kebele are mostly known by natural forest than the others kebele in the district.

For example.N1 and N2 are the two groups (kebele) from the population of Mari mansa district and the samples were taken from the two selected group. In taking sample from the selected group and the sample size determination of the kebele were based on the forest coverage. See the follow expression for sampling.

$$\mathrm{N1};\ 1, 2, 3, 4, 5, \ldots \ldots \ldots .100$$

$$\mathrm{N2},;\ 1{,}2{,}3 \ldots \ldots\ \ \ldots \ldots \ldots ...80$$

Where N 1, is Semu kebele group with selected sample size 100 peoples

N2, is Nekir kebele group with selected sample size 80 peoples

Thus, by using the above sampling techniques the survey data to identify more causing factors for natural forest change and problems occurred are obtained by the procedure shown below.

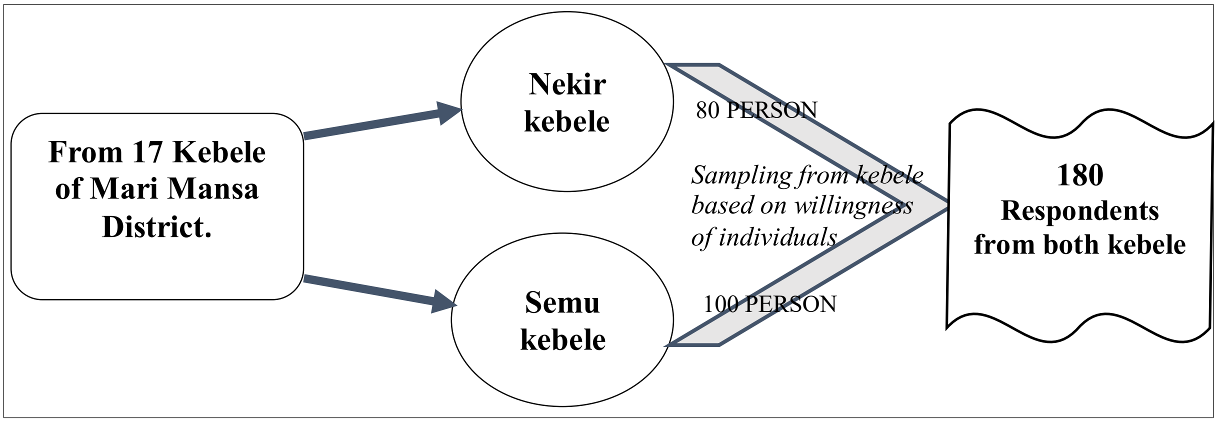


Figure 3. 4 Chart of Stratified sampling procedures

3.3.2. Data pre-processing Methods.

The set of procedures used/followed during data pre-processing are show in fig below.

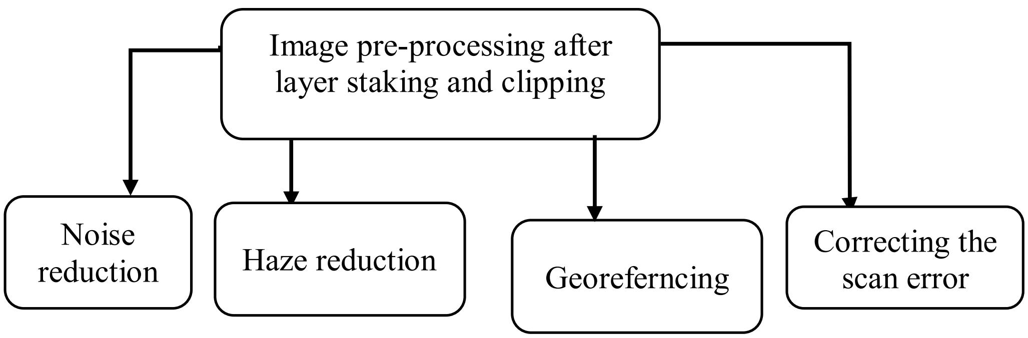


Figure 3. 5 Chart of image pre-processing

3.3.3 Classification methods used for the study

In classifying the three year images based on the above land use types the following procedure were followed to classify each year classifications.

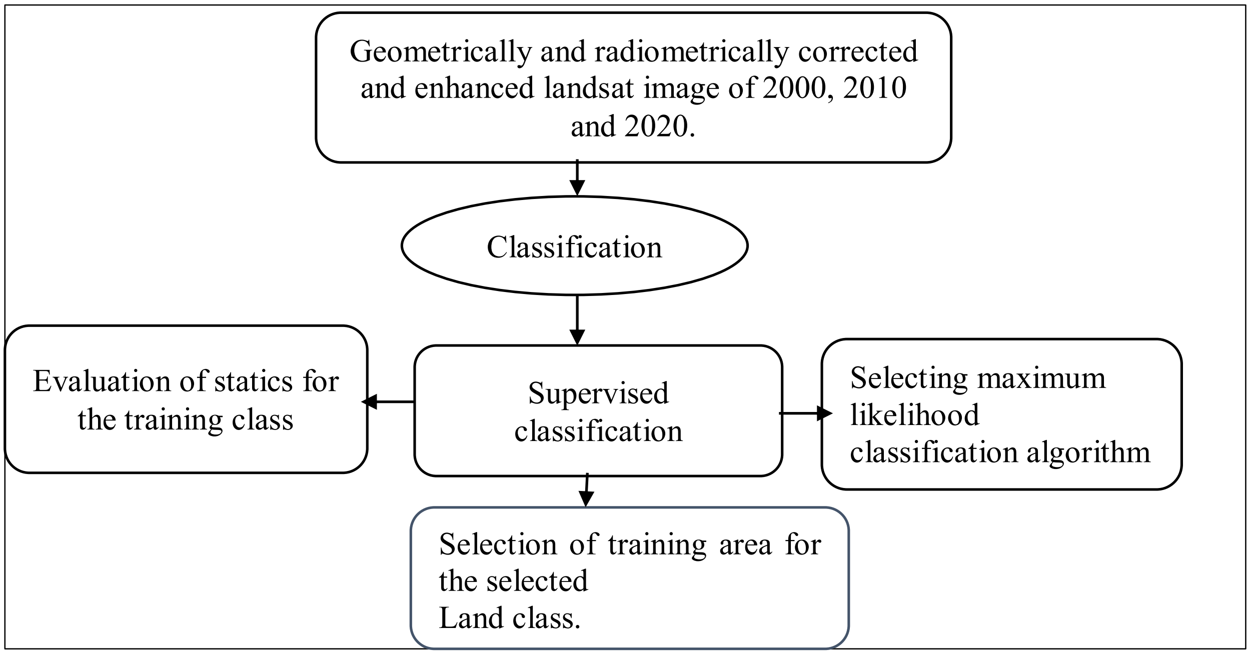


Figure 3. 6 Chart of Classification procedures

3.3.4 Accuracy Assessment

For each year classification **t**he accuracy assessment of the year 2000, 2010 and 2020 classification were assessed by using the collected GCP points of each class from field survey and Google earth. Each points are taken as aground truth for the classification the location of each class were compared to the ground truth by using the following formulas. For more clarification see the appendix part of accuracy computation.

User accuracy= $\frac{\text{Number of correctly classified pixels in each class}}{\text{Total number of pixels in each catagory}}$ *100%................eq (1)

Over all accuracy= $\frac{\text{Total number of correctly classified diagonal pixel}}{\text{Total number of referance pixe}} * 100\%$......eq (2)

And for coefficient of kappa $k = \frac{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}$*100%...... ....eq (3)

Where;-

N is the total number of sites in the matrix, r is the number of rows in the matrix

3.3.5 Methods of change analysis.

It shows the procedures followed during change analysis of LU/LC of 2000, 2010 and 2020 and extracting the forest map from classified image using supervised technique.

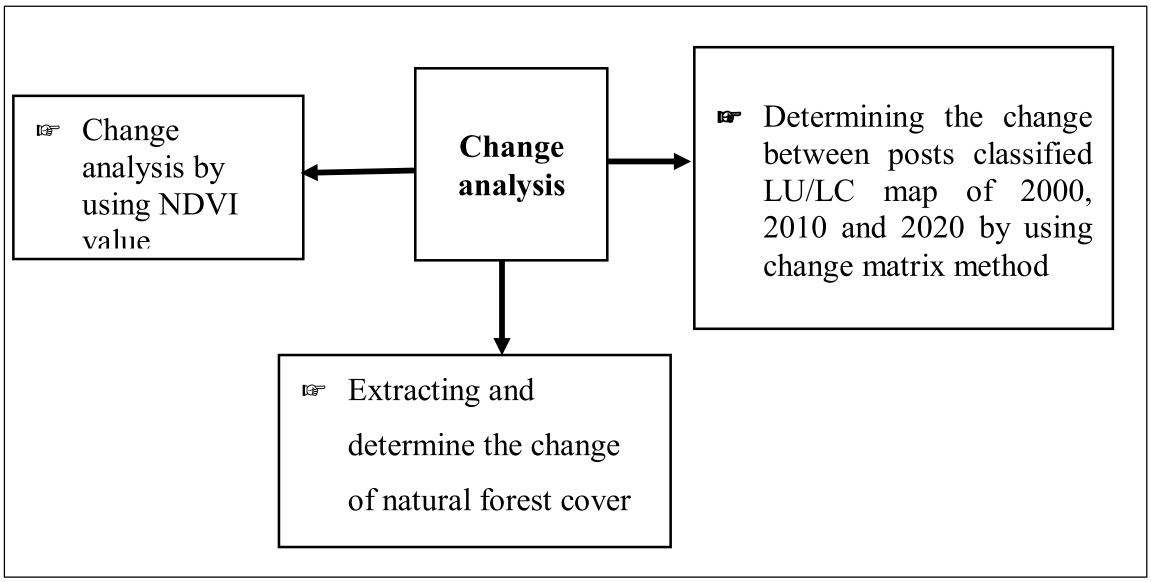


Figure 3. 7 Chart of procedures for change analysis

By using arc tool in ArcGIS the maximum and minimum value of NDVI can calculated as follows. $\mathrm{NDVI} = \frac{\mathrm{NIR-R}}{\mathrm{NIR+R}}$…………..eq (4)

Where;-NIR; means near infra-red, for landsat 8-OLI-TIRS it is band 5 and for landst-7-ETM" band 4.

Whereas, R; means red for landsat 8-OLI-TIRS it is band 4 for landst-7-ETM" band 3 respectively.

3.3.6 Methods for future prediction.

The set of steps followed to get the future prediction of land use land cover and natural forest cover of Mari Mansa were as follows.

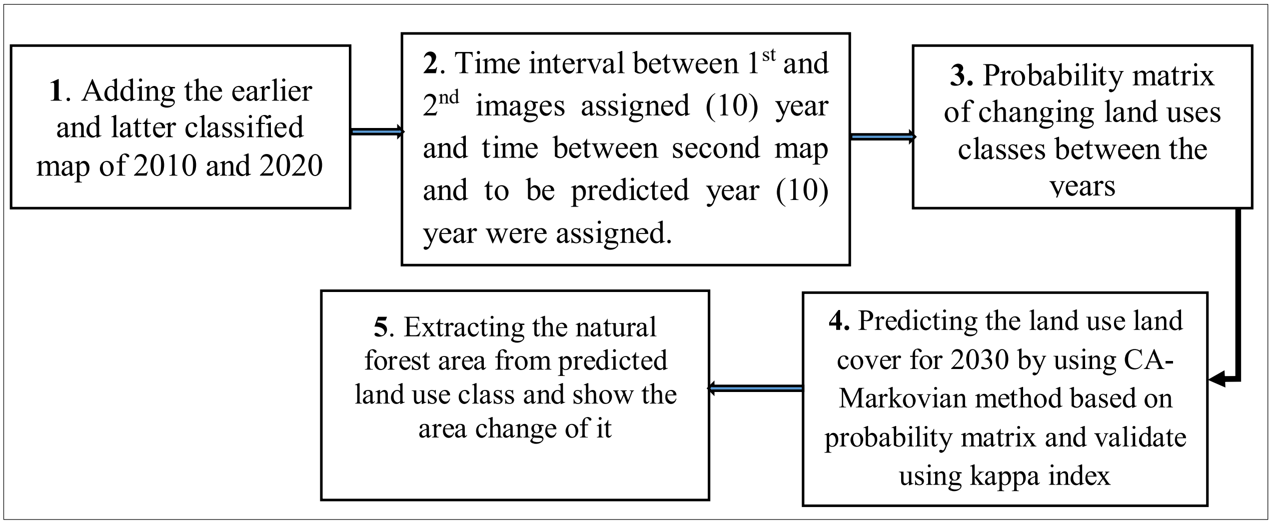


Figure 3. 8 chart of procedure for prediction.

The prediction model can also be validated by using kappa index values as shown below

- Kappa for no information ($K_{no} = \frac{M_{(m)}\,N_{(n)}}{P_{(p)}-N_{(n)}}$) ……….eq (4.5)

- Kappa for location ($K_{location} = \frac{M_{(m)}\,N_{(n)}}{P_{(m)}-N_{(n)}}$)…………..eq (4.6)

- Kappa standard ($K_{standard} = \frac{M_{(m)}\,M_{(n)}}{P_{(p)}-N_{(n)}}$)……………eq (4.7)

Where; Where no information is $N(n)$, medium grid cell-level information is $M(m)$, and perfect grid cell-level information across the landscape is $P(p)$.

The above methods are the set of procedures which is seriously and carefully followed to attain the specific objective of the research.

Moreover, the data used, data sources and the procedures were generalized in flow chart of the study illustrated in figure 3.9 below.

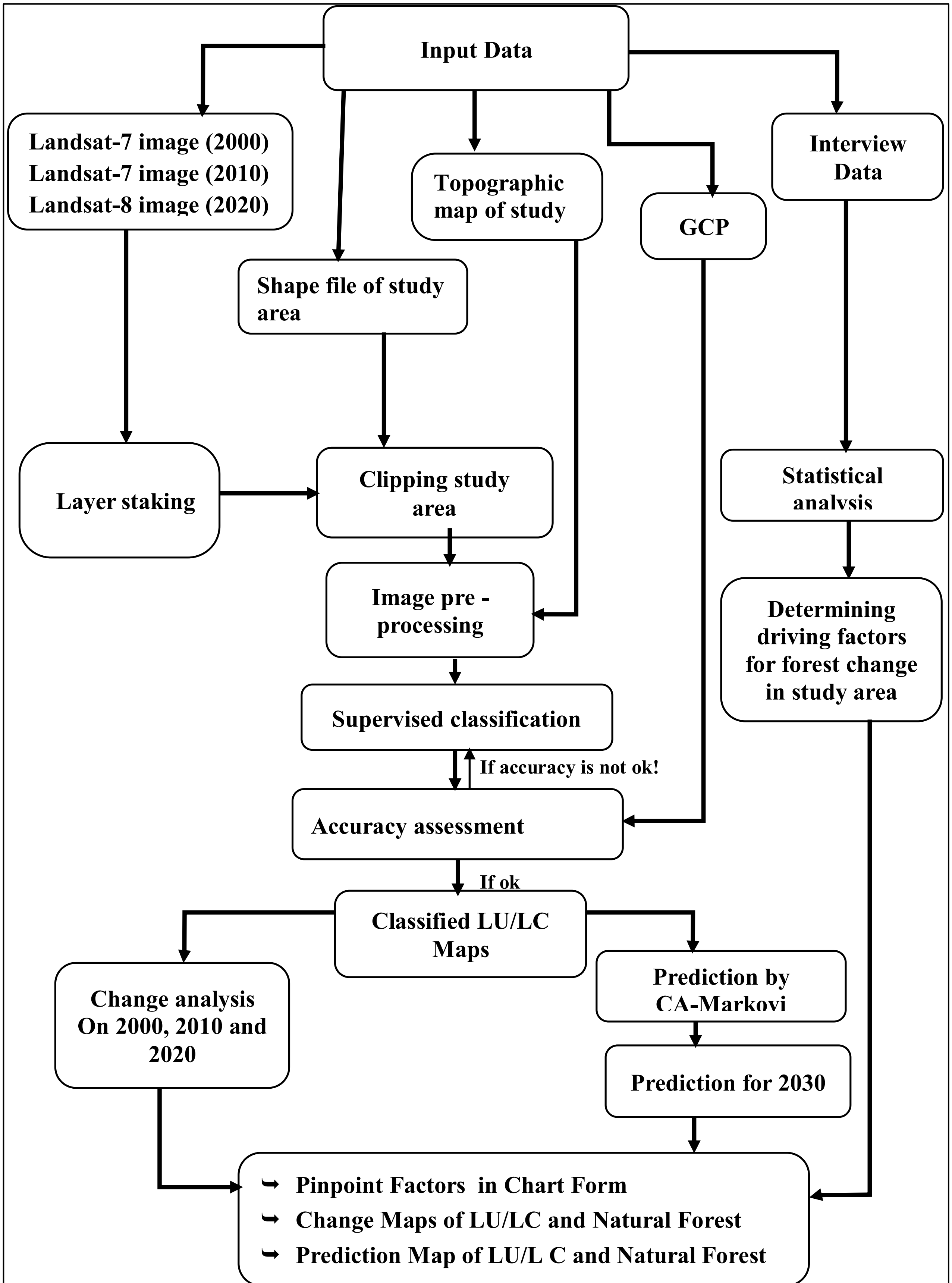


Figure 3. 9 Methodological flow chart of the study

CHAPTER IV: RESULT AND DISCUSION

In this section of the study, data analysis used to obtain the desired results, findings and results are of the study were presented and discussed sequentially. Hence, in presenting result, it can be presented in form of chart, table, graph and map to illustrate information of the attained result done in each step.

4.1. Data Analysis

4.1.1. Statistical Analysis for Community Based Data

Statistical analysis is the science of collecting, exploring and presenting large amounts of data to discover underlying patterns and trends and also to interpret. Statistics are applied in this research to become more scientific about decisions that need to be made. Thus, from both kebele the total one hundred eighty samples are collected. From this thirty one were female and one hundred forty nine are males. The gender based frequency analysis of total respondents on both forest causing factors and the problems due to the forest change was represented as follows.

Gender based frequency of respondents from both kebele

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	149	82.8	82.8	82.8
	Female	31	17.2	17.2	100.0
	Total	180	100.0	100.0	

Table 4. 1 Gender based frequency analysis of respondents

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 natural forest to be changed and what was the happened problems due the change of natural forest in study area. Regarding to the factors and problems, the results were well explained in result section of statistical analysis. Thus, to attain the required goal 82.8% of males and 17.2% of female are participated to respond the prepared questions properly. Therefore based on their response the famous factors in the study area and its result were pinpointed. Thus, the result of respondents on the factors and its causes can more clarified in the result section.

4.1.2. Image pre-processing

Preprocessing functions involve those operations that are normally required for extraction of information. Image analysis (pre-processing) done in this study was done after layer staking and clipping of study area were, radiometric correction and geometric corrections.

Layer Stacking: This process is primary process after acquiring satellite images as most of the satellite images are provided in different bands. Layer stacking is the process through which all the bands of that specific satellite image stacked in to a single file. Therefore for all the landsat images, landsat 7-ETM" of 2000,2010 and landsat 8-OLI-TIRS of 2020 layer staking is done in ERDAS 2014.Afte layer staking ,band designations for the Landsat images was done for example the true color band for landsat 8-OLI-TIRS was (4,3,2) for R,G,B respectively and for landsat7-ETM" images for the true color R,G and B were (3,2,1) respectively. For classification understanding the band designation of each landsat is very important point to differentiate the land classes of the given study area. For further information see the band designation of both landsat-7-ETM" and landsat-8-OLI-TIRS in appendix part.

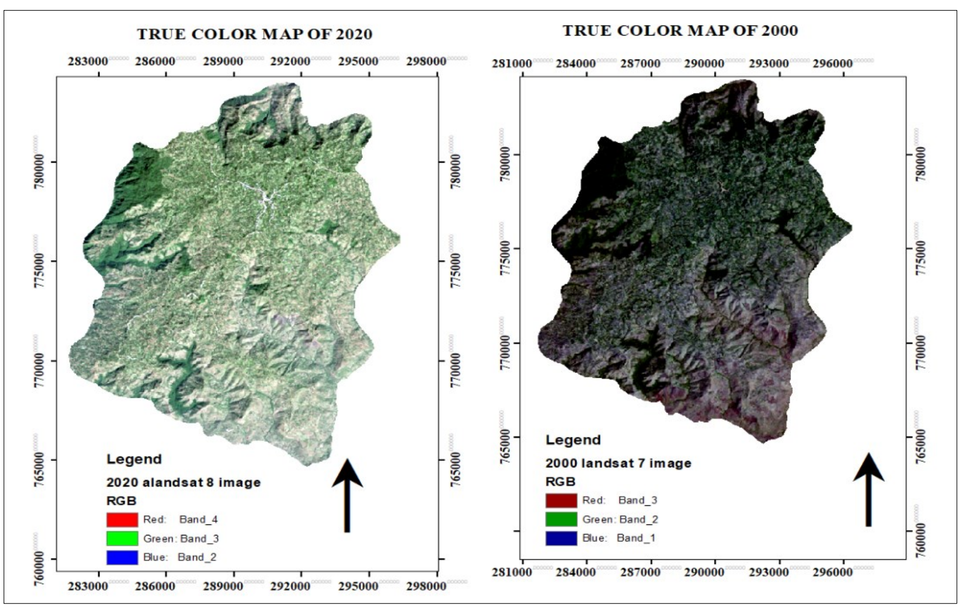


Figure 4. 1 True color map of 2000 and 2020.

For landsat 7-ETM" 2010 there was scanline error on the downloaded image. This problem was fixed in ArcGIS by downloading landsat tool box and adding it in to Arc tool box. After adding landsat tool box in to arc tool box and box the each bands are corrected by using added landsat tool box. See fig 4.2 below.

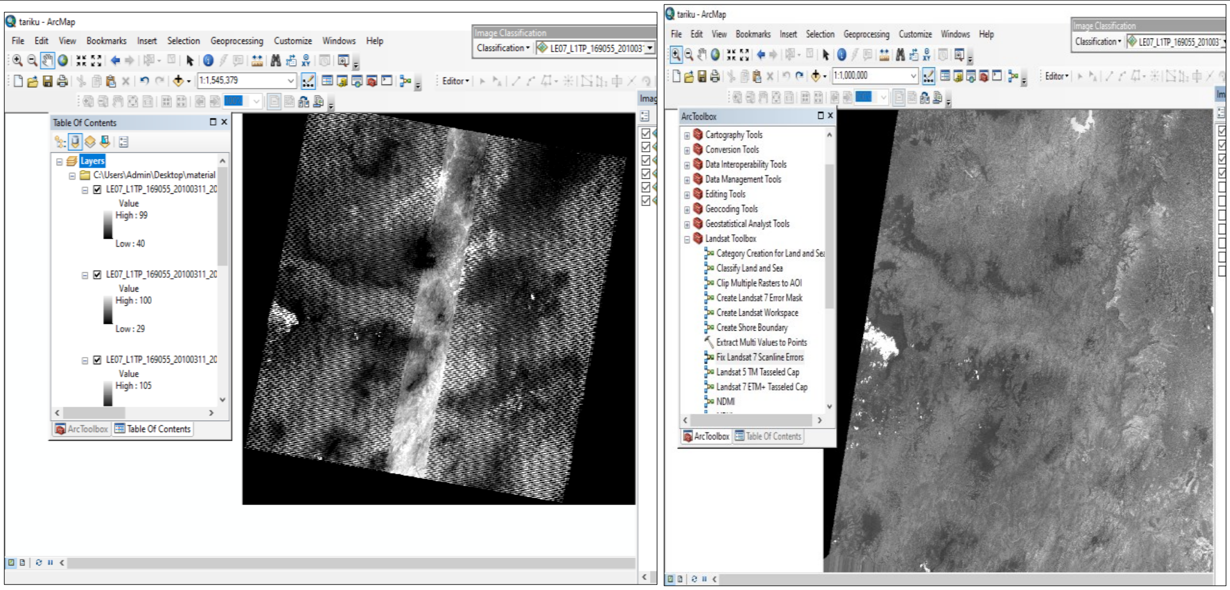


Figure 4. 2 Correction for Landsat 7-ETM" image with scanline error.

Landsat 7-ETM" image with scanline error is difficult for identify features for classification. Therefore, the error of each band scanline have fixed and made good to work on it is done by using landsat tool.

Radiometric corrections include correcting the data for sensor irregularities and unwanted sensor or atmospheric noise. After that, the data accurately represent the reflected or emitted radiation measured by the sensor. For the study the used landsat images of 2000, 2010 and 2020 the radiometric correction like, haze reduction and noise reduction to improve the image quality. Atmospheric effects can cause imagery to have a limited dynamic range, appearing as haziness or reduced contrast. Therefore haze reduction is used to correct this effect. Whereas, noise reduction reduce the amount of noise in a raster layer.

Clipping; is the extraction of the study area by using shape file of vector data or by digitizing the area of interest. For this study the clipping of study area images of all the three years were done by using shape file.

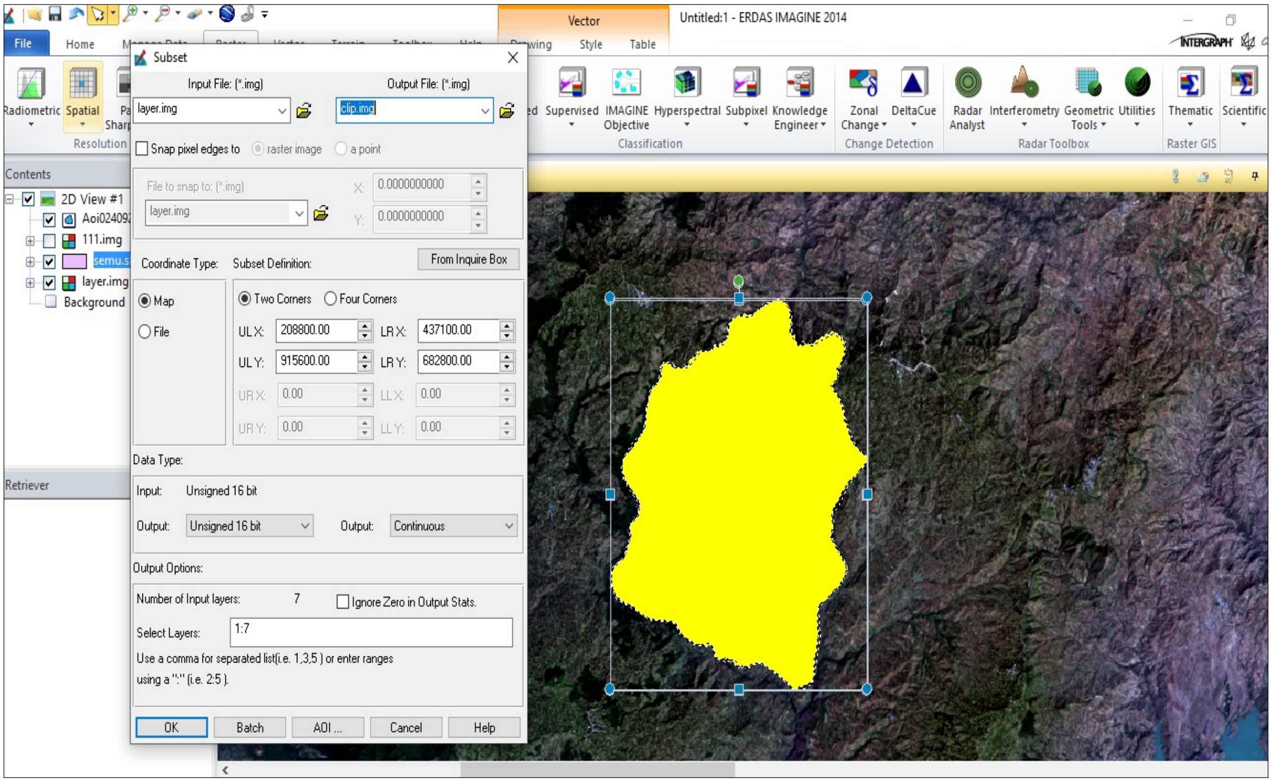


Figure 4. 3 Clipping of study area.

Comparing images of different periods requires a series of image enhancement activities and needs increasing its quality through image enhancement (Lillesand, , 2000).All images were individually geocoded and geo referenced. Surprisingly, satellite images downloaded from global land cover facility was ortorectified (geo-referenced).However, the collected GCP for ground truth are in local coordinate system. Thus for referencing with the classified land use the georeferncing to local coordinate system was made from topographic sheet of study area

In this study, image enhancement, is used to improve the appearance of the imagery to assist in visual interpretation and analysis. Examples of enhancement functions include contrast stretching to increase the tonal distinction between various features in a scene, and spatial filtering to enhance specific spatial patterns in an image.

4.1.3. Image classification

After carried out the necessary pre-processing and image enhancement in ERDAS 2014, classification is done in ArcGIS 10.8. Classification is replacement of visual analysis of the image data with quantitative techniques for automating the identification of features in a scene.

Furthermore, image Classification is a procedure to automatically categorize all pixel in an image of a terrain into land use and land cover classes. This concept is dealt under broad subject, namely, “pattern recognition”. Spectral pattern recognition refers to the family of classification procedures that utilizes this pixel-by-pixel spectral information as the basis for automated land cover classification. Spatial pattern recognition of image on the basis of the spatial relationship with pixel surrounding. It categorizes all pixels in an image into land cover classes. Classification may either be supervised or unsupervised .For this study supervised classification is used due to the researcher prior knowledge about the area.

4.1.3.1. Supervised Classification.

In supervised classification, representative samples for each land cover class was selected. The software then uses these “training sites” and applies them to the entire image. According to (Campbell & Wynne, 2011), different phases in supervised Classification technique are as follows: (i) Appropriate classification scheme for analysis is adopted,(ii),Selection of representative training sites and collection of spectral signatures, (iii),Evaluation of statics for the training site spectral data, (iv)The statics are analyzed to select the appropriate features to be used in classification process,(v),Appropriate classification algorithm is selected and (vi),Then classify the image into ‘n’ number of classes

The landsat 8-OLI-TIRS image of 2020, and landsat7-ETM”image of 2000 and 2010 were classified using the Maximum Likelihood supervised classification algorithm.

Maximum Likelihood algorithm calculates the probability distributions for the classes, related to Bayes’ theorem, estimating if a pixel belongs to a land cover class. In particular, the probability distributions for the classes are assumed in the form of multivariate normal models. (Richards & Jia, 2006), in order to use this algorithm, a sufficient number of pixels is required for each training area.

MAXLIKE undertakes a Maximum Likelihood classification of remotely sensed data based on information contained in a set of signature files.

The Maximum Likelihood classification is based on the probability density function associated with a particular training site signature. Pixels are assigned to the most likely class based on a comparison of the posterior probability that it belongs to each of the signatures being considered

MAXLIKE is also known as a Bayesian classifier since it has the ability to incorporate prior knowledge using Bayes' Theorem. Prior knowledge is expressed as a prior probability that each class exists. It can be specified as a single value applicable to all pixels, or as an image expressing different prior probabilities for each pixel.

Table 4.2.Below shows the major land use/land cover classes and its description. To reduce confusion in classifying the numbers of classes has selected as four major land use classes.

No.	Major Land use classes	Descriptions
1	Forest	Areas covered by natural forest rather than any man made forest.
2	Farm land	Areas of land ploughed/prepared for growing rain fed Crops. This category includes areas currently under crop; fallow, and land under preparation were classified as farm lands.
3	Plantation	Areas covered by bamboo tree, inset and tree plantation
4	Settlement	All urban and rural, settlements with road networks

Table 4. 2 LU/LC category description

4.1.4. Accuracy Assessment

Land cover maps derived from remote sensing always contain some sort of errors due to several factors which range from classification technique to method of satellite data capture In order to wisely use the land cover maps which are derived from remote sensing and the accompanying land resource statistics, the 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 latter. Accuracy levels that are acceptable for certain task ma y be unacceptable for others.

The common means of expressing classification accuracy is the preparation of classification error matrixes. An error matrix (confusion matrix) is a square array of numbers organized in rows and columns which express the number of sample units assigned to a particular category relative to the actual category as indicated by reference data. These tables produce many statistical measures of thematic accuracy including overall classification accuracy, percentage and the kappa coefficient, an index that estimates the influence of chance (Congalton et. Al.1999).

In this study, an error matrix was generated based on the years 2000, 2010 and 2020 land use/land cover classification and area of interest data (Table 4.3 below).The accuracy is essentially a measure of how many ground truth pixels were classified correctly.

The kappa value is a measure of the agreement between classification and reference data. None of the kappa values in any of the images were very high. The ranked the kappa values, ranging from -1 to 1, into 3 groups: 1) those greater than 0.80 represented as strong agreement between the classification and reference data; 2) those between 0.40 and 0.80 represented as moderate agreement; and 3) those less than 0.40 represented as poor agreement (Landis & Koch, 1977).

The kappa value of classified land classes of the years 2000, 2010 and 2020 were, 90%, 86.02% and 91.1% respectively. Therefore, according to (Landis & Koch, 1977) of kappa rank they represent strong agreement between the classified and collected GCP reference data.

In calculating the accuracy by using the control points the collected GCP points are added to each land classes and the classified classes are evaluated by using the ground truth point. The class was accurately classified when the added corresponding ground truth points overlaps with the classified land use class. Thus, based on this the calculated accuracy values are shown in table below. For more clarification of each step see appendix part.

Year		Land use classes				Overall accuracy in %	Kappa (%)
		Settlement	Forest	Farm land	plantation		
2000	User accuracy in %	100	87.5	100	100	96.96	90
2010		100	76.6	100	100	90.5	86.02
2020		100	100	88.89	75	93.5	91.1

Table 4. 3 Accuracy assessment summary

Source; computed from the ground truth points.

- ☞ Therefore, the kappa value indicates the three period classification were correctly classified and it was highly acceptable.

4.1.5. Change Analysis

This kind of change detection method identifies where and how much change has occurred. In this study, three dates of satellite imageries (2000, 2010 and 2020) were used to determine the changes by generating quantitative information on spatial and temporal distribution. Four aspects of forest cover change detection characteristics are identified such as farm land, forest, plantation and settlement. Detecting the changes that have occurred, identifying the nature of the change, measuring the temporal and areal extent of the change, and assessing the spatial pattern of the change were investigated. Moreover, the change in area between the years 2000 and 2010, 2010 and2020 and also between 2000 and 2020 have investigated in detail. For more information see result section of change detection.

Furthermore, the change between each selected year can be identified by using NDVI (normalized difference vegetation index) value. Which range between -1 and 1.thus based on the reflectance the feature class classes can be identified. For clarification see the result section of NDVI based change detection of different year land sat images.

4.1.6. Future prediction for 2030 of LU/LC

Markov Chain, determines the amount of change using the earlier and later land cover maps along with the date specified. The procedure determines exactly how much land would be expected to transition from the later date to the prediction date based on a projection of the transition potentials into the future and creates a transition probabilities file.

According to, (Takada et al., 2010) the transition probabilities file is a matrix that records the probability that each land cover category will change to every other category. The transition probability (Pij) matrix in a state which is calculated as follows;-

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

$where\ pij\ mean\ the\ probablity\ of\ land\ use\ change\ from\ period\ i\ to\ j$

This shows the probability of land use class change between two period of time, for this study the probability computed from 2010 and 2020 land use classification.

For this study image used as earlier and later are 2010 and 2020 land use/land cover maps. Based on the projection of this two period land classes the transition probability for next 2030 were created. See the following fig.4.4

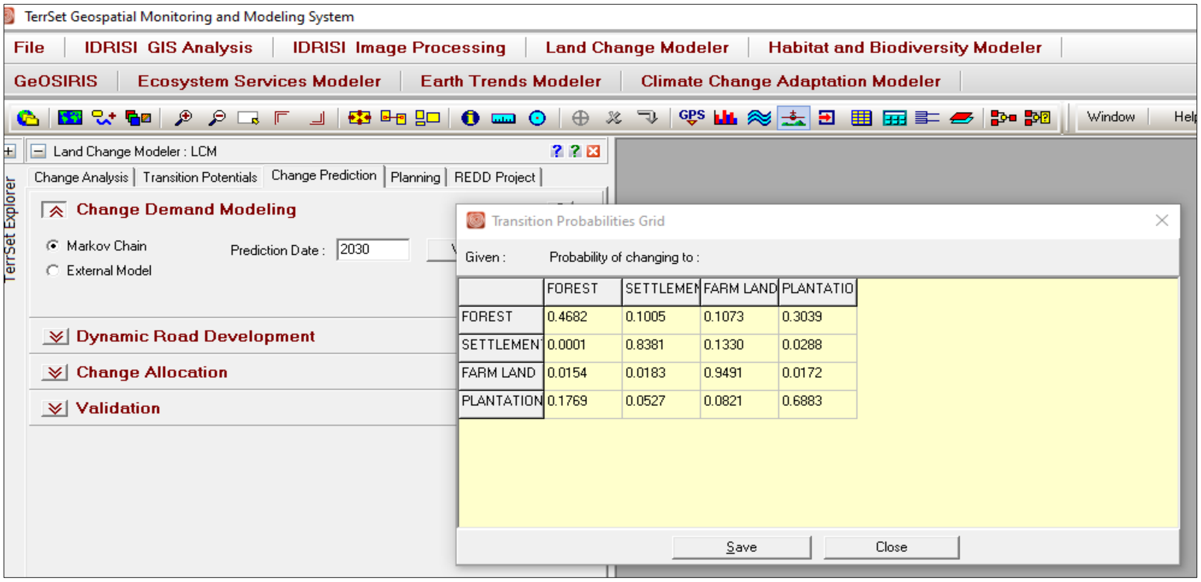


Figure 4. 4 probability matrix of land use change. *Source; From Idrisi change modeler.*

4.1.7. Validation of prediction

Validate gives also the traditional Kappa Index of Agreement (KIA) and some more useful variations on the KIA. KIA is denoted also by Kstandard. Thus, in addition to calculating the standard KIA, validate offers three more statistics: Kappa for no information (denoted Kno), Kappa for grid-cell level location (denoted Klocation), and Kappa for stratum-level location denoted (KlocationStrata).

The kappa values of the CA–Markov model for LUCC simulation ranged from -1 to 1,where positive values are a sign of agreement, and negative values illustrate of a lack of agreement Kappa ≤ 0.5 shows low agreement, $0.5 \leq$ Kappa ≤ 0.75 marks a moderate level of agreement, and $0.75 \leq$ Kappa ≤ 1 indicates a high level of agreement.

Thus, the software compute for kappa index values by using the above formula for the predicted land use class based on the reference image for this the used reference map was LU/LC map of 2020. Therefore the result of the kappa index value was mentioned in result section.

4.2. Findings

4.2.1. Statistical analysis of community based data

To determine the more affecting factors that drives the natural forest to be changed in study area, the interview data, from the community were taken from 31 females and 149 males in total of 180 persons from both selected kebele. For collected community based data, the result of frequency analysis by SPSS software were done for the forest changing factors and the problems occurred due to forest change was illustrated below.

No.	Factors of Forest change	Respondents			
		Male	Female	total	Total in %
1	Expansion of farm land	120	23	143	79.4
2	Overgrazing	128	24	152	84.4
3	Cutting tree or house construction	78	26	104	57.8
4	Fire wood consumption	127	29	156	86.7
5	Charcoal extraction	19	13	32	17.8
6	Timber production	121	28	149	82.8

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

Source: community based interview data

The above table 4.4 shows the six factors which were identified from the community. Based on the numbers of respondents for each factors ,fire wood consumption, overgrazing, timber production expansion of farm land, cutting wood for house construction and charcoal extraction have been the driving factors for the natural forest change. Thus, for the factors like fire wood consumption, overgrazing, timber production and expansion the numbers of respondents in percent were 86.7%, 84.4%, 82.8 and 79.4% respectively. This shows that this orderly listed factors highly affects natural forest cover in study area. Moreover, the numbers of respondents in percent for cutting trees for house construction and charcoal extraction were 57.7% and 17.7% respectively. The less number of respondents cannot mean it have no effect on forest change. Hence, it has its own size effect on the forest change.

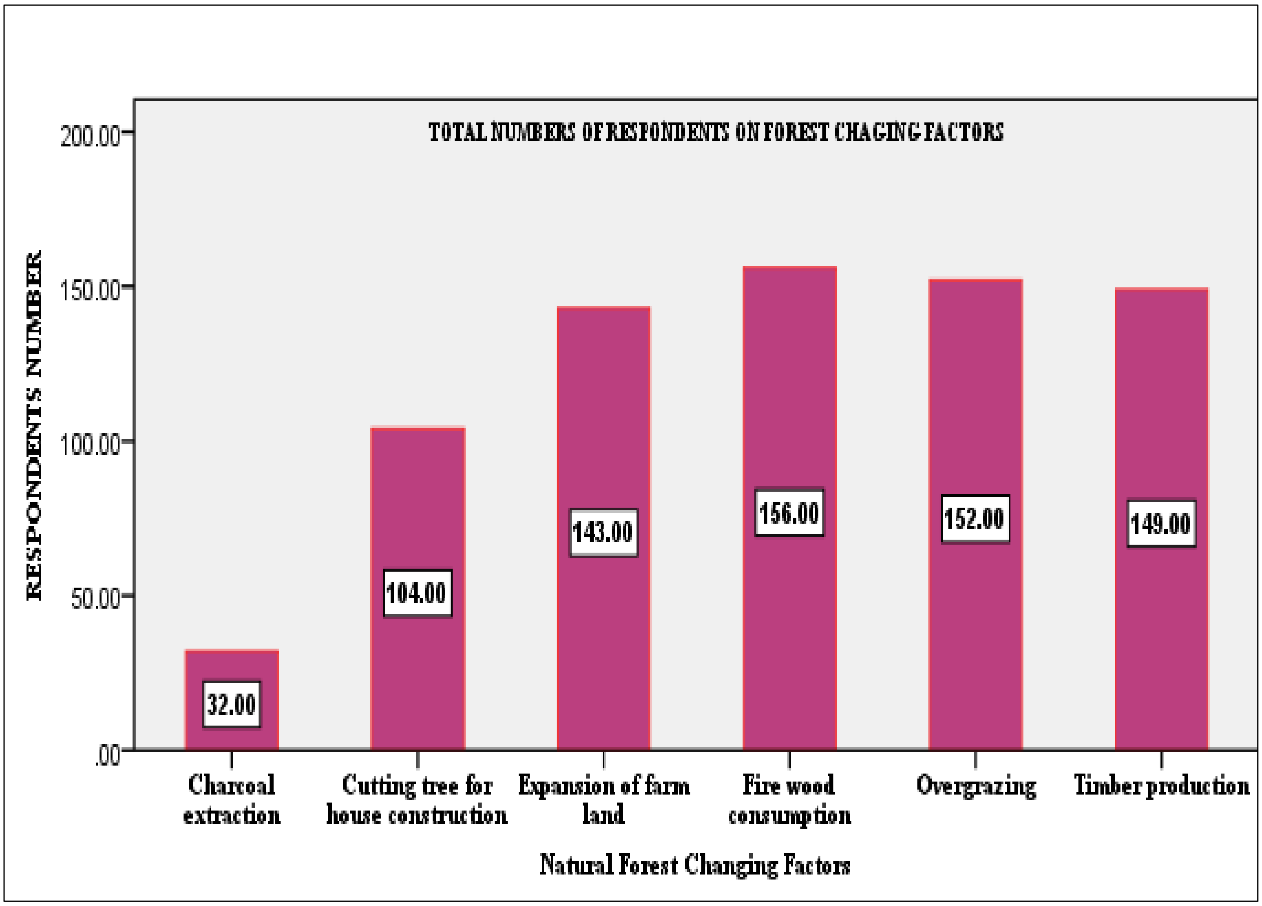


Figure.4. 5 Bar graph of respondents' number on forest changing factors.

Source; Frequency analysis in SPSS software

The above fig 4.5 shows that the overgrazing, fire wood consumption, timber production and farm land expansion were area the famous factors which highly affect the natural forest. In addition charcoal extraction and cutting trees for house identified factor for natural forest change in the study area.

Due to the increments of forest changing factors the amount of forest change will lead to some problems. Based on frequency analysis of respondents' number in SPSS, due the forest change the occurred problems in the study area was shown in table 4.5 below.

No	Problems occurred due to Forest change	Respondents			
		Male	Female	total	Total in %
1	Low agricultural production	100	18	118	22.5
2	Climate change	121	26	147	28.05
3	Losing wild life	131	18	149	28.44
4	Honey production decrement	89	21	110	20.99

Table 4. 5 Respondents' number on problem due forest change.

Source; community based interview data.

From table 4.5 above of the numbers of respondents on the problems in study area due to forest change was show in graphically in fig 4.6.below

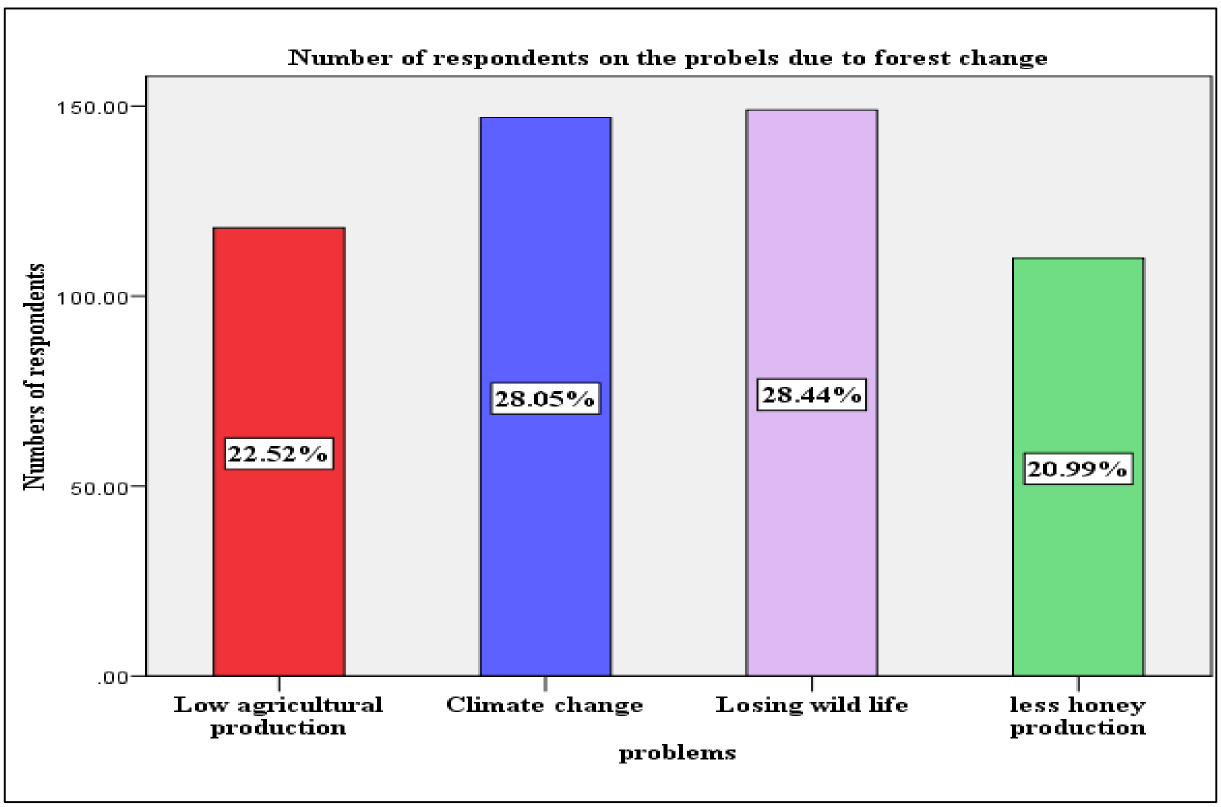


Figure 4. 6 Bar graph of respondents' number on problem due to forest change

Source; frequency analysis of numbers of respondents on problems due to forest change

The fig above show that there is serious problem like losing wild life, climate change, deforestation and degradation of forest.as the respondents told that, they have dread for the future life due to the happened problem that affect the living conditions and the ecosystem at all.

4.2.2. Land use /land cover classification.

Land use/land cover of the study area were categorized in to four major types; these are: Natural forest plantation, farmland and settlement. Therefore, the result of three periods land use/land cover classification map of the study area is presented in the figure 4.7, fig 4.8 and fig 4.9 below.

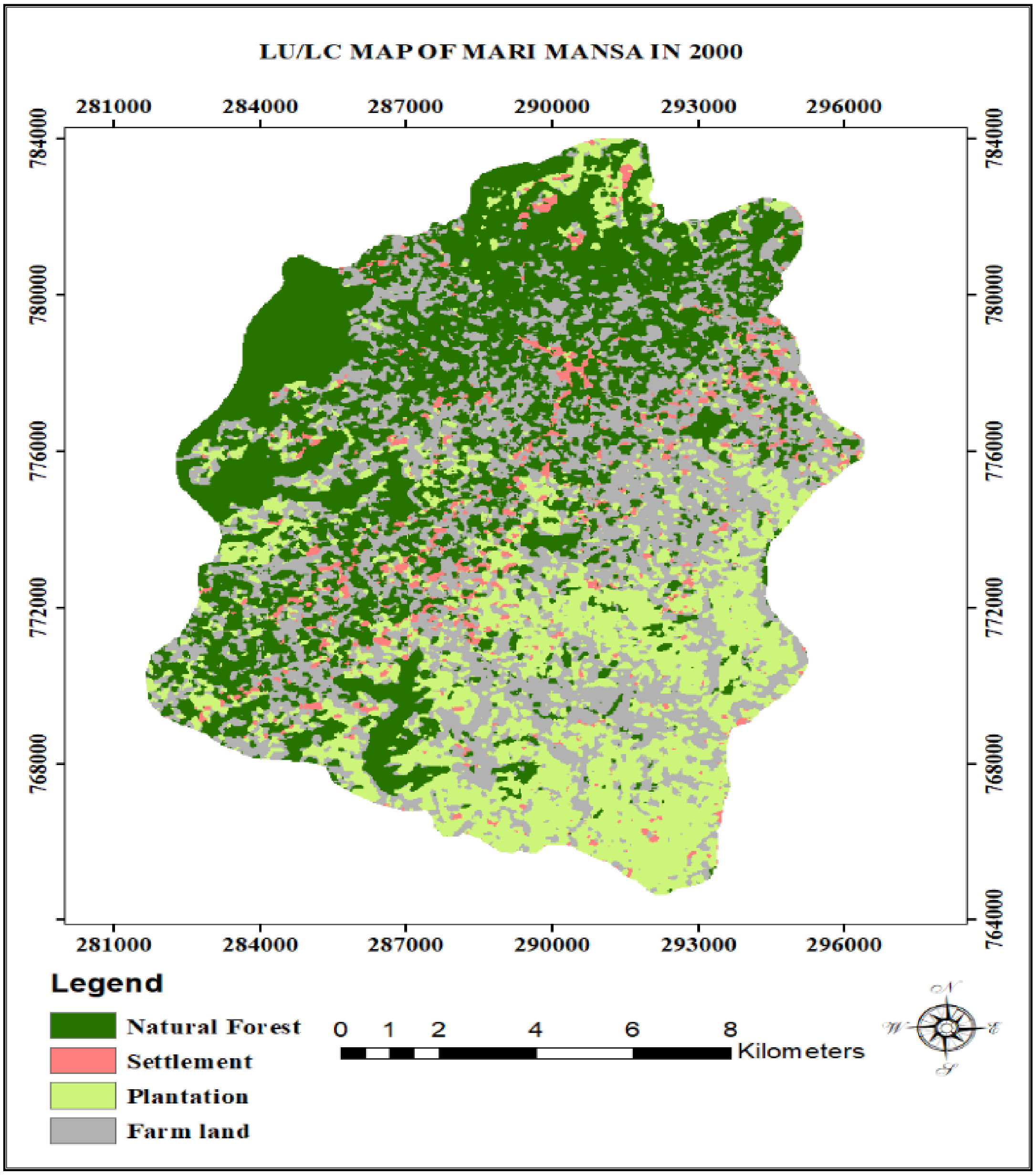


Figure 4. 7 Land use/land cover map of Mari mansa in 2000

From the land use/land cover map of study area in 2000 shown above in fig.4.7, the natural forest area covers 36% from total area, settlement covers 7.51% .whereas, plantation and farm land covers 24% and 34.47% respectively.

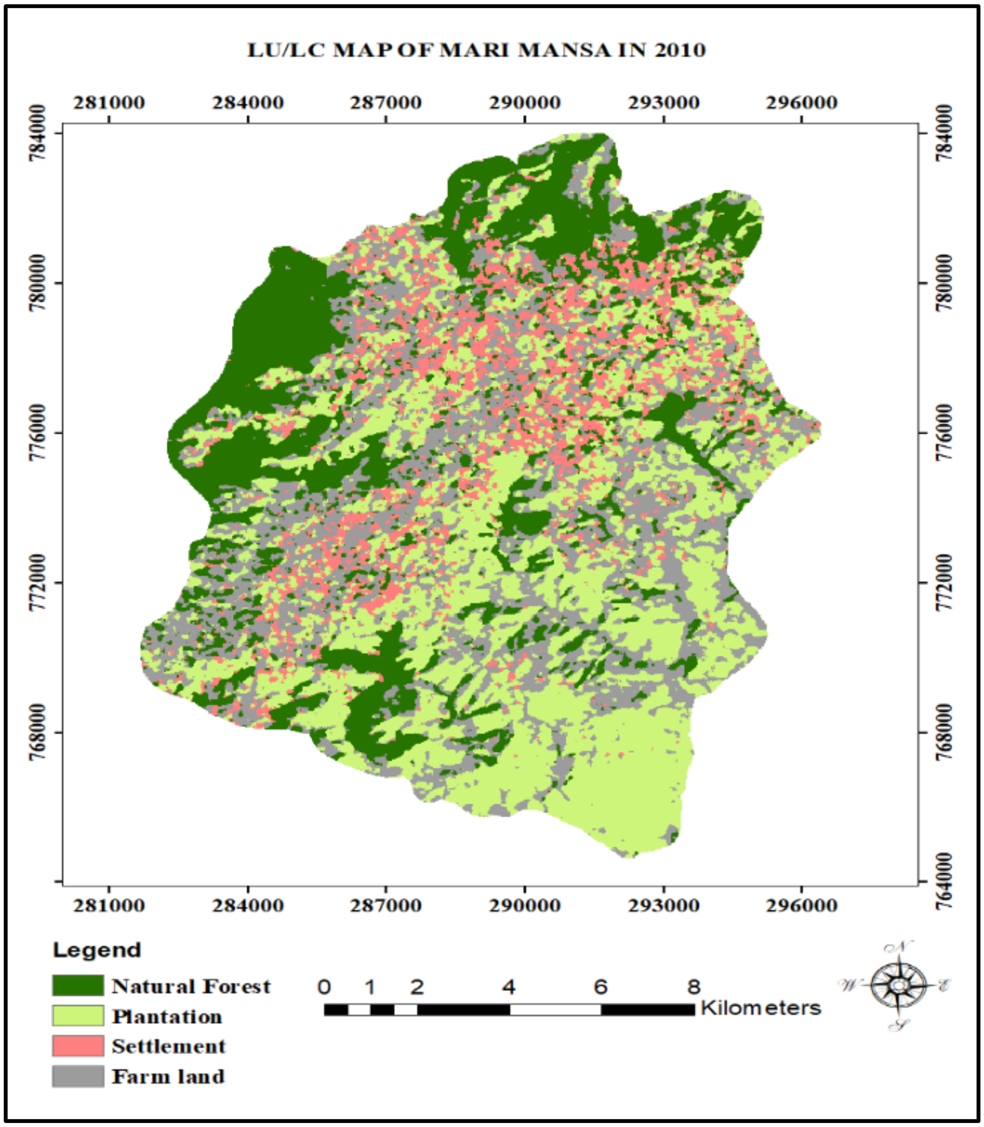


Figure 4. 8 Land use/land cove map of Mari mansa in 2010.

In 2010 land use and land cover map of study area, farm land covers 36.1% from total area, settlement covers 15.5%, forest covers 24% and plantation covers 24.4%. While, in 2020 land use/land cover map of study area, the forest covers 10.17% from total area, plantation covers 24.11%, settlement covers 21.57% and farm land cover an area of 44.15% from total area.as illustrated in figure 4.9 below.

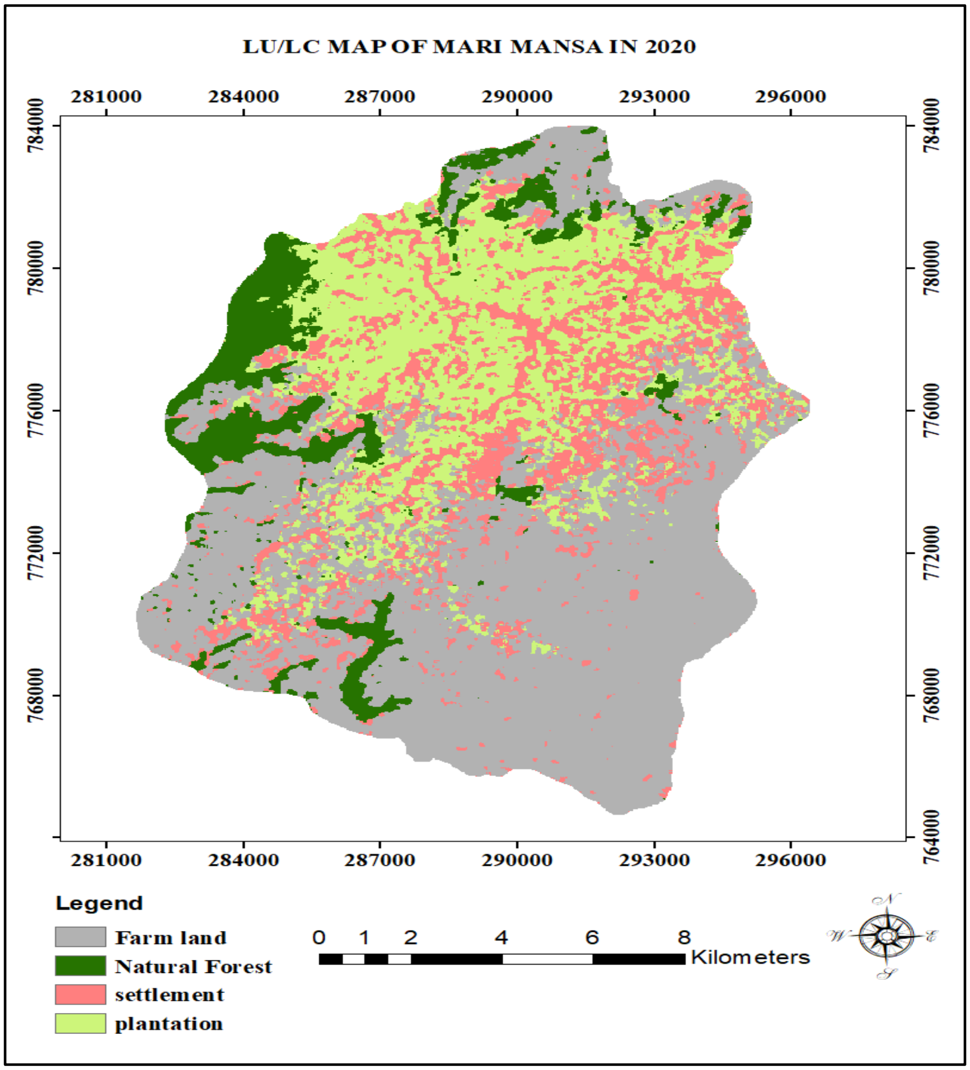


Figure 4. 9 Land use/land cover of Mari mansa in 2020

In the above fig, 4.9 it illustrates that, most of the area was covered by farm land and next to this class plantation ranked in second in area coverage. Finally, the forest class ranked last in area coverage in the study area during 2020.

The results of land-use/ land cover map show that the area of forest and declined in both periods (I,e,it decreased between in the years 2000 and 2010 as well as shows the same trend of decrement between in the year 2010 and 2020).

Primarily, the forest cover was higher than others classes while in final year it shows, the forest coverage was lower than other classes. Comparatively, Farm land class shows a sharp increase in the first period and an increase in the second period due to shift of both forest types to farm land. In addition, settlement show general trend of increase in both periods and plantation show minimum decrement in first period and increment in second period. This is just the general impression of land cover dynamics based on comparison of individual land cover maps of the years 2000, 2010 and 2020. The following table 4.4 shows the area coverage of land use/land cover classes of each year in ha.

Year	Land use land cover type	Area in hectare(ha)	Total area in ha
2000	Farm land	6045.864	18309
	Forest	6537.445	
	Plantation	4382.388	
	Settlement	1343.227	
2010	Farm land	6614.040	18309
	Forest	4392.486	
	Plantation	4461.625	
	Settlement	2841.047	
2020	Farm land	8083.373	18309
	Forest	1862.860	
	Plantation	4414.167	
	Settlement	3948.379	

Table 4. 6 Area of land classes of the year 2000, 2010 and 2020

Source; From ArcGIS attribute table of each year classification.

The area of each land use class from the attribute table was calculated as;-

$$Area\ of\ land\ use\ classs\ in\ hectare = \frac{(30*30)*number\ of\ pixels/count}{10000} \ldots\ldots\ldots\ldots eq\ (4.1)$$

*Where;-30*30 means pixel size*

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

In table 4.5, below, the total area coverage of each year land use land cover classes in percentage and their area change between the years was clearly illustrated. The area in percent can computed as;

$$Area\ each\ land\ use\ class\ in\ \% = \frac{\text{Area of land use class}}{\text{Total area of land use classes}} * 100\% \ldots\ldots\ldots eq\ (4.2)$$

Thus the area change in percent means the difference between the areas in percent of two periods. Which can calculated as follows.

Change in percentage=P2-P1; where:-

(P1) Means the initial area of class in percent and (P2) the final area of classes in percent**.**

No.	land use/ land cover classes	Years					
		2000		2010		2020	
		Area in %	Δ between 2000-2010	Area in %	Δbetween 2010-2020	Area in %	Δbetween 2000-2020
1	Forest	36	-12	24	-13.83	10.17	-25.83
2	Settlement	7.01	8.16	15.5	6.07	21.57	14.23
3	Plantation	24	0.4	24.4	-0.29	24.11	0.11
4	Farm land	33.0	2.63	36.1	8.15	44.15	10.685
5	Total	100		100		100	

Table 4. 7 Land use/Land cover Area in percent and their change in 2000, 2010 and 2020.

Source; From ArcGIS attribute table of each year classification.

The bar graph below show the area cover of land use and land cover map of 2000, 2010 and 2020. Thus,it shows natural forest area was decessing during the three period,conversly,the other land use class like, farm land,settlement and plantatios increasing between the selected time series.see the area coverage differnce in figure below.

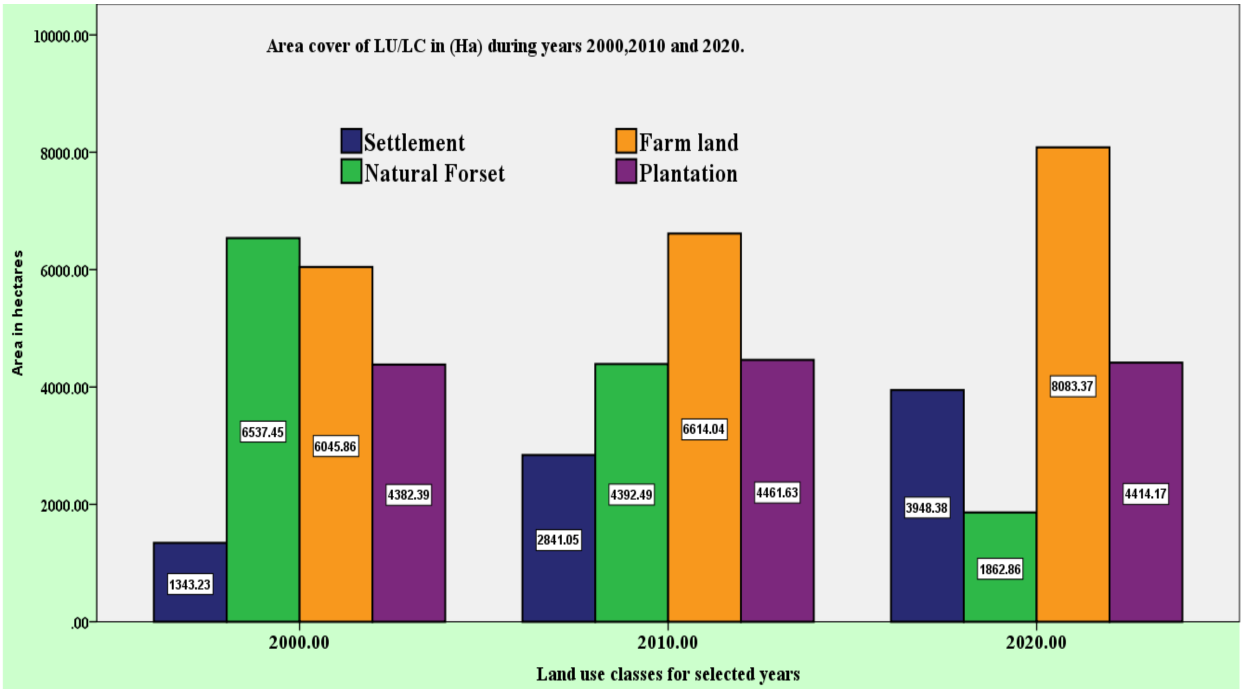


Figure 4. 10 Bar graph of land use/land cover in hectares during 2000, 2010 and 2020

Source; from table 4.6

The changes in area of different land use classes between the stated years can be interpreted in many ways like bar graph shown above. Moreover, the pie chart below which portrays percentage of area cover 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 in fig 4.11 below

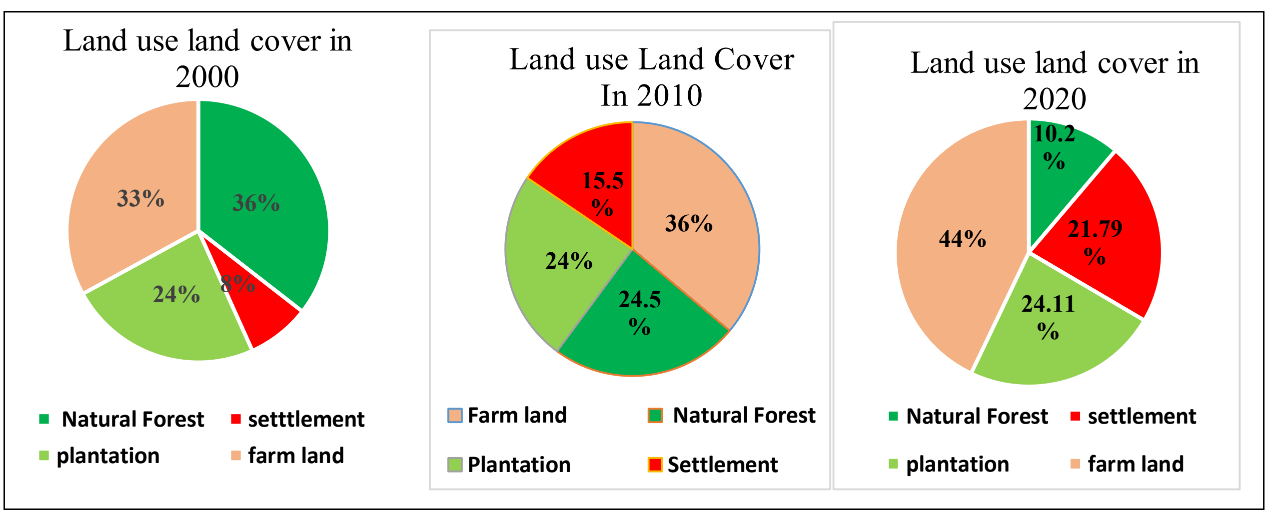


Figure. 4. 11 pie charts of land use area coverage in percentage for selected years

Source; from table 4.7

The pie chart shows that the area coverage in percentage of land use between the selected years. Comparing the percentage value of forest cover between the three pie charts shows that the forest class was decreased in 24% and farm land shows 11% increment and settlement shows 14% increment between the year 2000 and 2020. Moreover, the plantation shows increment by 0.11% between the initial and final period of selected time series.

4.2.3. Change detection based on post classification of selected years.

4.2.3.1. Change between 2000 and 2010

From the following change map there is conversion of classes between the year 2000 and 2010.Thus, for the area change between the stated year of land uses classes like, farm land, natural forest, plantation and settlement in hectares were 568.176, -2145.22, 79.237 and 1497.868 respectively. The conversion between forest to forest or farm land to farm land (i.e, between the same land use classes) show unchanged area during the period. In another word the conversion from one class to another class alter the area converge of the classes.

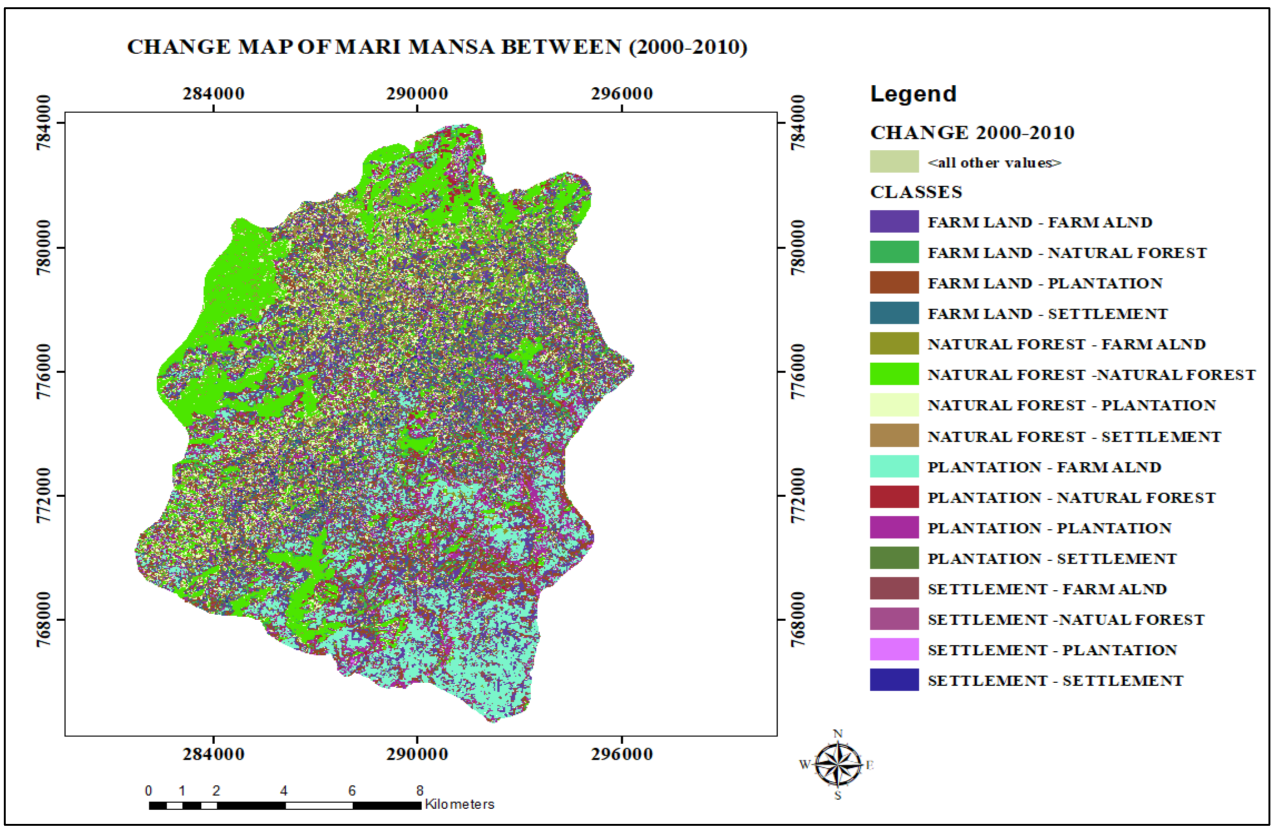


Figure 4. 12 Change map between 2000 and 2010

Based on the above fig 4.12 of change map between the year 2000 and 2010, the change matrix table between these years can be shown in table 4.6 below.

Land class		Area of Land use class (ha) in 2010 (final)				
		Farm land	Natural forest	Plantation	Settlement	Grand total
Area of Land use class in (ha) in 2000 (initial)	Farm land	4967.067	0.443	59.52	1018.834	6045.864
	Natural forest	683.852	4241.487	381.538	1230.567	6537.445
	Plantation	267.559	`77.031	3729.466	308.331	4382.388
	Settlement	695.562	73.263	291.1008	283.3029	1343.227
	Grand total	6614.040	4392.225	4461.625	2841.035	18309
	Change	568. 76	-2145.02	79.237	1497. 0	~0

Table 4. 8 Change matrix table of land uses between 2000 and 2010.

Source; ArcGIS change matrix between 2000 and 2010

In above table 4.8 the diagonal number indicates unchanged area, whereas the numbers in the class total row indicate final state where as the class total column indicates the initial state.

4.2.3.2 Change between 2010 and 2020

This period shows similar trend with the previous period in some land classes. However, the coverage of plantation show some decrement. The area covered by farm land and settlement were increased while the area covered by forest and plantation were reduced. The major change observed in this period were decrease in the overall area of natural forest from 4392.486 ha in 2010 to 1862.511135 ha by (2529.98 ha) in 2020 and an increase in the areas of farm land from 6614.040 ha in 2010 to 8083.932 by (1469.89 ha) and, increase settlements by 1107.076 ha. In opposite to this, the plantation decreased by 47.55 ha. Moreover, the following fig 4.13 also show the conversion between the land classes of the year 2010 and 2020.

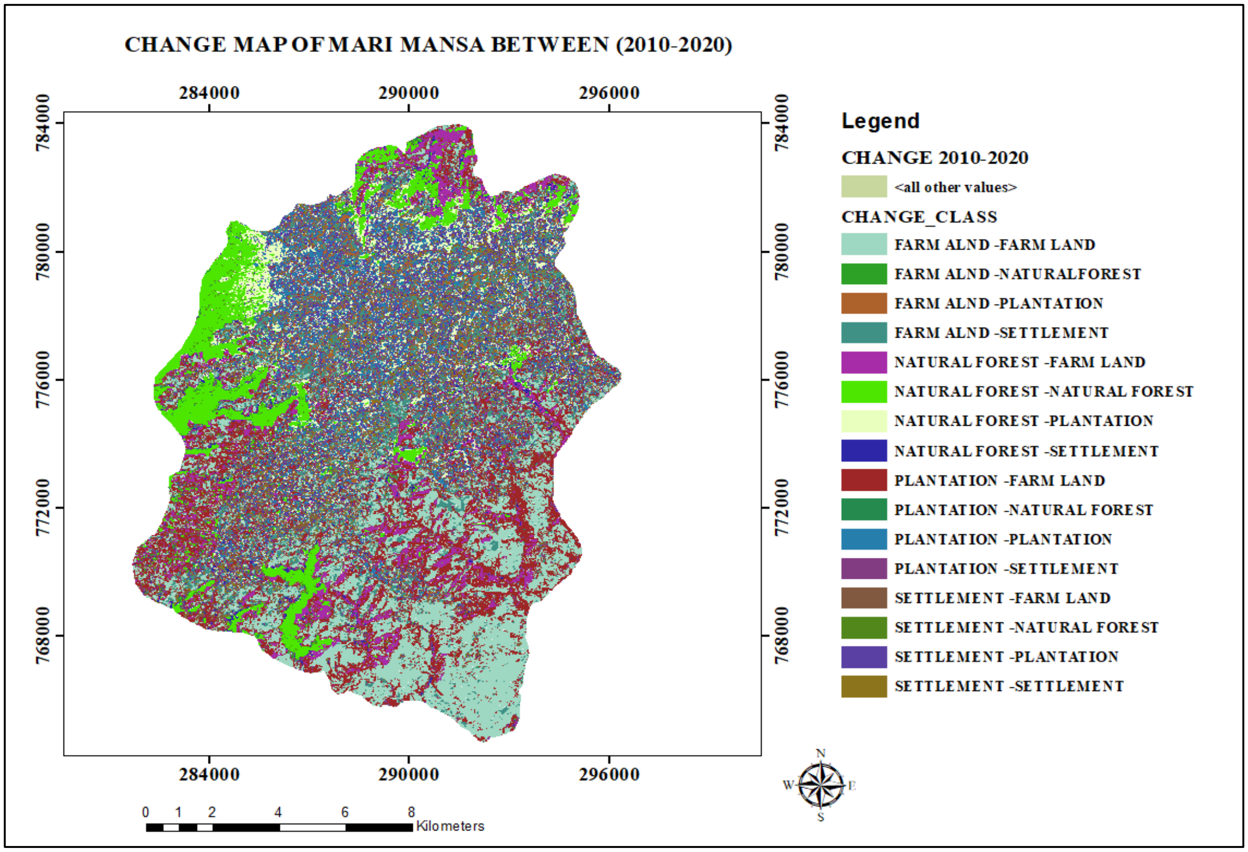


Figure 4. 13 Change map of 2010 and 2020

Based on the above fig the change matrix table between the land use classes of the year 2010 and 2020 was show in table below.

Land class		Area of Land use class in (ha) in 2020(final))				
		Farm land	Natural forest	Plantation	Settlement	Grand total
Area of Land use class in (ha) in 2010 (initial)	Farm land	5950.76359	0.024091	43.15091	610.201	6614.040
	Natural forest	1118.86222	1862.260088	1105.7642	305.5998	4392.486
	Plantation	322.28633	0.221785	3127.9893	1011.484	4461.625
	Settlement	683.020734	0.005171	137.1833	2020.8387	2841.047
	Grand total	8083.932	1862.511135	4414.0877	3948.123	18309.
	Change	1469.89	-2529.98	-47.55	1107.076	~0

Table 4. 9 Change matrix table of land uses between 2010 and 2020

Source; ArcGIS change matrix between 2010 and 2020

In above table 4.9 the diagonal number indicates unchanged area, whereas the numbers in the class total row indicate final state where as the class total column indicates the initial state.

4.2.3.3. Change between 2000 and 2020 (the overall change)

The change between these years shows the overall change between the initial year and the final year. During the initial period most of the area was covered by forest and in final year the least coverage in percent was forest. The forest cover was decreased from 6045.922 ha in 2000 to 1862.860 ha in 2020 with decrement of 4,674.758 ha between the years. Conversely, farm land, settlement and plantation shows increment by 2037 ha, 2064 ha and 32 ha respectively.

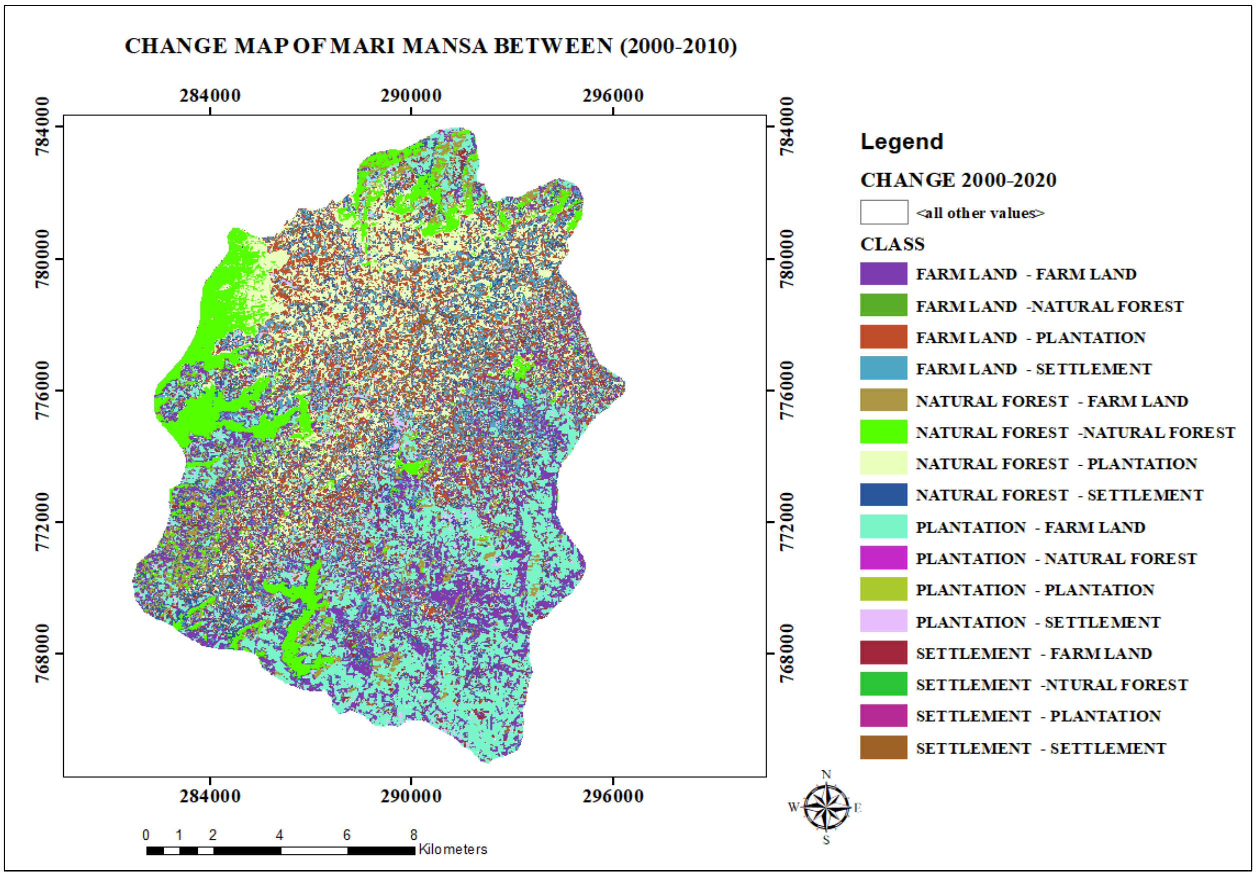


Figure 4. 14 Change map of 2000 between 2020

In the following change matrix table 4.10, between the year 2000 and 2020 shows the change between the land classes and unchanged area. The total numbers of row indicates the area coverage of each class in 2020 and the total number of column shows the area coverage of the land classes in 2000.whereas, the diagonal shows unchanged area

Land class		Area of Land use class (ha) in 2020 (final)				
		Farm land	Natural forest	Plantation	Settlement	Grand total
Area of Land class (ha) in 2000 (initial)	Farm land	4314.917	28.034	35.102	1667.867	6045.922
	Natural forest	970.432	1833.126	2655.642	1078.417	6537.618
	Plantation	2210.767	0.599	1664.654	505.289	4382.309
	Settlement	587.255	0.100	59.768	696.804	1343.929
	Grand total	8083.373	1862.860	4414.167	3948.389	18309
	Change	2037.451	-4,674.758	31.858	2,604.45	~0

Table 4.10 Change matrix table of land uses between 2000- 2020

Source; ArcGIS change matrix between 2010 -2020

Based on the above tables of the gain and loss of land use classes between the selected years can be summarized in figure below.

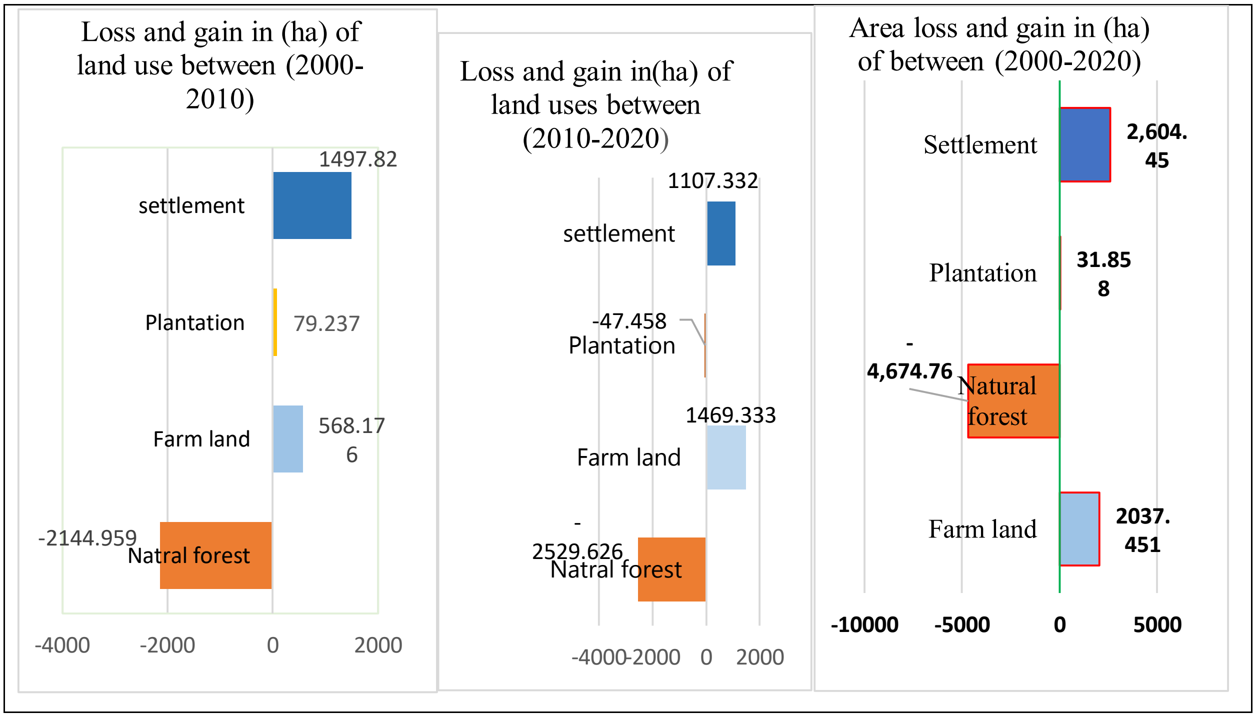


Figure 4. 15 Graph of area loss and gain of classes between 2000, 2010 and 2020.

In the above area losses and gain between three different periods, the natural forest shows high losses in area coverage through all periods and the land use like farm land, settlement shows the area gain between the three different periods. However, plantation gained in first and loss in second period. Thus, the gain of other land use and the loss of some land use type like natural forest shows the conversion from natural forest to other land use.

Based on the change analysis between the year 2000, 2010 and 2020, there is the land use class change from one to another and it can be described in the following table 4.9, below.

No.	Land cover change from (2000 to 2010)	Land cover change from (2010 to 2020)	Remark
1,	From natural forest to farm land From natural forest to settlement	From natural forest to farm land From natural forest to settlement	Deforestation
2	From farm land to settlement From plantation to settlement	From farm land to settlement From plantation to settlement	Built up area increment (Population increment)
3	From farm land to plantation From natural forest to plantation From settlement to plantation	From farm land to plantation From natural forest to plantation From settlement to plantation	plantation increment
4	From natural forest to farm land From plantation to farm land	From natural forest to farm land From plantation to farm land From settlement to farm land	Expansion of farm land

Table 4. 11 General description for the matrix change

Source; ArcGIS change matrix between each year.

From above three change map between the years, there is land use class conversion from one land use class to another class. This conversion resulted with the area cover increment in one land use class and decrement in the second land use class. This relationship between the land uses classes were clearly explained by using correlation. Correlation is the study of the degree of linear relationship between two variables. Correlation is also used to determine how well a particular line actually fits a given set of paired observations. Thus, the value of correlation coefficient measures the strength of the relationship between two variables. Therefore, this correlation in this study used to know the relationship between forest land, settlement, farm land and plantation. This coefficient of correlation can be computed as follow.

$$R_{xy}=\frac{\sum(xi-\bar{x})(yi-\bar{y})}{\sqrt{\sum(xi-\bar{x})^2\sum(yi-\bar{y})^2}}\text{.............................eq (4.3)}$$

Where r_{xy} coefficient of correlation between variable x and y

$xi\ and\ yi\ are\ variables$

$\bar{y}$ and $\bar{x}$ are mean value of the two different variables

Thus the value of r always ranges between $(-1 \leq r \leq 1)$.

(-1) mean perfect negative relation mean when one increases the other decrease.

(1) Means perfect positive relationship meant when one variable increases the second also simultaneously increase.

Therefore the relationship between the classes based on the area coverage was correlated as follows.

Land use type	Natural forest	Farm land	Plantation	Settlement
Natural forest	1			
Farm land	-0.9795596	1		
Plantation	-0.354496	0.1591591	1	
Settlement	-0.9910624	0.9439708	0.4760638	1

Table 4.12 correlation of land use classes

Source; computed from area cover of land use type during the selected time series**.**

In above table show the relationship between the different land use classes. The diagonal value (1) show the class is strongly related with themselves. However, farm land and natural forest have almost perfect negative relationship the same is true for natural forest and settlement. In generally, the first column value negative shows forest cover decreases as other classes increase.

4.2.4. Change detection by using NDVI.

NDVI image differencing cannot provide detailed change information. However, it can give the information of increase or decrease in NDVI value which indicate the vegetation cover. The values varies between -1 and + 1, where negative values are representing other than vegetation and positive values are representing less vegetation to dense or healthy vegetation (John & David, 2000).

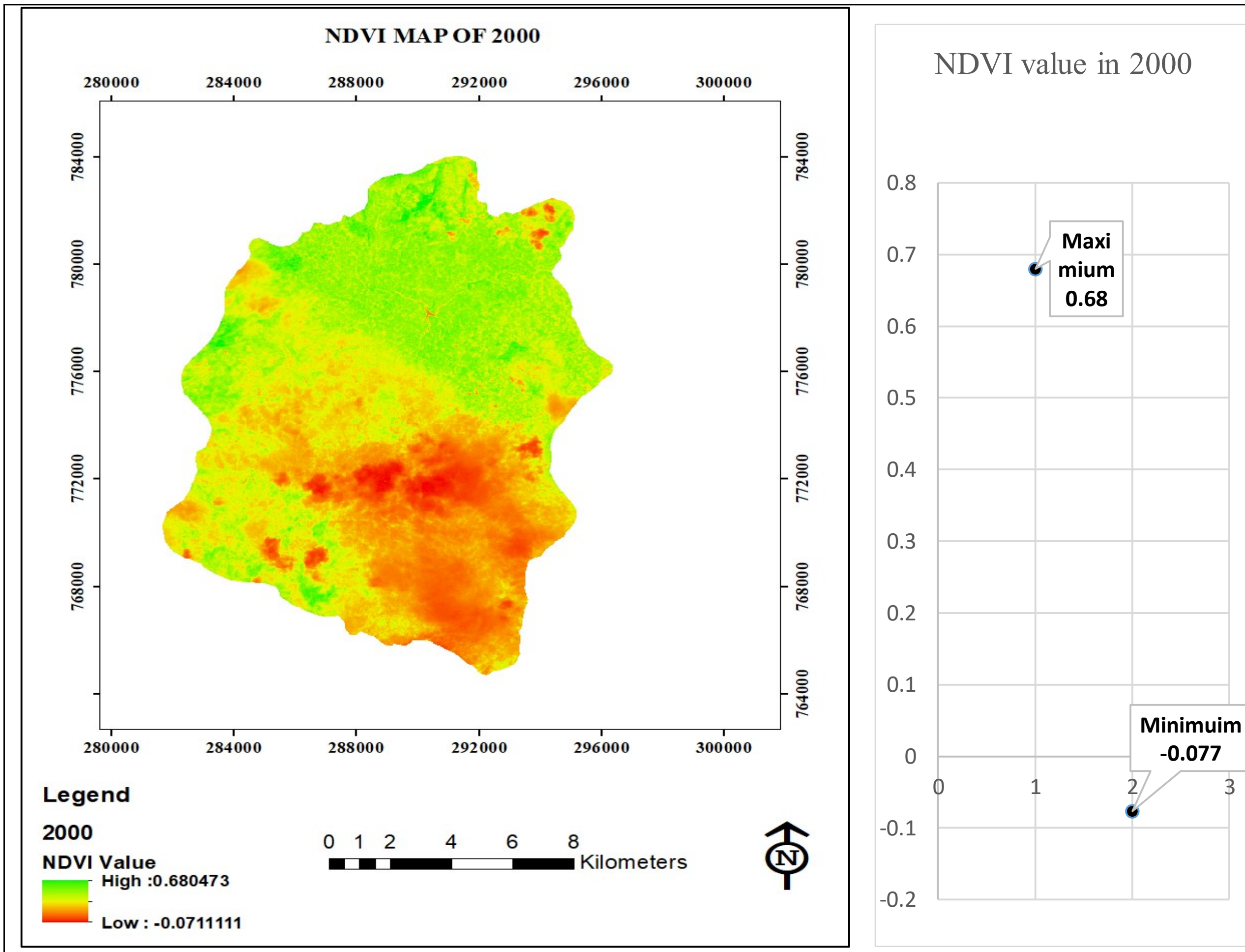


Figure 4. 16 NDVI map of 2000 and with its graph of max and min value

The above NDVI map of 2000 and its maximum and minimum value shown in graph illustrate the dark green color indicates high vegetation (forest) cover and the yellow shows the less vegetation (forest) cover or vice versa.

1

[1] The value of maximum and minimum NDVI value were from the its statistics in ARCGIS
In figure description max mean maximum and min mean minimum.

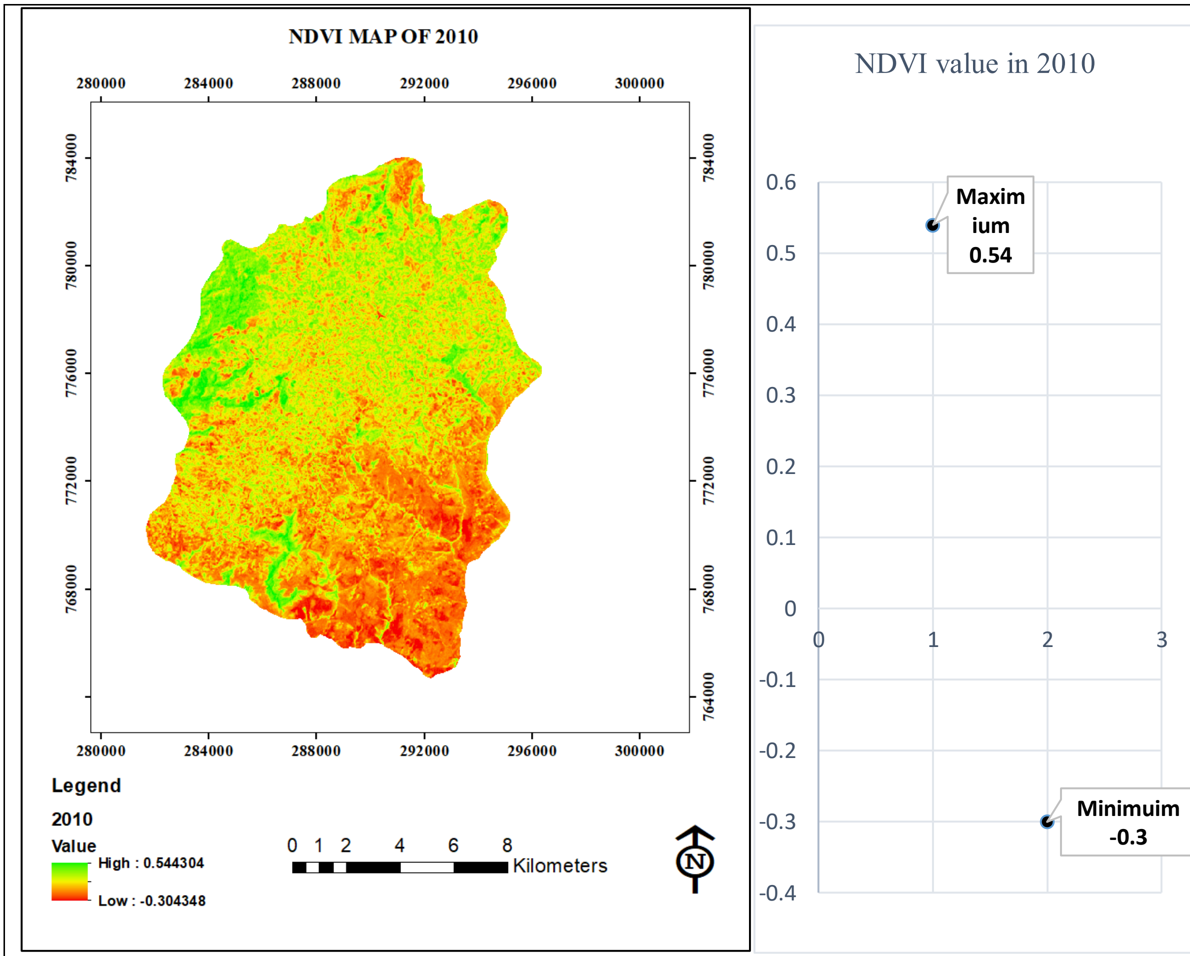


Figure 4. 17 NDVI map of 2010 and with its graph of max and min value

From the above result, that show shows the NDVI value of landsat 2010 image conceals that the maximum and minimum value are change from the previous selected year. Thus, the maximum and minimum value of NDVI during this year was 0.544 and -0.30 respectively. The result clearly shows that the dark green color is decreasing from 0.68 to 0.54 between 2000 and 2010.This show the forest coverage was decreasing during the stated period of time. However, the minimum value of NDVI was increasing between the stated years.

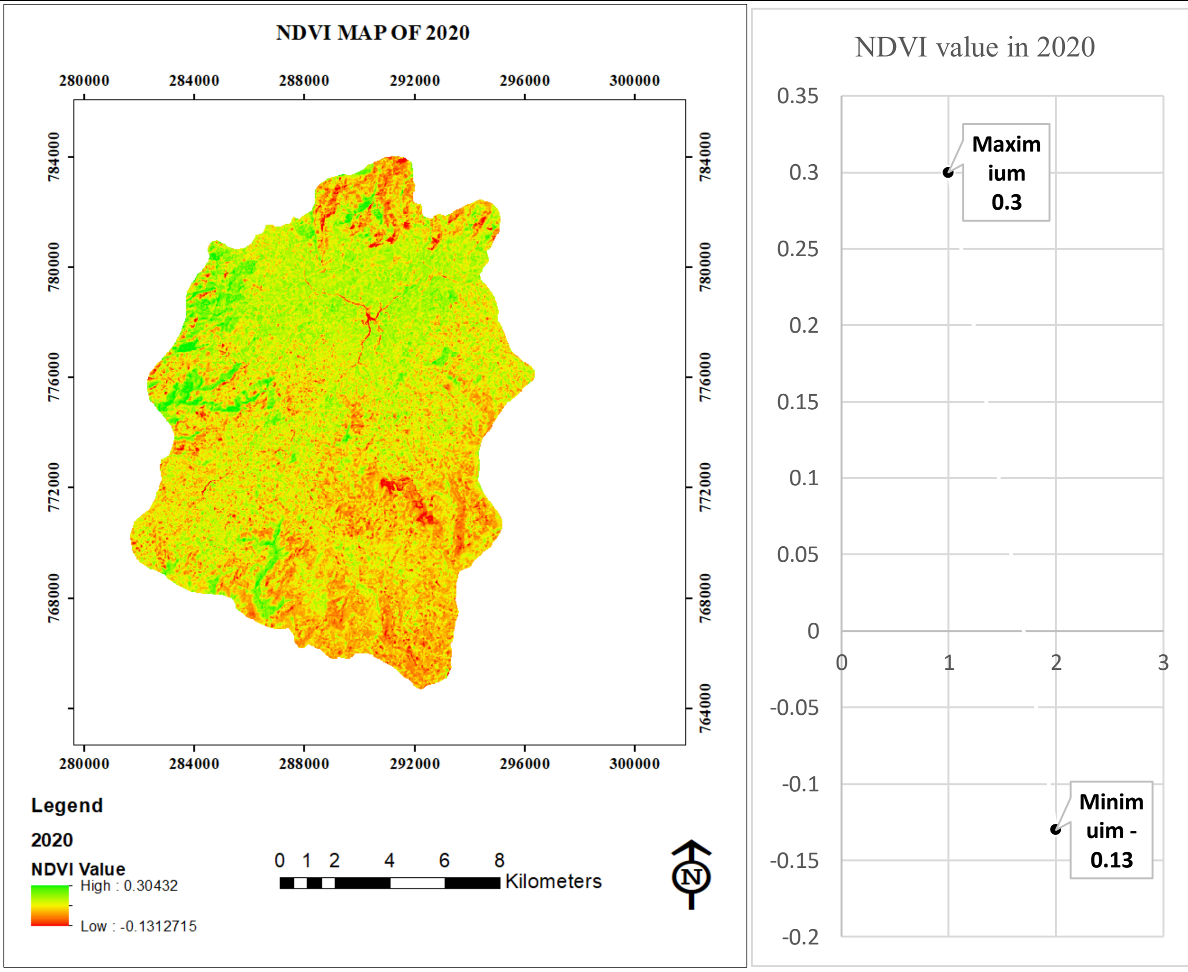


Figure 4. 18 NDVI map of 2020 and with its graph of max and min value

From the above fig 4.18 the maximum NDVI value was 0.30432 and minimum value was -0.13127. This value shows the vegetation cover was decreasing from the previous periods. The NDVI value showed slight reduction from 0.54 in the year 2010 to 0.3 in the year 2020. The darker red color, the lower the NDVI value and the less the vegetation and vice versa. This comparison result shows that highest vegetation cover was observed in 2000, whereas average vegetation cover was observed in 2010 but the lowest vegetation coverage was observed in the year 2020. This comparison can be better explained by its mean and standard deviation of the two periods (2000-2020) period images. The mean values are decreased from 0.29 in 2000 to 0.07 in 2020.for more information see NDVI summary (Table 4.13).

NDVI	Year		
	2000	2010	2020
Maximum	0.68	0.54	0.30
Minimum	-0.077	-0.3	-0.13
Mean	0.29	0.08	0.07
Standard deviation	0.15	0.147	0.128

Table 4. 13 NDVI value summary

Source; From NDVI statistics in ArcGIS.

The value in the table shows that the highest mean value of NDVI in the 2000 image showed the reverse of the lowest mean value of NDVI in 2020. That indicates satellite image showed the lowest vegetation coverage. Hence, the status of vegetation cover was better in 2000 than 2020 satellite images in the study area. In the same way, the standard deviation of the NDVI value shows that there was a continuous decrease from 0.15 in 2000 to 0.147 in 2010 and 0.128 in the year 2020. This means that the status of vegetation change from its mean value of NDVI is varying more in the 2000 image when it is compared with that of 2010 and 2020 satellite image. Hence, the rate of vegetation change was high in 2020 satellite image than the change of vegetation in 2010 and 2000. The result of the NDVI values showed that the density of vegetation cover, in general, was reduced and the forests, in particular, were depleted from time to time and this inferred that there were continuous deforestation and forest degradation.

4.2.5. Forest cover during selected period (2000, 2010 and 2020).

In this study, three period natural forest map was extracted from their corresponding LU/LC classification. Extracting forest map is used to visualize the distribution and rate of forest cover change with in selected time series. Moreover, digital image interpretation of forest cover area for each year was performed and total area of the natural forest cover during the stated time series. That shows the area coverage of forest cover was decreasing from 2000 to 2020 and was illustrated in the following line graph.

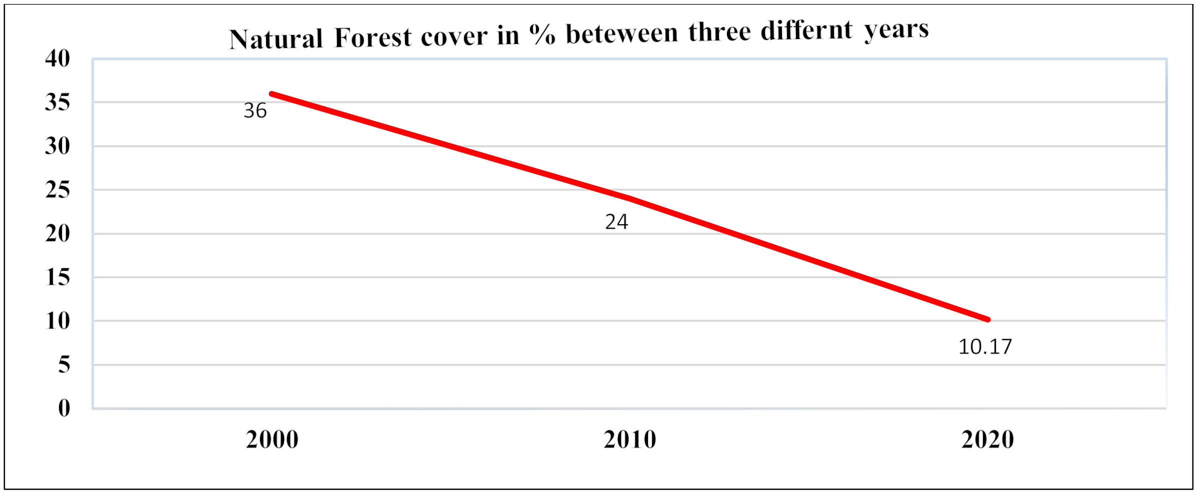
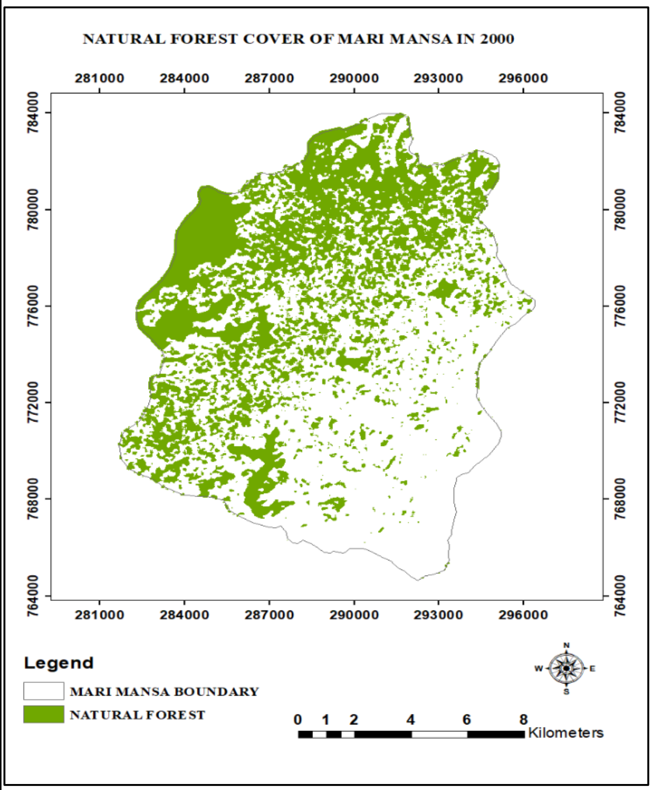


Figure. 4. 19 Line graph of forest area in 2000, 2010 and 2020

Source; From Table 4.2.

In addition to the graphical representation of the forest cover of each year, the extracted natural forest was also illustrated in map form as shown in figs below.



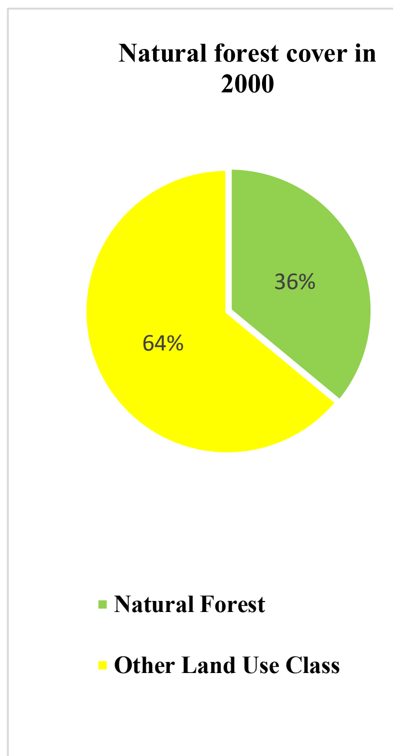
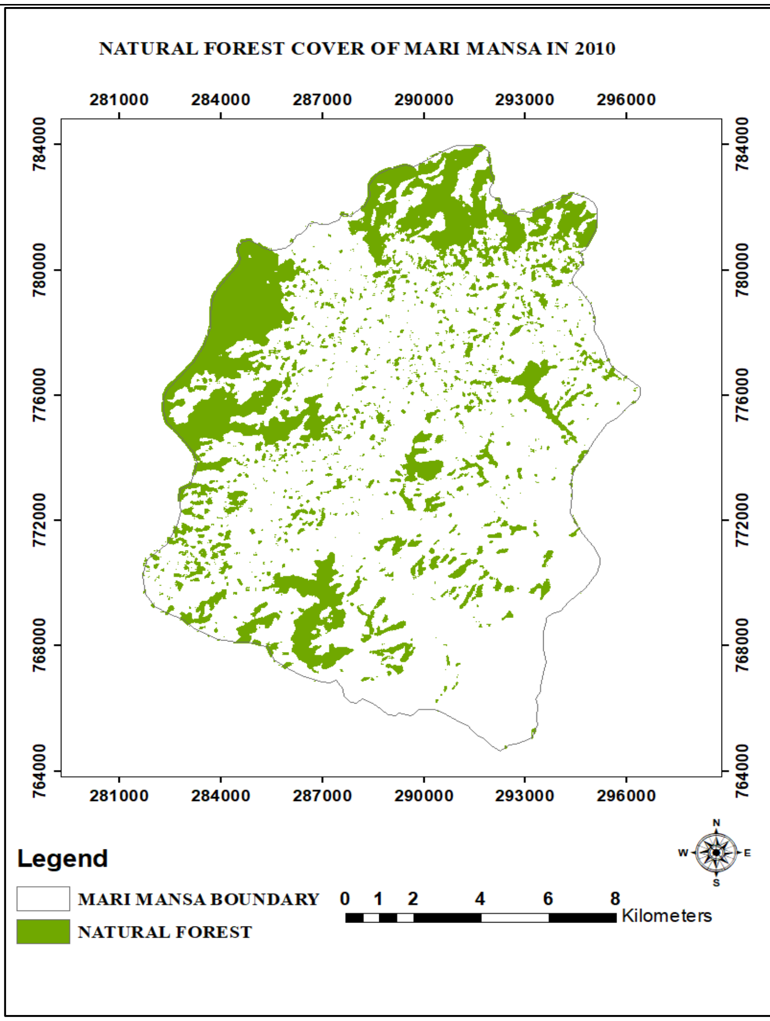


Figure 4. 20 Forest map of Mari mansa in 2000 Figure 4. 21 pie chart showing forest cover in 2000

In above figure 4.20 and 4.21 both map and charts illustrates the area coverage of natural forest and others total classes. Thus, from the total area of study area the forest covers 36% in 2000 and the rest 64% area were covered by other land use classes like settlement, farm land and plantation.



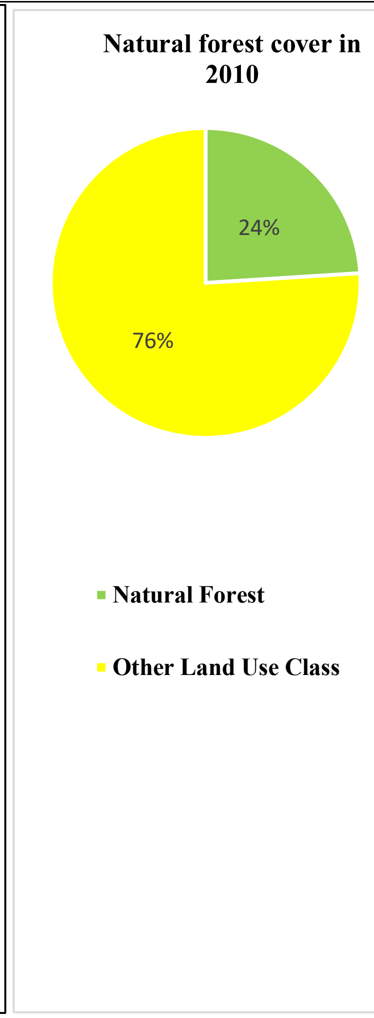


Figure. 4. 22 Forest map of mari mansa in 2010 Figure 4. 23 pie chart of forest cover in 2010

The result in above figure 4.22 and 4.23, clearly illustrates the natural forest coverage in 2010 and the total classes coverage.Thus, the result reavels that in previous period the forest cover is greater than qaurter of the study area but in 2010 the forest coverage was 24% whis is less than quarter of the study area. [2]

[2] All 2000, 2010 and 2020 natural forest maps area extracted from their LU/LC classification and the pie chart was included to show natural forest area clearly and easily relative to other land use.

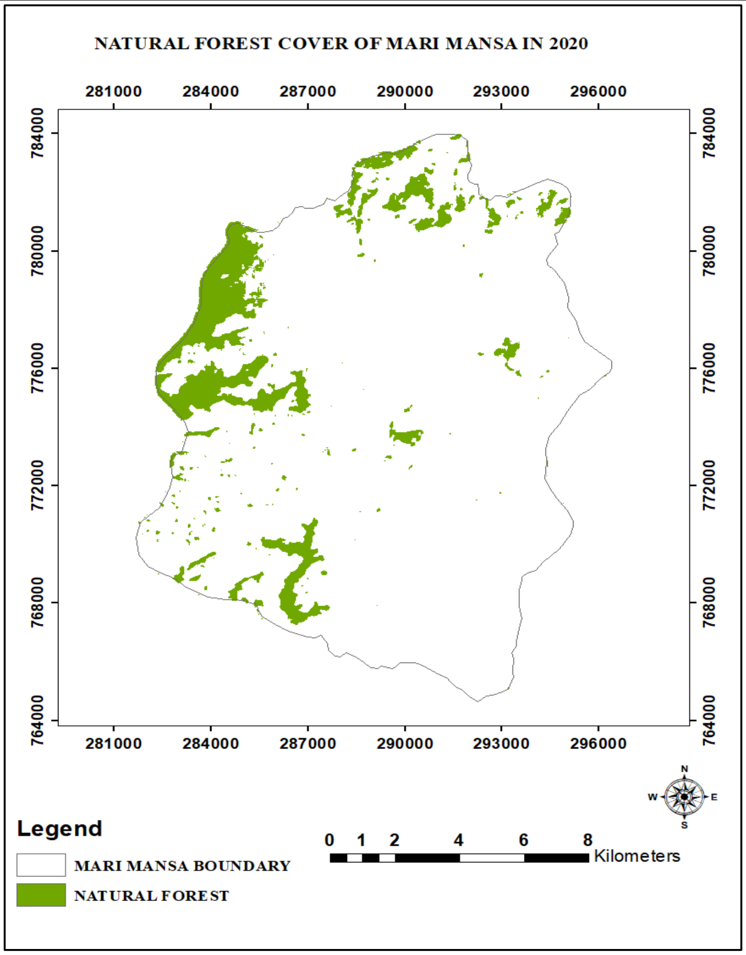


Figure 4. 24Forest map of Mari mansa in 2020

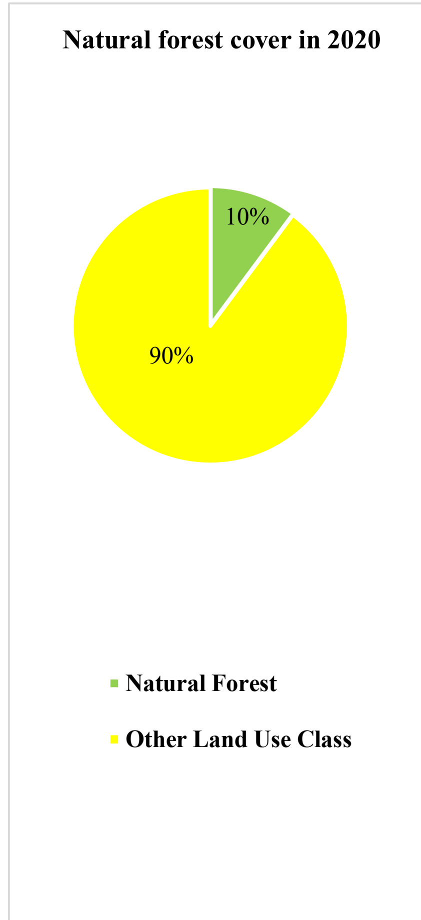


Figure 4. 25 pie chart of forest cover in 2020

The natural forest map of 2020 show that the natural forest covers 10% from the total of study area. This shows that the natural forest was decreasing from between the selected period by high rate.

4.2.6. Future Prediction for 2030 of LU/LC

Using the transition potential maps created in the Transition Potentials tab, the quantity of change in each transition can be modeled by using land change modeler (LCM). For this purpose the selected modeler is Markovian chain. This is the user defined modeler that determines the area of change using the earlier and later land cover maps along with the date specified. The procedure determines exactly how much land would be expected to transition from the later date to the prediction date based on a projection of the transition potentials into the future and creates a transition probabilities file. The transition probabilities file is a matrix that records the probability that each land cover category will change to every other category. The transition areas matrix is a text file that records the number of pixels that are expected to change from each land cover type to each other land cover type over the specified number of time units. In both of these files, the rows represent the older land cover categories and the columns represent the newer categories. See the following table.4.14, transition probability matrix

	Forest	Settlement	Farm land	plantation	Sum of each row
Forest	0.4683	0.1005	0.1073	0.3039	1.0000
Settlement	0.0001	0.8381	0.1330	0.0228	1.0000
Farm land	0.0004	0.00083	0.9841	0.0072	1.0000
Plantation	0.1769	0.0527	0.0821	0.6883	1.0000

Table 4. 14 Transition probability matrix of classes

Source; from prediction modeler

For 10 year period starting at 2010, we therefore expect 46.83% of forest to persist and 10.73% to change to farm land, 10.5 % to settlement with no reversion back to forest. These are the results yielded by Land Change Modeler as the projection date is changed from 2020 to 2030 (but in every case, projecting from a starting date of 2010). And 98.41 % of farm land persist and 0.08% to settlement and also 20.072% to plantation. Whereas for 83.81 % of settlement persist and 13.03% to farm land. Finally, for 68.83 % of plantation persist and 5.27 % to farm land. Thus persistence value of forest is less than others classes in that means the forest area have high probability to be changed. The less percent of persistence the high change and high percent of persistence less change in class or vice versa.

4.2.7. Validation of predicted LU/LC map

Concerning the model validation and based on the comparison of predicted LULC and actual LULC map, the K coefficient for quantity and location was derived. The statistics show that Kno is 0.947, Klocation is 1, Klocation strata is 0.894 and Kstandard is 0.8269 respectively. Thus, there were almost no or small quantification and location errors. The simulation for this scenario has perfect ability to specify location accurately and it also has perfect ability to specify quantity accurately. For validation purpose, Kappa Index of Agreement (KIA) was used for predicting the LULC map of 2030. See Table 4.15 below.

Indicators	predicted
Kno	0.947
Klocation	1.0000
Klocation Strata	0.894
K standard	0.984

Table 4. 15 Kappa coefficient (index of agreement) of LULC predicted summary

Source; validation statistics in Terrset software.

All the kappa value shown in above were greater than 85%. Thus, the prediction validation results confirms the predicted LU/LC class was highly acceptable and the result of predicted map for 2030 was as shown in fig below.

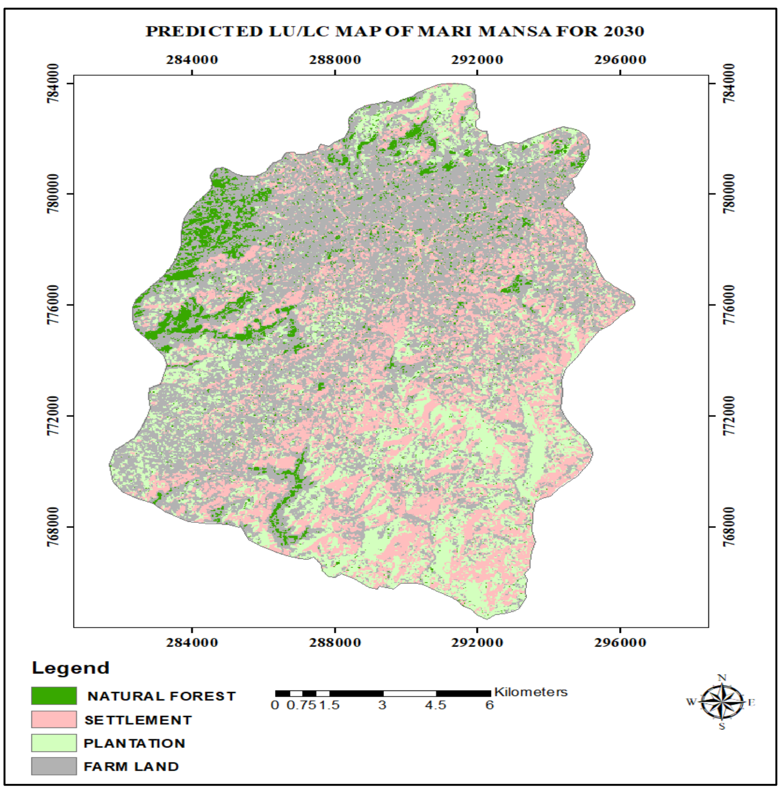


Figure 4. 26 predicted LU/LC map for 2030

From the above predicted map for 2030, the forest cover in ha was 1015.5, for settlement was 4688.82 ha and for plantation and farm land were 3958.38 ha and 8646.72 ha respectively. Moreover, their percentage coverage from total were, forest covers 5.5% from total area, settlement covers 25.2%, plantation covers 21.6% and farm land covers 47.7% from the total area .thus the coverage of forest was decreasing, on the other hand ,the farm land area was increasing. See table 4.15, below about the area coverage of each classes in percent and in ha.

Land classes of 2030	Area in Ha	Area in percent
Forest	1015.56	5.50
Settlement	4688.82	25.2
Plantation	3958.38	21.6
Farm land	8646.71	47.7
Total		100

Table 4. 16 Area coverage of predicted 2030 map.

Source; ArcGIS attribute of the predicted classes

From the year 2000 to the predicted year the coverage of natural forest was decreasing from period to period .conversely, the other land use classes like settlement and farm land were increasing. For more information see the table below.

No.	Land classes	Years		
		2020	2030 (Predicted)	
		Area in %	Area in %	Change%2020 to 2030
1	Forest	10.17	5.50	-4.67
2	Settlement	21.57	25.2	3.63
3	Plantation	24.11	21.6	-2.51
4	Farm land	44.15	47.7	3.55
5	Total	100	100	

Table 4. 17 The area change in percent

Source; ArcGIS attribute table of the classifications and prediction

In above table illustrates the area cover of each year in percent and its changes between different periods of time. Thus, the change between each period it shows the positive and negative values. The negative value shows us there was area decrement of land use class between the periods of time. Whereas, positive value shows there is area increment between two periods of time. The value of natural forest area between all period and up to predicted 2030 indicates area decrement at all. Specifically, see the predicted natural forest map of study area for 2030 which is extracted from the predicted LU/LC map.

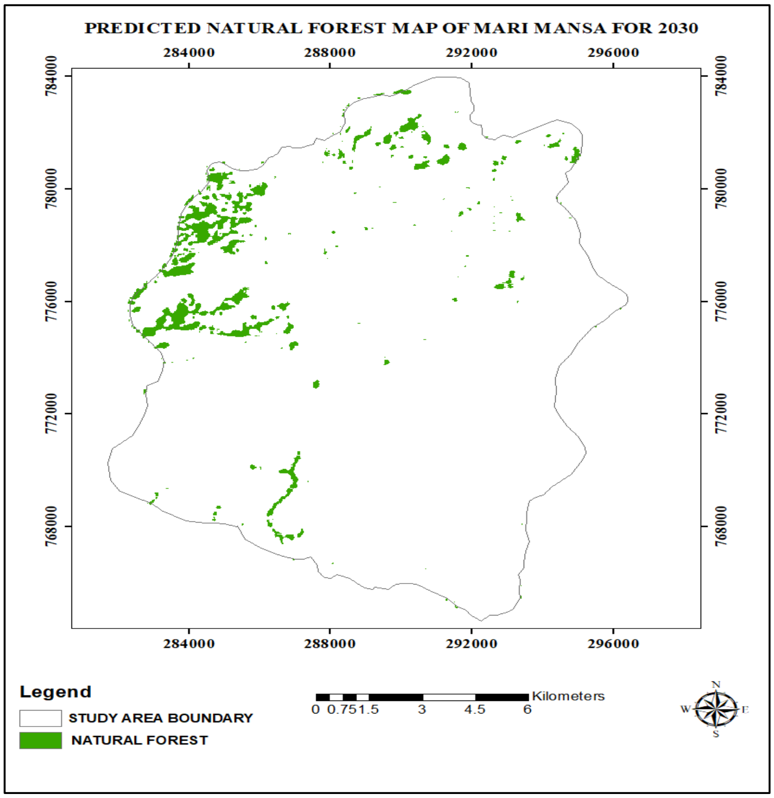


Figure 4. 27 predicted natural forest map for 2030 area

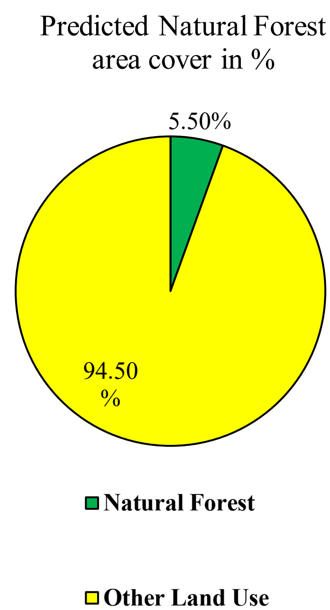


Figure 4. 28 pie chart of predicted forest

Particularly, the result of predicted natural forest area cover shows, it declined by 4.67% between the predicted year of 2030 and 2020.This shows the natural forest in the study area was already approaching to zero due to anthropogenic factors and by some natural phenomenon**.** Thus, the mostly known natural forest changing factors in the study area can be identified from the community are the major causes for this continuous decline of natural forest. Finally, the predicted natural area shows around 30% decrement from 2000 and the predicted year (2030).[3]

[3] The above predicted natural forest map was extracted from predicted LU/LC map of 2030.

4.3. Discussion

Based on the research finding carried above, the results to be discussed include, statistical analysis to determine the affecting factors for forest change and the observed problems due to forest change, change detection between the different period of time-based on the classified map and NDVI value and future prediction on an area. Thus, the listed results are discussed as follows.

4.3.1. Discussion on factors for forest change and problems observed.

Based on the finding from the frequency analysis on the numbers of respondents for forest changing factor, it suggests there are different causes of natural forest deforestation in the study area.

The finding of this section shows, there are numbers of factors that causes the natural forest to be changed from time to time. These factors were obtained from the community of selected kebele are which are famous in natural forest in the district. Thus, expansion of farm land, timber production, overgrazing, cutting trees for house construction material, for fire wood, and charcoal extraction were the main factors identified in the study area. Based on the numbers of respondents on each factor. The rank of factors identified were, overgrazing, fire wood consumption cutting trees for house construction, timber production, expansion of farm land, and charcoal extraction .This rank shows the factors like over grazing, expansion of farm land, fire wood consumption and timber production highly affect the forest change relative to those and charcoal extraction .However, this is not mean that charcoal has no impact on forest change, it has its size negative effect on natural forest change.

In agreement to this finding, (Netsanet, 2007),stated causes for natural forest change like agricultural land expansion, wood extraction, infrastructure expansion and others that change the physical state of the land. Furthermore as discussed by (Girma & Hassan, 2014), human induced environmental impact also increased to fulfill the increased requirement of land resources, and it directly affects the forest land cover. From the result of the frequency analysis of respondents on the problem due to forest change, there problems which was resulted from the natural forest change includes, losing of wild life, climate change, agricultural unproductivity and losing honey production are some of the identified ones.

4.3.2. Discussion on Change Result

In this section the extent, trend, and the change rate of each identified land cover classes of entire study area findings and the change of natural forest for the three study periods (2000, 2010 and 2020) were discussed. Furthermore, the correlation between the area change of natural forest and other land use classes discussed.

The total natural forest area was 6537.445 ha during the year 2000, it was 4392.225 ha in the year 2010 and 1862.51 ha in the year 2020. This shows that, 2145.22 ha converted into any other land use classes during first ten year and 2529.98 ha converted into any other land use class during second ten year. Consistent to this finding, (Reusing, M. 2001) stated that high forest cover of Ethiopia decreased from 50,410 km^2 to 45,055km^2 or from 4.75 % to 3.93% of the total land area from 1973-1990. He calculated deforestation rate of 1,630 km^2 per year. In agreement to mentioned finding, from the findings of this study the calculated deforestation rate during the first and second ten years observed on the study area was 2.14522 km^2/year and 2.52998 km^2/year respectively. Moreover, it shows the decrement of 12% and 14% between the first and second ten years respectively.

In case of farm land there has been observed increase area of 568.176 ha (2.63%) and 1469.89 ha (8.1%) in the first and the second ten years. Natural forest resources in the study area have experienced so much pressure due to increasing of conversion to agriculture. In agreement to this finding, (Abera, 2019), in Ethiopia, the farm land has increased from 9.44 million hectares in 2001 to 15.4 million hectares in 2009 alone (i.e., 6 million ha in 8 years).Thus, the study area is as apart of Ethiopia, that the natural forest decrement indubitably seen. The study have positive implication with the mentioned scholar and the conversion of natural forest land to farm land decrease the natural forest coverage.

The settlement areas also increase of 1497.8 ha (8.16%) and 11071.1 ha (6.07%) in first and second ten years respectively. Whereas the plantation areas shows increment in first ten years and decrement in the second ten years .whereas, the plantation cover in (ha) was 4382.388 ha, 4461.625 ha, and 4414.167 ha during the year 2000, 2010 and 2020 respectively. This shows 79.232 ha (0.4%) increment in first ten years and 47.458 ha (0.29%) decrement during second ten years.

Based on the conversion of classes, it is possible to correlate the land class type based on their area increment and decrement .Thus, from the result of correlation table the forest classes and farm land classes have (-0.98 ~ -1) mean almost perfect negative correlation ship, it mean when the area of forest cover decrease the area of farm land increase and also the same is true for forest and settlement relation. Moreover the area of natural forest was decreasing when the area of settlement, plantation are increasing based on the correlation value.

4.3.3. Discussion on change detection based on NDVI result

Results of NDVI analysis provide evidence for land cover /use change. The major changes in NDVI correspond to areas that had lost forest cover substantially with in twenty years. Thus, the findings from NDVI value suggest that there decrement from 0.68 in 2000 to 0.3 in 2020 during 20 years. The difference of 0.38 show that cover of vegetation is decreasing between the stated years. Furthermore the mean value also decreasing from 0.29 to 0.07 in 2000 and 2020 respectively. Simultaneously the standard deviation of NDVI value decreases from 0.15 to 0.128 in the year between 2000 and 2020.The decrement of NDVI value indicate the forest coverage was decreases from period to period.

4.3.4. Discussion on the future prediction for 2030 result of LU/LC

The findings from the change between the predicted and previous (2020) land class suggests that, forest cover decreases 4.67%, settlement increases 3.63% farm land increases 3.55% whereas plantation decreases 2.51% between the predicted 2030 and previous 2020 land classes. In agreement to this finding, it is predicted that forest area are projected to continue to decline at alarming rates in some regions (d'Annunzio et al., 2015).

Evidently, the integrated effects of natural forest changes in the study area can lead to the highly variable response of rainfall and temperature over time. The prediction result shows that there will be great loss of natural forest cover which will lead to high rate problem due to forest change if the same trend is continued up to the predicted date. In addition, the dynamic change on the forest can make great dread in losing of wild life. Thus, these findings have great importance for environmental managers to make strategies to sustain natural forest ecosystems in the area. Hence, sound plantation strategy should not only aim to increase forest biomass, but also recover the function of natural forests to ensure a stable climate in the area.

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

- The result from frequency analysis revealed that, the main cause of deforestation identified from the community in the study area were expansion of agricultural land, cutting of wood plant, for fuel wood consumption and over grazing in the forest land and charcoal extraction.

- Due to high natural forest decline rate in the study area some problems like decline agricultural product, decrement of honey production, climate change and loss of some wild life species like lion and deer were observed. (Source, interview data from community).

- During the years 2000, 2010 and 2020 the study area covered by natural forest was about 36%, 24% and 10.17% of the area respectively. Unlike, the areal extent of farm land in the years 2000, 2010 and 2020 were 33.47%, 36.1% and 44.15% respectively .similarly, the area covered by the settlement was about 7.51%, 15.5 % and 21.57 % in the years in 2000, 2010 and 2020. Finally the area coverage of plantation during the year 2000, 2010 and 2020 was, 24%, 24.4% and 24.11% respectively. In this land use approximately no high difference observed.

- In prediction result, the probability matrix table tells the transition of natural forests to natural forest was 0.4683 (46.83%). This shows that more than half of the forest area has been converted to other land classes. Nevertheless, for the probability matrix between farm lands to farm land was 98.41% this shows approximately there is complete persistence of farm land. Thus, the conversation of natural forest from natural forest area to another land use classes results to deforestation. The prediction of natural forest cover shows the forest cover will be 5.5%.This shows if the same trend continues up to the predicted year the natural forest are being finished. Conversely, the farmland, plantation and settlement will be 47.7% 21.6% and 25.2% respectively. This is due to the conversion of forest land to another land classes. This prediction shows that the trend of forest was highly declining mostly by human activities and natural phenomenon.

- Hence, all the result of natural forest change investigation of this study indicates that the status of the natural forest was decreasing due to the identified factors. Deficient of taking necessary measurement on the natural forest causing factors lead to decline of it during time series. This decline of natural forest can continue to total loss of the natural forest and the species it consist unless necessary measurement taken to reverse the problem.

5.2 Recommendation

The study identified that, the decrease of natural forest cover of the study area during the selected period of time was due to the factors like, expansion of agricultural/settlement land, charcoal making, intensive fuel wood extraction, cutting trees for construction, timber production and overgrazing. Thus, the change of natural forest was resulted with losing wild life species like lion and deer, climate change and agricultural product decrement. Therefore, to implement appropriate natural forest land management strategies and based on the finding of the study, the following recommendation points are forwarded to minimize deforestation of natural forest in the study area:-

- ☞ Natural forest is the one of very important resource to the community. Besides, the importance of the natural forest was very crucial for wildlife. As the data from the respondents there were many wildlife like hyena, monkey, baboon, tiger, Impala and ape were exist in the forest. The conservation of natural forest and this wildlife existed inside it was better opportunity to attract the tourist which have great importance to the economy of the district. Therefore, with this regard the concerned governmental body and all the community should give more attention about forest resource of the study area.

- ☞ The concerned body of Mari mansa district should create awareness about advantages different family planning mechanisms for rural household heads to minimize the population growth and provide different family planning techniques for household heads to balance population growth with the carrying capacity of environment.

- ☞ The Mari mansa district micro and small enterprise, natural resource management and mineral and energy offices should create other job opportunities for peoples who engaged their life by selling forest product like charcoal, fuel wood and timber.
- ☞ The concerned body of Mari mansa district must be create awareness about different sources of energy for household heads like hydroelectric power and distribute for household heads up to rural area to minimize fuel wood and charcoal consumption.

- Local communities should participate in different natural forest conservation mechanism like in afforestation, reforestation and agro-forestry program and also the management of planted trees by considering as their benefit.
- Non-governmental organization and private sectors should participate to give training about natural forest resources management and family planning techniques.
- Most of household heads are clearing forest to increase their crop product by expanding crop land. So, Mari mansa district agriculture and rural development office must supply modern inputs of agriculture like fertilizer for rural household heads to minimize deforestation by striving to increase productivity of the land.
- To reduce the effect of cutting forest tree for house construction, the agricultural office of Mari mansa district in collaboration with the natural resource management office and the experts of kebele should have to provide different tree seedlings for the community to plant on their own land and teach them to use for any purpose from their own tree product.
- As the natural forest in study area contains diverse fauna species, flora species, historical caves and very attractive natural waterfall inside it the concerned body should have to do research study on the suitability area selection for tourist site that may have dual purpose in terms of economic aspect and may helpful to protect and conserve the natural forest area.
- Finally, for LU/LC change projection it is better to use CLUMONDO model because it consists both spatial analyst module and non-spatial analyst module.

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APPENDICES

Annex: I. Survey Questioner for Natural Forest cover Changes

The main purpose of this questionnaires is to collect first-hand information for the study that attempt to assess/investigate the causing factors of natural forest in the study area .Thus, general aim of the study was to investigate natural forest cover change by using geospatial technology in Mari mansa district, Dawro zone, southern Ethiopia. This study will try to describe the way and the rate at which forest cover is change and local community awareness and participation in reforestation. 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 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 support our team effort.

General direction

No need of writing your name. - Give only a single answer for close ended questions. If your response to the question is not included in the given alternatives, please, specify your answer on the space provided at the end of the alternatives.

Note:

I. You are not required to reveal your name

II. If you have additional comments please write in the space provided

III. Encircle your choice from the given alternatives and for blank space write the answer in provided space.

Part I: Respondent's background

1. Sex:

a) Male

b) Female

2. Educational Status:
    a. No education
    b. Basic education
    c. Elementary school (1-8)
    d. High school and preparatory
    e. Diploma level
    f. first-degree
    g. Second-degree level
    h. 3rd degree level

3. Current Family Size ______

4. For how long you are living in this residential area?

a) Since last year

b) For 1-3 years

c) For 3-5 years

d) For 5-10 years

e) More than 10 years

9. Occupation?

a. Merchant

b. Government employee

c. Farmer

d. Labor worker

e. Other

5. Average monthly income:

a. Less than 1000 birr per-month

b. 1001-1500 birr per-months

c. 1501-2000 birr per-months

d. 2000-2500 birr per-months

e. 3001-3500 birr per-months

f. > 3500 birr per-months

6. Your permanent address region ______ zone_______ District _________ kebele ___

7. Marital status;-

a. single   b. married
c. divorced   d. widowed

8. Family size change in: - 1992______, 2002_____2012_____

Part II: Community participation and awareness in forest utilization and protection

10. Who is responsible to protect Guda natural forest?

a. Local community including you

b. Government body assigned for this purpose only

c. Both government and local community

d. Others, please Specify ________________________________

11. If your answer for question number 10 is a and/or c what is your main role in protecting natural forest

a. ______________________________________

b. ______________________________________

c. ______________________________________

12. In you view, is the Guda natural forest is well protected?

a. yes b. no

13. If your answer for the question number 12 is "no", what is the main problems?

a) ___________________________________

b) ___________________________________

c) ___________________________________

d) ___________________________________

14. In your view what is the status of Guda Natural forest coverage and diversity of species

a. Both diversity and coverage are increasing

b. Both diversity and coverage is decreasing

c. Diversity is well protected but coverage is decreasing

d. Coverage is well protected but some important species is affected

e. No change at all

f. Any other change you have been observing ______________________________

15. What are the major reason for the forest cover and diversity change?

a. ___________________ c. ___________________

b. ____________________

16. Do you fill that Guda Natural Forest is important for your day to day life?

a. Yes it is very important

b. Noting I am getting from this forest
c. Some how

17. If your answer for the question number 16 is yes what are the main importance of this forest for you?

a. As sources of construction material for housing
b. As energy sources (firewood)
c. For timber production
d. charcoal production
e. resident for important Wild life
f. using for environmental balances
g. any other , please specify ______________________________

18. What are the major wildlife in Guda natural forest? List some of them.

a. ____
b. ____
c. ____
d. ____
e. ____

19. Did you attend or get any training and awareness creation on importance and protection of natural forest

a. Yes somehow long time ago
b. Nothing in my life
c. Yes regularly
d. I think it may not need

20. Did you observed any activity to enhance community participation and awareness creation in your area in natural forest management and conservation

a. yes sometimes
b. Yes regularly since recent
c. Nothing at all

Annex II: **Accuracies assessment calculation for classifications of each year**

- **For 2000 classification**

Lu land cover	Settlement	Farm land	plantation	Forest	user
Settlement	14	0	0	0	14
Farm land	0	4	0	0	4
Plantation	0	0	3	1	4
Forest	0	1	0	8	9
Producer	14	5	3	9	93.5%

- Over all accuracy= $\frac{\text{Total number of correctly classified diagonal pixel}}{\text{Total number of referance pixel}} * 100\%$
- Overall accuracy= $\frac{14+4+3+8}{31}$ *100%= $\frac{29}{31}$ *100%=0.935*100%
- Therefore the overall accuracy=93.5%
- User accuracy= $\frac{\text{Number of correctly classified pixels in each class}}{\text{Total number of pixels in each catagory}}$ *100%

So for each class was as follows

Settlement = $\frac{14}{14}$ *100%=100%

Plantation = $\frac{3}{4}$ *100%=75%

Farm land= $\frac{4}{4}$ 100%=100%

Forest = $\frac{8}{9}$ *100%=88.89%

K= $\frac{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}$

$N\sum_{i=1}^{r} xii$=31*(14 + 4 + 3 + 8) =899

$\sum_{i=1}^{r}(x_{i+\times}x_{+i})$=14*14+4*5+4*3+9*9=309

$N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(x_{i+\times}x_{+i})$=899-309 =590

$N^2 - \sum_{i=1}^{r}(x_{i+\times}x_{+i})$=31*31-309 =652

K=590/652=0.90

K (%) =90% so classification was correctly classified.

- **For 2010 classification**

Lu land cover	Settlement	plantation	Farm land	Forest	user
Settlement	6	0	0	0	6
Plantation	0	5	0	0	5
Farm land	1	2	11	0	14
Forest	0	0	0	5	5
Producer	7	7	11	5	90%

- Over all accuracy= $\frac{\text{Total number of correctly classified diagonal pixel}}{\text{Total number of referance pixe}} * 100\%$
- Overall accuracy= $\frac{6+5+11+5}{30}$ *100%= $\frac{27}{30}$ *100%=0.9*100%
- Therefore the overall accuracy=90%
- User accuracy= $\frac{\textit{Number of correctly classified pixels in each class}}{\textit{Total number of pixels in each catagory}}$ *100%=

So for each class was as follows

Settlement = $\frac{6}{6}$ *100%=100%

Plantation = $\frac{5}{5}$ 100%=100%

Farm land = $\frac{11}{14}$ *100%=78.6%

Forest = $\frac{5}{5}$ *100%=100%

$$K = \frac{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}$$

$N\sum_{i=1}^{r} xii$=30*$(6 + 5 + 11 + 5)$ =810

$\sum_{i=1}^{r}(x_{i+\times}x_{+i})$=6*7+7*5+14*11+5*5 =256

$\boldsymbol{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}$=810-256 =554

$\boldsymbol{N^2 - \sum_{i=1}^{r}(x_{i+\times}x_{+i})}$=30*30-256 =644

K=554/644=0.860205

K (%) = 86.02% so classification was correctly classified

- **For classification of 2020**

Lu land cover	Settlement	plantation	Forest	Farm	user
Settlement	14	0	0	0	14
Plantation	0	11	0	0	11
Forest	0	1	9	0	10
Farm	0	0	0	7	7
Producer	14	12	9	7	~98%

- Over all accuracy= $\frac{\text{Total number of correctly classified diagonal pixel}}{\text{Total number of referance pixe}} * 100\%$
- Overall accuracy= $\frac{14+11+9+7}{42}$ *100%= $\frac{41}{42}$ *100%=0.9762*100%
- Therefore the overall accuracy=97.62%
- User accuracy= $\frac{\boldsymbol{Number\ of\ correctly\ classified\ pixels\ in\ each\ class}}{\boldsymbol{Total\ number\ of\ pixels\ in\ each\ catagory}}$ *100%

So for each class was as follows:-

Settlement = $\frac{14}{14}$ *100%=100 Plantation = $\frac{11}{11}$ *100%=100%

Farm land = $\frac{7}{7}$ *100%=100% Forest = $\frac{9}{10}$ *100%=90%

$$\mathbf{K}=\frac{N\sum_{i=1}^{r} xii-\sum_{i=1}^{r}(x_{i+\times}x_{+i})}{N^2-\sum_{i=1}^{r}(x_{i+\times}x_{+i})}$$

$\boldsymbol{N\sum_{i=1}^{r} xii}$=42*(14 + 11 + 9 + 7) =1890

$\sum_{i=1}^{r}(x_{i+\times}x_{+i})$=196+132+90+49 =467

$N\sum_{i=1}^{r} xii-\sum_{i=1}^{r}(x_{i+\times}x_{+i})$=1890-467 =1423

$N^2 - \sum_{i=1}^{r}(x_{i+\times}x_{+i})$=42*42-467=1764

K=1297/1423 =0.911

Therefore, k (%) =91.1 (ok)

Summary table of accuracy assessment calculation

Year	Over all accuracy in %	Coefficient of kappa(K) in %
2000	93.5	90
2010	90.5	86.02
2020	98	91.1

LULC class	User accuracy in %		
	2000	2010	2020
Settlement	100	100	100
Farm land	87.5	76.6	100
Forest	100	100	90
Plantation	100	100	100

Annex-III. Landsat Band Designation

Landsat 7 Enhanced Thematic Mapper Plus (ETM+)

Landsat 7	Wavelength (micrometers)	Resolution (meters)
Band 1	0.45-0.52	30
Band 2	0.52-0.60	30
Band 3	0.63-0.69	30
Band 4	0.77-0.90	30
Band 5	1.55-1.75	30
Band 6	10.40-12.50	60 (30)
Band 7	209.-2.35	30
Band 8	.52-.90	15

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Coastal aerosol	0.43-0.45	30
Band 2 - Blue	0.45-0.51	30
Band 3 - Green	0.53-0.59	30
Band 4 - Red	0.64-0.67	30
Band 5 - Near Infrared (NIR)	0.85-0.88	30
Band 6 - SWIR 1	1.57-1.65	30
Band 7 - SWIR 2	2.11-2.29	30
Band 8 - Panchromatic	0.50-0.68	15
Band 9 - Cirrus	1.36-1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.6-11.19	100
Band 11 - Thermal Infrared (TIRS) 2	11.50-12.51	100

Source; internet

Annex-IV; GCP pints for ground truthing (from field survey)

Nothing	Easting	Description
778383.0350	285401.0027	Forest
778407.7830	284347.0541	Forest
779054.0772	284995.0889	Forest
777327.0182	283913.9120	Forest
780358.0016	284863.7661	Forest
777037.1954	283726.0560	Forest
774886.0039	283527.0711	Forest
767818.8788	286418.0831	Forest
769651.6891	284694.7621	Settlement
779553.2451	293953.0987	Settlement
779029.0653	292656.0270	Settlement
782927.7713	289387.3421	Settlement
777895.7689	290223.0007	Settlement
778714.0870	289518.4218	Settlement
779632.3891	292806.4517	Settlement
779951.6731	290441.0789	Settlement
770155.8921	284411.3351	Settlement
769651.6891	284694.7621	Settlement
779553.2451	293953.0987	Settlement
779029.0653	292656.0270	Settlement
778925.6754	289908.4671	Settlement
778615.0521	287585.0043	Plantation
776209.0067	289933.0230	Plantation
774610.5671	291314.0576	Plantation
774866.1812	289826.0478	Plantation
773593.9815	290095.3200	Plantation
775728.1342	291441.0173	Plantation
774446.0472	292212.3497	Plantation
777247.7614	294562.0893	Plantation
778055.0680	285751.0034	Farm Land
774111.6701	294426.5341	Farm Land
778743.0341	287171.9172	Farm Land
779286.0710	286877.0007	Farm Land
778493.0453	290486.2714	Farm Land
777460.4321	293070.0861	Farm Land
780056.8710	291349.8912	Farm Land
779065.0541	291114.3491	Farm Land
775809.4100	287294.8243	Farm Land
778067.6817	286945.1689	Farm Land
768192.1265	287209.0478	Farm Land