FOREST COVER CHANGE TREND AND ITS DRIVING FORCES IN HUGUMBURDA GRAKAHSU NATIONAL FOREST PRIORITY AREA, SOUTH TIGRAI, ETHIOPIA

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ACRONYMS

CA	Cellular Automata
CSA	Central Statistical Agency
DEM	Digital Elevation Model
DN	Digital Number
EPRDF	Ethiopian People's Revolutionary Democratic Front
EROS	Earth Resources Observation Science
FAO	Food and Agriculture Organization
FCC	Forest Cover Change
FGD	Focused Group Discussion
FWCDA	Forest and Wildlife Conservation and Development Authority
GCP	Ground Control Points
GIS	Geographic Information System
GPS	Global Positioning System
Ha	Hectare
HGNFPA	Hugumburda Grakahsu National Forest Priority Area
IPCC	Intergovernmental Panel on Climate Change
K	Kappa Coefficient
KIIs	Key Informants Interviews
LULCC	Land Use Land Cover Change
m. a.s.l.	Meter above sea level
MEFCC	Ministry of Environment Forest and Climate Change
MCE	Multi-Criteria Evaluation
MLC	Maximum Likelihood Classifier
mm	Millimeter
MOLUSCE	Modules for Land Use Change Evaluation
NFPAs	National Forest Priority Areas

NIR	Near-infra red
NMSA	National Meteorological Services Agency
OLI	Operational Land Imager
PFM	Participatory Forest Management
RS	Remote Sensing
SPSS	Statistical Package for Social Science
SRTM	Shuttle Radar Topography Mission
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
UNEP	United Nations Environmental Program
UNFF	United Nations Forum for Forestry
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
WGS 84	World Geodetic System 1984

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIXES

ABSTRACT

Detecting and monitoring forest cover change can enable understanding previous, current and the future conditions of the forest. The objectives of this research was to detect the forest cover change using multi-temporal satellite images, quantify the rate of Change, to identify the proximate and underlying driving forces of forest cover change to develop model and predict the change on forest cover from 2018 to 2034 using Cellular Automata Simulation Model in Hugumburda Grakahsu National Forest Priority Area. Satellite images of 1990, 2002, 2014 and 2018 were used to do the change detection analyzes. household survey, key information interview and focus group discussion are used to collect the Socio-economic data. IMPACT Toolbox software and, Quantum GIS were used to analyzed the data. Cellular Automata Simulation Model was used to predict future forest cover change. The result revealed that during the study period (1990-2002) and (2002-2018) forest coverage increased by 1815.30 ha (28.25%) and decreased by 727.56 ha (8.83) respectively. If the existing rate of forest cover change continue forest is predicted to decrease by 2,739.24 ha, (36.46%) of the existed forest in 2018 will be lost in 2034. The major proximate drivers of forest cover change in the study area are Overgrazing, Wood extraction, Crop activities, and Settlement expansion. Weak policy implementation, lack of strong institutional arrangement, high human population growth, socio-political & cultural factors, and urbanization are also the main underlining drivers in the study area. This study recommends applying Reduction Emission from Forest Degradation and Deforestation Plus and Participatory forest management to reduce the alarming rate of deforestation in the study area.

Keywords: QGIS, IMPACT Toolbox, Forest cover change Drives, Ethiopia

1. INTRODUCTION

1.1BACKGROUND

Forests are essential sources of income to millions of individuals and means of development of numerous countries. They are critical for sinks of carbon and contribute to the rate of climate change, soil formation, and water regulation and are expected to offer direct employment to at least 10 million individuals (Tubiello, 2015).

A study by Naemi et *al*. (2011) stated that the world forest has been diminishing from time to time due to the growing human population for many centuries. Unfortunately, the deforestation rate (0.5%) has enlarged tremendously in developing countries in the last 50 to 100 years. In Africa, forests cover about (21.4%) of the land area which matches to 674 million hectares where Eastern Africa alone cover around (13%) of the land area under the forests and woodlands (Forkuo and Frimpong, 2012). The forest resources of Ethiopia are declining each in size and quality; in the early 1950s, high forest coverage which was 16 % of the land area were reduced to 3.3 % in the early 1980s, and further declined to 2.7 % in early 1990s (Melaku, 2001). According to a study carried out by Brink et *al.* (2014), the distribution of forest cover in Ethiopia was 15,114,000 ha, 13,705,000 ha, 13,000,000 ha and 12,296,000 ha in the years 1990, 2000, 2005 and 2010 respectively.

According to Feoli et *al*. (2002), improving the management of the natural resources while providing ecological services and immediate economic requirements is the main research and development challenges for the degraded areas of northern Ethiopia. In the 1980, 58 'National Forest Priority Areas (NFPA's)' covering an area of 3.6 million ha were demarcated that should guarantee better protection of the forest. Instead, expertise shows that degradation doesn't stop at the borders of these NFPAs (Reusing, 2000). The demarcation of NFPAs created a great deal of conflict with local communities who lost their farming and pasture to National Forest Priority areas and during the fall of the military regime in 1991, a lot of these forest areas were ‘reclaimed’ by local people (Melaku, 2003). Since then demarcation of the forest estate has more or less stopped due to lack of investment in the sector and the lack of capacity and resources at the local level to carry out such activities (Ayana et. *al*. 2013; Teketay et. *al*. 2010). The lack of clear boundaries and weak on-the-ground enforcement has meant that these state forests are in practice “open access” (Melaku, 2003; Ayana et.*al*. 2013). Other studies indicated that the protection of these NFPA's has not been effective due to the increasing human and livestock pressure on the resource base and lack of sustainable management and failure to fully recognize the rights and interests of local communities in forest products and forestlands (Leul e.t *al*, 2010). The Federal Forest Proclamation(No. 542/2007) provides the general framework for the sector and enforcement at the state level; however, for the law to be effectively implemented, detailed directives and regulations are needed (Tafere et. *al*., 2013).

However, the different studies didn't show the magnitude of forest cover change, rate, and trends of change. Therefore RS based Change detection and modeling of FCC enable to understand previous, current and future conditions of the forest ecosystem, Since monitoring of forest cover change is one of the main applications of remote sensing-based change detection Yismaw et *al*. (2014), So conducting this research was an important issue because updated datasets on LULC change provide critical inputs to evaluate complex causes and responses to project future trends better, ranging from local, regional, to global scales (Prenzel, 2004).

1.2 STATEMENT OF THE PROBLEM

Hugumburda Grakahsu National Forest Priority Area (NFPA) was recognized to introduce an enhanced management system. Zenebe and Sisay (1998) noted that this forest resource is on the verge of complete depletion due to the high population pressure and increasing demand for agricultural land. Forestland encroachment and illegal cutting of trees are uncontrolled and a result depleting most valuable indigenous tree species, and wild animals, are becoming severely affected in the study area.

Even though this study tries to show the forest is under critical problem, he fails to quantify the rate of forest cover change. Besides, adequate studies was not conducted which identify the main underlining & proximate drivers of forest cover Change, since LULC change differs with time. That is why this study has quantified the rate and trend of forest cover change, identified the major proximate and underlying driving forces of forest cover change over the last 28 years, modeling and predicted forest cover from 2018 to 2034 of the study area; which is very important to develop for further sustainable management plans of the NFPA.

1.3 OBJECTIVES

1.3.1 GENERAL OBJECTIVE

The overall objective of this study was to detect the forest cover change through multi-temporal satellite images and identify the driving forces in LULC of Hugumburda Grakahsu National Forest Priority Area in the Northern Ethiopia Tigray Regional State.

1.3.2 SPECIFIC OBJECTIVES

1. To detect the forest cover change using multi-temporal satellite images from 1990 to 2002 and from 2002 and 2018 and quantify the rate of Change.

2. To identify the proximate and underlying driving forces of forest cover change for the time period between 1990 and 2018.

3. To develop model and predict the change on forest cover from 2018 to 2034 using Cellular Automata Simulation Model

1.4 RESEARCH QUESTIONS

1. What are the forest cover change and rates between the years 1990 and 2018 in the study area?

2. What are the Proximate and Underlying driving forces of forest cover change?

3. What will be the future forest cover change from the year 2018 to 2034?

1.5 JUSTIFICATION OF THE STUDY

The result of the study will have different advantages for the local, national and global communities. By evaluating the historical and current FCC trend and driving forces behind the changes, it helps to understand the deforestation rate and what type of changes will be also expected in the future. It can provide information to policy and decision-makers to design appropriate policies and strategies for monitoring deforestation and promote sustainable management of forest resources of the study area. Government and non-government organizations, researchers and local communities can benefit from the result of this research.

1.6 SCOPE OF THE STUDY

The study was conducted in HGNFPA. The National forest touches four woredas, namely; Enda-Mekoni, Raya-Azebo, Raya-Alamata, and Ofla. There are 12 Kebeles found inside and in the periphery of the study area. The Study used Landsat TM 5 years 1990 and 2002 and Landsat 8 OLI/TIRS 2014 and 2018 to analyze forest cover change in the study area for the last 28 years. Spatial variables (proximity to road and settlement, slope and elevation was also used to calibrate develop model. IMPACT Toolbox and MOLUSCE plugin were used for LULC classification, Change detection analyzed and modeling prediction. Household survey, KIIs, FGDs and field observation was conducted to collect the socio-economic data. SPSS version 22 was used to analyzed the FCC drivers.

2. LITERATURE REVIEW

2.1 CONCEPTS AND DEFINITIONS

Clear and correct concepts and definitions of forests are significant to manage it.

Forest definition present the hypothetical, institutional, and operational ground for policymakers and monitoring systems that drive deforestation, reforestation, forest degradation, and restoration (Van and Minang, 2009).

Forest concepts and definitions management tend to value and perceive forest transitions the modification over time within the stability between forest loss and forest gain enclosed by a geographical area where each loss and gain square measure outlined in terms of tree cover. In most cases, forest loss is determined and rapid and can be documented with a series of satellite imagery, whereas forest gain, is a highly variable, and protracted process that is demanding to document and monitor with usually used forest definitions and technology (Chazdon, 2014).

The purposeful, structural, and compositional properties of new tree cover differ significantly from those of the forest or non-forest ecosystems they restore (Chazdon, 2016). New tree cover can take many forms from impulsive natural regeneration to single-species plantations of non-native trees. Local forest disturbance and ingrowths that convoy tree harvesting and silvicultural management are also complicated to detect and monitor.

Differentiating among these completely different varieties of tree cover gain poses a way bigger challenge than distinguishing areas wherever forest cover has been removed. Generally used forest definitions that perform well for assessing rates of deforestation as considered by rates of transformation of forest to non-forest land uses have not proved useful in assessing forest restoration and regeneration.

From the "land cover" viewpoint, forests are viewed as ecosystems or vegetation types supporting exceptional assemblages of plants and animals. But from the "land use" viewpoint, forests are landholdings that are legally designated as forest, despite their current vegetation. Within this construct, a legally designated "forest" can be devoid of trees, at least temporarily. No single prepared forest definition can, or should, exemplify all of these dimensions. (Chazdon et *al*., 2016).

2.1.1 FOREST DEFINITIONS ADOPTED BY DIFFERENT ORGANIZATIONS

United Nations Food and Agriculture Organization **(**Gold, 2006): Land with tree crown cover of more than 10 % and area of more than 0.5 ha. The trees ought to be able to reach a minimum height of 5 m at maturity in situ. May consist either of closed forest or open forest formations with a continuous vegetation tree crown Cover exceeds 10%. Young natural stands and plantations established for forestry reasons which have yet to reach a crown thickness of 10 % or tree height of 5 m are also incorporated under forest. Ethiopian National Definition of Forest (MEFCC, 2016): 'Land spanning at least 0.5 ha covered by trees reaching a height of at least 2 m and a canopy cover of at least 20% or trees with the likely to reach these thresholds in situ in due course'. The research is done using this definition.

2.2 RS AND GIS IN FOREST COVER CHANGE DETECTION

Remote Sensing could be a method of endeavor data concerning the Earth's surface while not being in contact with it by sensing and recording reflected or emitted energy and processing, investigating and applying that information. RS method for forest cover change detection and monitoring has been used to assess the differences in forest cover over two or more periods caused by environmental condition and human events. RS and GIS are practical tools in estimating and validating ecosystem changes arising from forest use and forest management interventions(Hall et *al*., 2008).

Another unique value of RS data is that it provides a means of quickly identifying and delineating different forest types, a task that would be difficult and time-consuming using traditional ground surveys. Species classification can be performed with multispectral, hyperspectral, or air photo data interpretation. Satellite RS is a broadly used technique to produce LULC maps and to study vegetation cover (Fung et *al*., 1994). Usually, data about earth's features are acquired either from the aerial photography or from satellite imagery. Aerial photographs are in analog form while images are basically in digital form. The remote sensing detector measures the electromagnetic energy (energy reflected or backscattered) by the earth's surface. The measured energy is changed and stored as a digital number (DN) value, which ranges from 0-255 (for 8 bit data).

Most sensors reflected sunlight (passive remote sensing) but, some sensors detect energy provide their source of energy (active remote sensing) (Lillesand et *al*., 2000). The reflectance is low in both the blue and red regions of the spectrum, due to assimilation by chlorophyll for photosynthesis; however, it is high in the green region. In the near-infrared

(NIR) region, the reflectance is much higher than that in the visible band due to the cellular arrangement in the leaves (Mather et *al*., 1999). Hence, vegetation can be recognized by the high NIR but generally low visible reflectance. The reflectance of bare soil, in general, depends on its composition. However, the reflectance of clear water is normally low.

Digital or visual image-interpretation techniques are applied to extract information from the satellite image data. For accurate image classification, data collected from ground-truthing or ground survey is associated with image data. In this way, a map showing a variety of 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 distinctive reflective characteristics of the forest.

A geographic information system (GIS) is a framework for gathering, managing, and analyzing data of geographic data and designed to efficiently capture, store, update, manipulate, analyze, and display all forms of geographically referenced information (Carrara et al.,1995).

2.3 LAND USE AND LAND COVER CHANGE

Land use and land cover (LULC) change is a universal term for the human alteration of Earth's terrestrial surface. Accordingly, though humans have been modifying land to obtain food and other basics for thousands of years, recent rates, extents and intensities of LULC change are far larger than ever in history, driving extraordinary changes in ecosystems and environmental processes at local, regional and global scales (Ellis, 2008). According to Ringrose et al. (1998) LULC change in Africa is at present accelerating and causing widespread ecological problems and thus needs to be mapped. As the land is utilized, the cover is also adapted, thus land cover change. Land cover change is a general term for the human adjustment of the earth’s terrestrial surface. It is, therefore, significant to monitor and mediate the unenthusiastic consequences of land cover change while supporting the production of vital resources (DiGiano et *al*., 2013). Thus, from the above, it can be said that land cover changes have all the time been part of human societies given that wherever humans are, they make their activities impact the environment.

Land use is a more complicated term. Natural scientists define land use in terms of conditions of human activities like forestry, agriculture, and construction that change land surface processes as well as biodiversity, hydrology, and biogeochemistry (Ellis and Porter, 2008). Similarly, They stated that social scientists and land managers define land use generally to consist of the social and economic reasons for and inside that lands, such as subsistence versus commercial agriculture, rented vs. owned, or private vs. community land. The land cover indicates the biological and physical cover over the surface of the land, as well as water, vegetation, bare soil, and artificial structures (Ellis and Porter, 2008). Land cover refers to the surface cover over land, as well as vegetation, rock and humanly modified surfaces (Ellis et *al*., 2009). Also, land cover is a feature of the land that can be observed actually by remote sensing.

2.4 CHANGE DETECTION BASED ON IMPACT TOOLBOX

Change detection is the technique of categorizing differentiation of an object or phenomenon by observing it at different times. Fundamentally, it involves the ability to quantify temporal effects using multi-temporal data (Singh, 1989). Remote sensing offers a feasible source of data from which reorganized land cover information can be taken out efficiently to inventory and monitor changes successfully (Mas, 1999). Thus change detection has become the main function of remotely sensed data since repetitive coverage at short intervals and consistent image quality.

IMPACT Toolbox is a software using satellite imagery and it is proposing a series of modules simplifying those tasks, as many intermediate steps are wrapped in unique functions (Vogt, 2017). IMPACT Toolbox presents an arrangement of fundamentals of remote sensing, photo analysis and processing technologies in GIS, allowing users to just realize all necessary pre-processing steps while giving a fast and user-friendly for visual editing and map validation (Simonetti et. *al*., 2015).

This software is used for land use land cover classification based on Object-based Image Segmentation based on very latest and advanced IMPACT Toolbox open software.

Object-based image analysis is divided into three steps: Multi-resolution Segmentation, produce general classes, and categorization rules to be calculated hierarchical stages in a trial and error practice to characterize single objects of interest (Moeller et *al.,* 2004). The algorithm is an optimization method that minimizes the heterogeneity and maximizes their homogeneity based on defined parameters. Segmentation parameters namely; shape, scale, and compactness are defined through trial and error to successfully segment objects in an image (Yan et al., 2006).

2.5 ACCURACY ASSESSMENT

An accuracy assessment is carried out to evaluate the uncertainty of the forest area change estimates and to develop the forest area change estimates by correcting for the systematic error in the map. The accuracy assessment is carried out by obtaining Enhanced data for sample points and comparing this data with the map classification. Enhanced data can be higher resolution data than the resolution of the imagery used for the classification or a better interpretation, a human interpretation rather than an algorithm. An error matrix is a square array of numbers organized in rows and columns which expresses the number of sample units assigned to an exacting group related to the real group (Congalton, 1998). The overall accuracy is average with the accuracy of each class weighted by the proportion of test samples for that class in the total testing sets and 85% is its minimum threshold (Anderson, 1976). The overall accuracy is more accurate of accuracy (Yang, et *al*., 2001).

According to Paul (2013) the User's accuracy corresponds to the error of commission. It refers to the measurement of how many of the samples of a particular class matched correctly. On the other hand, the producer's accuracy corresponds to errors of omission. It is a measure of how much land in each LULC category was classified correctly. According to Frohn and Chaudhary (2013) Classification accuracy will be improved due to: 1) use of multiple scales in the segmentation procedure for categorization of incidences at the right scale; 2) incorporation of shape, textural, contextual, and spectral information in the classification process; and 3) use of multi-temporal data to capture both leaf on and leaf off properties of land cover categories.

The importance and power of the Kappa analysis are that it is possible to test if a LULC map is significantly better than if the map had been generated by randomly assigning labels to areas. It is wide used attributable to all parts within the classification error matrix, and not just the main diagonal, contribute to its calculation and because it compensates for change agreement (Naesset,1996). The Kappa coefficient lies normally on a scale between 0 and 1. Thus Kappa values are differentiated into three groups; a value larger than 0.80

stands for a strong agreement, a value between 0.40 and 0.80 stands for moderate agreement, and a value below 0.40 stands for poor agreement (Congalton,1998). Kappa can be used as an evaluation of agreement among model predictions and actuality if the values enclosed in an error matrix clarify a result considerably better than random (Jensen and Ji, 1999).

2.6 PREDICTION OF FUTURE FOREST COVER CHANGE

2.6.1 TRANSITION POTENTIAL MODELLING

Several techniques are existing for computing transitional potential maps. Multi-Criteria Evaluation, Artificial Neural Network, Logistic Regression and Weights of Evidence are available in the MOLUSCE plugin (Alghaliya, 2017).

MOLUSCE is a user-friendly plug-in for QGIS 2.0 and above and it is designed to analyze, model and simulate land use/cover changes. The plug-in incorporates well-known algorithms, which can be used in land use/cover change analysis, urban analysis as well as forestry applications and projects. MOLUSCE is well suited to analyze land use and forest cover changes between different time periods, model land use/cover transition potential or areas at risk of deforestation and simulate future land use and forest cover changes (Alghaliya, 2017).

Multi-Criteria Evaluation (MCE): is an approach and a technique to help decision-makers to explain, assess, sort, rank and select or reject based on evaluation based on numerous criteria (Sharifi, 2008). MCE technique uses land use cover information and the spatial variable as inputs for calibrating and modeling land use land cover changes. Open GIS software (QGIS) was used to facilitate this process.

The primary issue of Multi-criteria Evaluation (MCE) is how to join the information from different standards to form a single index of evaluation (Mideksa, 2009). Thus the first step to run MCE is come to a decision, investigating and producing proximity to forest cover area data stets or factor maps which were factors for forest disturbance. The interrelation among factors disturbing land-use change may be difficult. For a first approximation, combine all factors by conveying differential weights to each of the factors (Hall et *al*., 2019).

2.6.2 CELLULAR AUTOMATA MODEL

Cellular Automata (CA) model has been used to study land-use changes development takes place in each neighborhood are continually a purpose of the shape, size, and a number of the developed cells in the neighborhood (Wu, 1999 and White et *al*., 1997). The CA proposes a regular pattern of similar cells, each of which may be in one of a fixed number of separate states at separate time steps in its development (Torrens et *al*., 2001). System dynamics are determined by transition rules which map the present state of a cell’s neighborhood at a time, to an outcome cell situation at the time.

2.6. 3 VALIDATION

The variation in accuracy of the model predictions depends on the time scale used, the number of land classes modeled and the accuracy of initializing data. Topographic features are more important than climate variables for large scale simulations where the topography is harsh (Hall et *al*., 2019). Similarly, he stated that land-use change is influenced greatly by population growth and land-use policy, but physical features determine the pattern of land-use change. The value of predicted forest in this study to the year 2014 based on forest and non-forest reclassified LULC of Years 1990 and 2002 to compare based on actual forest and non-forest LULC 2014 is the way of validation. Araya and Cabral (2010) the value greater than 80% is reasonable to make future projection.

2.7 DRIVERS OF DEFORESTATION AND FOREST DEGRADATION

Internationally, crop expansion and timber extraction are the main driving forces at the back of deforestation, commercial and subsistence activities responsible for 40% and 33% respectively, and infrastructure expansion, mining, and urban development cumulatively being responsible for the rest (Hosonuma et *al*., 2012). He also indicated in this study, Africa with small-scale activities such as charcoal production and fuelwood collection still playing a central role despite these general trends, the drivers of deforestation are dynamic and it is likely that rising demand will result in the homogenization of threats as the activities responsible for deforestation throughout the tropics come to play an increasing role in Africa also.

Apart from Northern Africa, East African countries show the second-highest decline rates of conservation forests in the continent (Abate and Abate, 2017). Although Ethiopia has a wide range of vegetation covers, soil types, and topography in Africa; it is still one of the most critically affected by deforestation due to its rising population (Singh, 1989).

Ethiopia has suffered extreme historical deforestation, principally due to agricultural expansion coupled with population growth (Hailu et *al*., (2015). The leftover indigenous forest cover is concentrated in remote mountain areas and small forest patches of huge protection importance (Bongers and Tennigkeit, 2010). Expansion of urban areas and inappropriate administration of forests by a state actors are other drivers of deforestation (Zhu et *al*., 2016). It can be argued that continued forest degradation and deforestation confound poverty alleviation efforts on two fronts. The poorest communities living within or nearby to forested areas are often dependent on forests for survival (Wolosin et *al*., 2012). Deforestation and forest degradation therefore excessively affect them. Their susceptibility becomes further marked with changing climatic patterns, which change forest activity.

Solomon et *al*. (2018) carried out a study in Wujig Mahgo Waren forest which is adjacent to Hugumburda-Grakahsu NFPA shows that; fuelwood collection, cultivated land expansion, population growth; free grazing, logging for income generation and drought were the major drivers of forest cover change. Deforestation and forest degradation to be driven primarily by overgrazing, fuelwood extraction and charcoal production next by agricultural development, construction and timber production in Ethiopia. population growth, insecure land tenure, and poor law enforcement were also identified as underlying causes of deforestation and degradation (MEFCC, 2016).

Although various strategies for tree planting and natural resource conservation in the Ethiopian highlands are proposed, their successful implementation will be limited unless social, economic, and policy issues are addressed properly (Kidu et *al*., 2017).

The causes of deforestation accompanied by the loss of biodiversity can be explained on 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 reasons for deforestation (Mideksa, 2009).

Another aspect that harms the ecological value of forests is conventional tourism (Mideksa, 2009). As the human population increased, the demand for arable land was inevitable and, gradually, agricultural activity started to dominate vast areas from a gentle slope to the steeper slopes of the high mountains and the conversion of land to agriculture had also extended into the flat swampy plains of the plateau (Hurni, 1993). Moreover, through the influence of humans, most of the high forests, 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. In his findings stated that the increasing demand for croplands, grazing land, construction poles and fuelwood including charcoal production are the main reason for the forest cover change in Ethiopia. Also, 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 an input for agricultural production and livestock grazing (Birhanu, 2014).

2.7.1 PROXIMATE CAUSES OF DEFORESTATION

Proximate causes of deforestation are to comprise (near-final or final) human actions that directly affect the environment (Qasim et *al*., 2013). In terms of scale, direct causes are seen to operate at the local level. Proximate causes are generally grouped into three broad categories: agricultural expansion, wood extraction, and expansion of infrastructure (Geist, 2002).

2.7.2 UNDERLYING CAUSES OF DEFORESTATION

Underlying driving forces can be seen as a complex of social, political, economic, technological, and cultural variables that encompass the initial situation in the human-environmental associations that are structural (Geist, 2002). Underlying drivers may activate directly at the local level, or indirectly from the national or global level. In this study Geist grouped underlying driving forces are into five broad categories. These are demographic factors (human population), economic factors (commercialization, development, economic growth), technological factors (technological change or progress), policy and institutional factors (change or impact of political-economic institutions, institutional change), and socio-political or cultural factors (values, public attitudes, beliefs, and individual or household behavior).

3. MATERIALS AND METHODS

3.1 DESCRIPTION OF THE STUDY AREA

3.1.1 LOCATION

Hugumburda-Grakahsu National Forest Priority Area is located in the southern zone of Tigray about 600 km north of Addis Ababa. Geographically, it is located between (1369311- 1403661) m latitude and between (549558 - 568606) m longitude (Figure 1). The elevation of the study area ranges from 1475 to 3284 m.a.s.l and its slope ranges from 0.34 to 89.1 % according to the extracted DEM map of this study (Table 6 and Figure 12).

Different studies indicated different areas in their research. Leul et *al*. (2010) indicated HGNFPA is covered total area of 21, 564.25 ha. Leul (2015), stated as the total coverage of HGNFPA is 24,175.80 ha and out of this, 532.75 ha is plantation forest whereas the rest disturbed natural forest, shrubs, scrubs, agricultural lands, and settlement area. But in This Study the total area of the NFPA had taken 21,564.44 ha, almost similar with (Leul et *al*., 2010) given by Regional Agricultural Beauro.

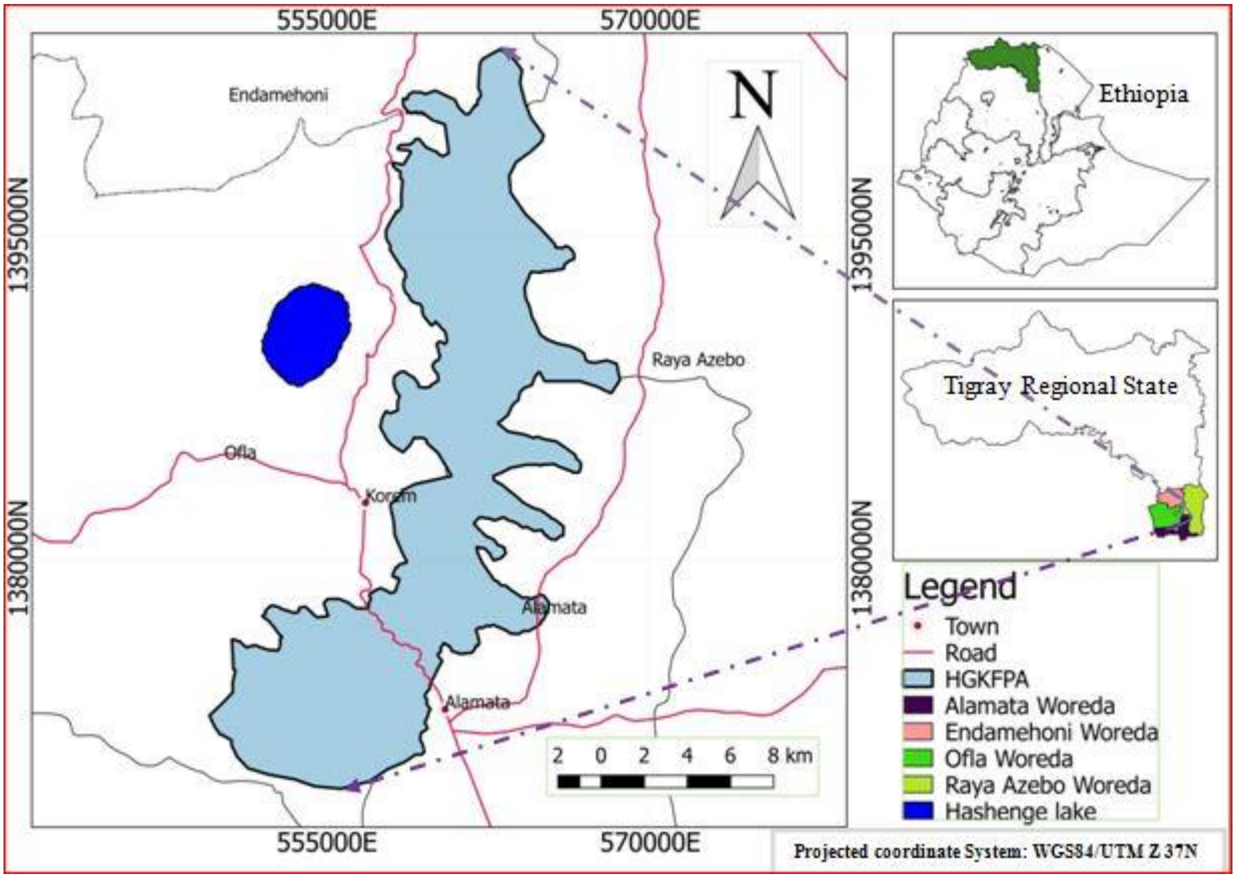


Figure 1: Map of the study area.

Source: Author

3.1.2 CLIMATE

Two meteorological stations; Alamata and Korem are available close to the study area. Leul et *al*. (2018) indicated that 35 years meteorological data (1978–2013) showed that the mean annual temperature for Alamata was 21.9 °C and the mean minimum and maximum were 12.1 and 33.5 °C, respectively and the mean annual temperature of Korem station was 15.3 °C with a mean minimum of 5.4 °C and a mean maximum of 24.7 °C. He also indicated in this study the hottest months are April and June, while coldness is from September to November. Similarly, the mean annual rainfall for Alamata and Korem is 705 and 986 mm, respectively, the low rainfall season is from February to May and the main rainy season is from June to September (Leul et *al*. (2018).

3.1.3 VEGETATION

The area was covered with dense forest composed of various native species at the beginning. According to Zenebe and Sisay (1998) the natural forest was exploited by Italian concessionary named Montu Doro, who installed Sawmills at Hugumburda in 1950.

According to Leul et *al*. (2010) the forest was formally put the auspices of State Forest Agency in 1965 and the area was also recognized as the National Forest Priority Areas in 1981. Lastly the boundary demarcation was undertaken after 12 years of the demarcation in 1993. He also indicated in this research the average cultivable landholding size of each household is estimated at 0.26 ha and the major crops are grown are wheat, barley, sorghum, pea, and Fababean. Agriculture is the mainstay of the economy in the area.

3.1.4 POPULATION

According to CSA (2007) Population and Housing Census of Ethiopia, the study Weredas in 2007; 108210; 136039; 118557; 142803 Population was lived in Enda-mekoni, Raya-Azebo, Raya-Alamata, and Ofla Weredas respectively. Totally 505,609 population lives in these weredas. Out of this 248,916 were male and 256,693 were male. According to CSA, (2013), Population projection values; a total of 581154; 592286; 603411 and 586513 population were lived in years 2014; 2015; 2016 and 2017 respectively in the study Weredas (Figure 2). There are 26,889 households within and around the forest boundary (CSA, 2007), out of which

5,496 households are fully within the forest area and the rest 21,393 in the periphery of the forest (Leul et *al*., 2010).

3.2 SPATIAL DATA COLLECTION METHODS

To investigate the forest cover change and rate of in the study years (1990-2018) cloud-free Landsat5 TM 1990 & 2002 and Landsat8 OLI/TIRS 2014 & 2018 was downloaded from freely available United States Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) via (https://earthexplorer.usgs.gov/). Landsat8 OLI/TIRS 2014 was used for model validation. To reduce the effect of seasonal variability images were downloaded between May and April, two months is less in cloud appearance in the study area and also the availability of time-series images. The base year 1990 was selected by considering the transition period of political power from military power to EPRDF and NFPA Boundary demarcation was undertaken in 1993 (Leul et *al*., 2010). The technical details of the satellite data that were used in the study are presented in (Table1).

DEM was downloaded from freely available (https://earthexplorer.usgs.gov/) using SRTM with 30 m x 30m resolution. Then spatial elevation data and spatial slope data of the study area were extracted from DEM using QGIS. The spatial data of settlement and road for the years 2002 and 2018 were digitized from the Google earth map of the study area.

150 Ground Control Points (GCPs) for accuracy assessment for the historical periods and 2018 were collected using Global Positioning System (GPS) from the field (Appendix 4). The GCPs are generated proportional to the area of land use land cover class using QGIS. To the inaccessible areas and for the images of the historical period GCPs were collected both with the help of high-resolution Google Earth satellite image of the reference years and by

interviewing Key informants and recording their code of the class in the attribute table of the shape file.

Table 1: Description of satellite imageries used in LULC change detection

Date of Acquisition	Satellite imagery	Spectral resolution	Scene coverage (Km*Km)	Path/row	Spatial resolution (m)	Cloud cover (%)
24/5/1990	Landsat 5 TM	Band 1 to 5 & 7	170*183	168/51	30	< 5
25/5/2002	Landsat 5 TM	Band 1 to 5 & 7	170*183	168/51	30	< 5
8/5/2014	Landsat 8 OIL/TIRIS	Band 2 to 7	185 * 180	168/51	30	< 5
23/4/2018	Landsat 8 OIL/TIRIS	Band 2 to 7	185 * 180	168/51	30	< 5

Source: USGS

3.3 SOCIO-ECONOMIC DATA COLLECTION METHODS

3.3.1 FIELD OBSERVATION

Field observation was carried twice throughout the study area: one during the social data collection period to have a broader understanding of study areas, and second, during collecting the Ground truth points using GPS with the help of local guide and draft classified maps derived from satellite images with reference years. Besides, interviews were held with the KIIs during the field observation.

3.3.2 HOUSEHOLD SURVEY

The study area covered four woredas; namely Raya Alamata, Raya Azebo, Enda-mekoni, and Ofla. One Kebele was selected from each Wereda using purposive sampling. Kulugize-lemlem, Werebayen, Tahtay-haya and Huguburda Kebeles were selected from the above Weredas respectively. The selection of the Kebeles was based on their proximity to the forest area, their dependence on the forest for their livelihood. According to Wolosin et *al.*, (2012), the poorest communities living within or nearby to forested areas are often dependent on forests for survival. Deforestation and forest degradation therefore excessively affect them. Their susceptibility becomes further marked with changing climatic patterns, which change forest activity. The selection of the participants were purposively who live for more than 28 years in the study area using the formula developed by (Israel, 1992).

$n = N/(1+N(e)^2)$..Equation (1)

Where 'n ' is the required sample, 'N' is the total HH population, 'e' permitted error (0.05) determined by the level of accuracy i.e. 95 %.

$$n = \frac{6208}{1 + 6208\,(0.05)^2} = 376$$

The interviewees were also calculated proportional to their HHs using the formula:

$n_x = (N_x/N)*n$..Equation (2)

Where' $n_{x'}$ is the sample size of the Kebeles,' N_x' is the HH population of the Kebeles , 'N' is the total HH population and 'n' is the total required sample.

$n_{\text{Werebayen}}$ = 2622/6208*376 = 159 HH

$n_{\text{Tahtay-haya}}$ = 1521/6208*376 = 92 HH

$n_{Huguburda}$ = 1135/6208*376 = 69 HH

$n_{Kulugize\text{-}lemlem}$ = 930/6208*376 = 56 HH

A total of 376 households; 159; 92; 69 and 56 households from Werebayen, Tahtay-haya, Huguburda and Kulugize-lemlem Kebeles respectively. The detail household sample size of Kebeles and total households are presented in (Appendix 7). Both closed and Open ended questionnaire were used to collect the socio-economic data (Appendix 8).

3.3.3. FOCUS GROUP DISCUSSIONS

A total of six focus group discussions (FGD) was carried. Two FGDs each was conducted in Kebeles Kulugize-lemlem and Werebayen. Because the forest is under pressure due to Kulugize-lemlem is nearest to Alamata town and also Werebayen Kebele is highly populated. Whereas in the rest two Kebeles one FGD of each was conducted. The FGDs were composed of five to eight members with different stakeholders such as; Woreda experts, Woreda Administrators, and Kebele Administrators and elders were involved. A total of forty-one participants was conducted in the six FGDs; Out of this the two FDGs having a total of twelve members were female. Topics and Checklist for discussion related to the drivers of forest cover change during the last 28 years and the current status of the forest were used (Table 2). The selection of FGDs participants was done with the help of Woreda experts and Kebele Administrations based on their age, elders who live more than 28 years at the study area, forest guards and experts was included in the FGD.

Table 2: FGD Participants

No	FGDs Members	Kebeles				
		Kulugize-lemlem	Werebayen	Tahtay-haya	Huguburda	Total
1	Woreda experts	1	1	1	1	4
2	Woreda Administrators	1	1	1	1	4
3	Kebele Administrators	4	4	2	2	12
4	Elders	9	4	4	4	21
Total		15	10	8	8	41

Source: Author

3.3.4 KEY INFORMANT INTERVIEWS

To obtain depth information about the study area and to collect ground control points of the historical period five key informant interviews (KIIs) were conducted in each selected Kebeles. A total of twenty KIIs were conducted; Out of these eight of them were female. The participants were selected purposely based on their age (Who live more than 28 years in the study area), have the knowledge and good information on the study area. A topics checklist was prepared to guide the key informants (Table 3).

Table 3: KII Participants

No	KIIs Members	Kebeles				
		Kulugize-lemlem	Werebayen	Tahtay-haya	Huguburda	Total
1	Elders	4	4	4	4	16
2	Forest guards	1	1	1	1	4
Total		5	5	5	5	20

Source: Author

3.4 DATA ANALYSIS

To take the advantage of advanced open-source software (Impact Toolbox Version 4.6.6 beta) over Supervised Classification, the Object-Based Image Segmentation Classification result was used in this research. Because the object-based image analysis has better accuracy than the pixel-based image classification result (Shiferaw, & Suryabhagavan, (2019)). Similarly, the Object-oriented approach can contribute to powerful automatic and semi-automatic analysis for most remote sensing applications (Benz, et *al*,.2004).

All spatial imagery was projected to projected coordinate system, WGS84/UTM Zone 37N datum. Image Pre-processing and post-processing had carried out. All spatial data had geometrically aligned with each other. Image pre-processing such as; (band setting (bands 1-5,7 for Landsat 5 & bands 2-7 for Landsat 8), image stacking, defining the specific study area, image enhancement, DEM extraction to slope and elevation) had carried out.

To eliminate the effects of atmospheric scattering, absorption and to increase the accuracy of surface type classification, radiometric correction had conducted by converting the raw digital number (DN) values to top of atmosphere (TOA) reflectance data from different sensors are calibrated to a common radiometric scale, minimizing spectral variations due to acquisition time, sun elevation, and sun-earth distance. Similarly image post-processing such as accuracy assessments, LULC Change, future forest cover prediction and statistics extraction such as LULC percentage along slope gradient and elevation and distance of settlement and road to the forest, reclassification to a forest and non-forest land-use land cove had conducted. The LULC was reclassified to forest and non-forest because it is very difficult to predict multiple land use types under a coarse resolution (Hall et al., 2019).

To conduct segmentation process the following segmentation parameters were applied to the IMPACT Toolbox algorism. Aggregation rule; majority, Segmentation algorithm; Multi-date segmentation, Strategy; Baatz, Scale (Minimum Mapping Unit (MMU)); 6 pixels which is equivalent to 0.5 ha to considering the definition of forest. Then 0.5, 0.75, 0.75 were used for Compactness, Similarity and Color respectively. Similarly False Color Composition of bands; RGB 4,3,2 and RGB 5,4,3 was used for Landsat5 and Landsat8 respectively. Finally, the segmented polygons having a common border were merged in QGIS (Laliberte et *al*., 2004).

Raster bands and associated weight to be used Scale factor. This factor controls the spectral heterogeneity of the image objects and is therefore correlated with their average size. Smaller it is, more objects you will get Color: Spectral component ranges between (0, 1). Compactness also similarly ranges between (1,0), which indicates morphological component. Similarity represents the minimum Euclidean Distance (expressed in DN values) to be used while merging segments. Low values will allow aggregation of heterogeneous objects (Simonetti et. *al*., 2015).

The shape consists of compactness and smoothness. Compactness indicates the closeness of pixels bunched in an object. Object-Based Image works on homogeneous objects produced by image segmentation and extra elements can be used in the classification. As an object is a group of pixels, object characteristics such as standard deviation, ratio, mean value, can be calculated with a single image object of one pixel and repeatedly merges them in several loops in pairs to larger units (Shiferaw, and Suryabhagavan, 2019).

To produce accuracy assessment and generate a LULC Conversion matrix for each study period an open-source software Quantum GIS (version 2.18) was used. To evaluate the accuracy of the classified images, the error matrix was generated based on the GCP that was collected from the field and in the help of high-resolution Google Earth satellite image of reference years and compiled in a matrix table.

Kappa was computed as, K = $\frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})}$ .... equation (3)

Where N is the total number of samples in the matrix, r corresponds to the number of rows in the matrix, x_{ii} is the number in row i and column i, x_{+i} is the total for row i, and x_{i+} the total for column i.

Producer's and User's accuracy was also calculated as follow respectively:

Producer's accuracy = Total no of samples correctly classified for a given category/Total no of samples classified to that particular category...equation (4)

User's accuracy = Total no of samples correctly classified in a given category/Total no of samples in that category...equation(5)

Total land use land cover Change (LULCC) in hectare was also calculated as follow:

Total LULC Change = A_f - A_i .... equation(6)

where A_f is the area of final year, and A_i is the area of the initial year

An annual rate of LULC change per hectare (ha)computed using the following formula:

$r = \frac{a-b}{t}$ .... equation (7)

Where r = Annual Rate of forest cover changes in ha, a = Recent year forest covers in ha, b = Initial year forest covers in ha, t = Number of years between a and b. Positive values indicate an increase whereas negative values imply a decrease in extent.

An annual rate of forest cover changes in percent (%) computed using the following formula:

$$r_{(\%)} = \frac{a-b}{a} * \frac{100}{t} \quad \text{......equation(8)}$$

Where r = Annual Rate of forest covers change in percent (%), a = Recent year forest covers in ha, b = Initial year forest covers in ha, t = Number of years between a and b. Positive values indicate an increase whereas negative values imply a decrease in extent.

Percentage area change across the time of analysis period was accounted for as:

$$\% \Delta = \frac{A_f - A_i}{A_i} \times 100 \quad \text{...... equation(9)}$$

Where % Δ is percentage of given LULC class Change, A_f is the area of final year, A_i is the area of the initial year.

A correlation was checked among the spatial data using Pearson's correlation. Proximity (distance to settlements and distance to the road) was calculated using Euclidean distance. As Euclidean distance is the most popular technique used by scholars in doing proximity of spatial variables with MCE method.

The Transition potential of the prediction model was developed and calibrated through reclassified proximity (settlements & road), reclassified (elevation & slope), and reclassified LULC map layers of 2002 and 2018 as spatial drivers Hall et al. (2019) and Alghaliya (2017) using MCE techniques in MOLUSCE plug-in (QGIS version 2.18). Assigning weights for each dataset and combining based on their weight was the subsequent procedure for conducting MCE in this study. MCE is a method that can be used to create a partiality for disturbance maps based on rules that relate independent variables to the likelihood of disturbance. These rules were set by empirical statistical techniques (Pontius et al., 2004).

Slope was reclassified into four categories, i.e., gentle slopes (0%–5%), moderate slopes (5%–15%), steep slopes (15%–30%), and very steep slopes (>30%), (FAO,1990). Elevation was reclassified based on agro-ecological zone of the study area according to Hurni (1998) as Dry lowlands ("Kola") 1000 to 1500 m.a.s.l, Sub- humid highlands ("Weyna Dega") from 1,500 to 2,300 m.a.s.l, humid highlands ("Dega") from 2,300 to 3,200 m.a.s.l and cold highlands ("Wurch") above 3,200 m.a.s.l. The reclassified slope and elevation data were overlaid with the LULC of 1990, 2002 & 2018 respectively in QGIS to calculate the distribution and change of LULC along slope gradient and elevation.

Model validation is an important step in the modeling process although there is no consensus on the criteria to assess the performance of land-use change models (Pontius, (2000)). Hence validation was conducted by cross-checking the predicted forest area change of reclassified to forest and non-forest LULC year 2014 (based on reclassified LULC of years 1990 & 2002) then comparing with the actual reclassified to forest and non-forest LULC year 2014. Comparing the result of the model prediction for time t_2 to the real map of time t_2 is the only way to quantify the predictive power of the model (Adanen & Getachew, 2017).

$$\text{Ratio}_{\text{correct}}(\%) = \frac{1}{N}\sum_{i=1}^{m} C_{ii}. \quad \text{..equation(10)}$$

Where: $\text{Ratio}_{\text{correct}}$ (%), is the overal accuracy (fitness of the model), *Cii, is* in the diagonal represents the number of pixels that are correctly classified for class *i,* N, is number of reference pixels.

Then prediction for the year 2034 was conducted using Cellular Automat Simulation (CAS) model in QGIS MOLUSCE plugin based on reclassified LULC map of 2002 & 2018. CA in addition to offers a new way of decision for dynamic method modeling, they have natural similarity with GIS and remotely sensed data (Wu, 1999 and White et *al*., 1997).

Statistical Package for the Social Sciences (SPSS version 22.0) Software and Microsoft office Excel were applied to analyze the qualitative data. The result was presented in maps, narratives, and summarized by descriptive statistics such as frequencies tables, figures, and graphs.

Table 4: Description of LULC Classes are according to (MEFCC,2016)

LULC CLASS CODE	LULC CLASS NAME	DESCRIPTION
F	Forest	'Land spanning at least 0.5 ha covered by trees (including bamboo) attaining a height of at least 2 m and a canopy cover of at least 20% or trees with the potential to reach these thresholds in situ in due course.'
SS	Shrubland & Scrubland	Land with shrubs/bushes canopy cover ≤ 20% or combined cover of bush, and shrubs ≤20%. Shrubs and bushes are woody perennial plants, <2 m in height at maturity in situ: And low bushes and stunted trees, mostly spiny either deciduous or evergreen. More than half of the surface of the ground is bare of vegetation.
A	Agriculture	Arable and fallow land that grow annual crops (wheat, maize, sorghum, „tef", Cotton etc) or perennial crops (, sugar cane, coffee and permanent fruit trees) on the small scale or commercial level by rain fed or irrigation schemes.
BR	Bare land	It is land of limited ability to support life and in which less than one-third of the area covered by vegetation or other cover. It may be constituted by bare exposed rock, Strip mines, quarries and gravel pits. Unusual conditions, such as a heavy rainfall, occasionally result in growth of a short- lived, more luxuriant plant cover.
BU	Built-up	An area is those areas composed of intensive use with much of the land by rural villages and roads.

Source: Adopted from (MFCC, 2016)

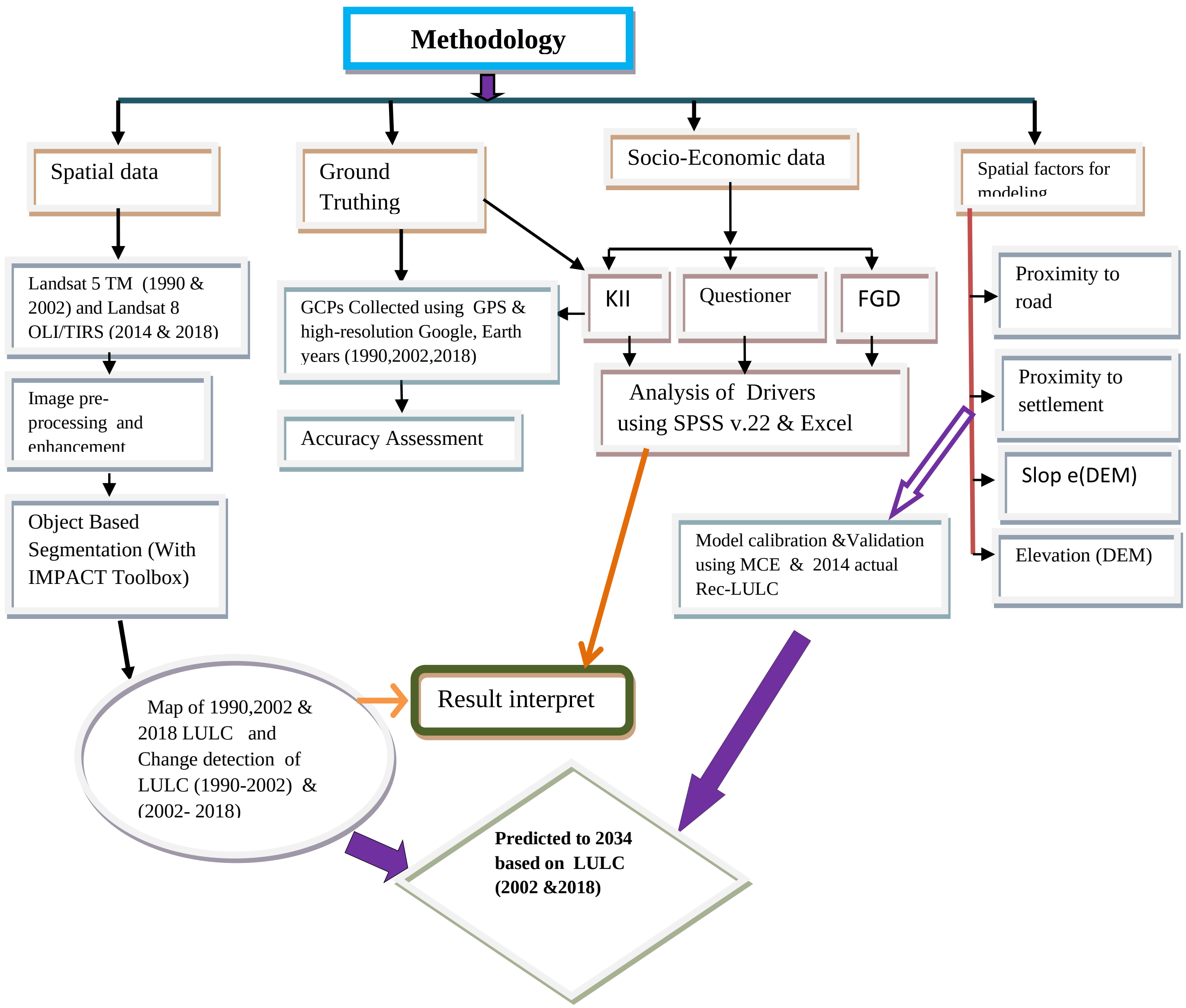


Figure 2: Research flow chart that shows the general Methodology

Source: Author adopted from different literature

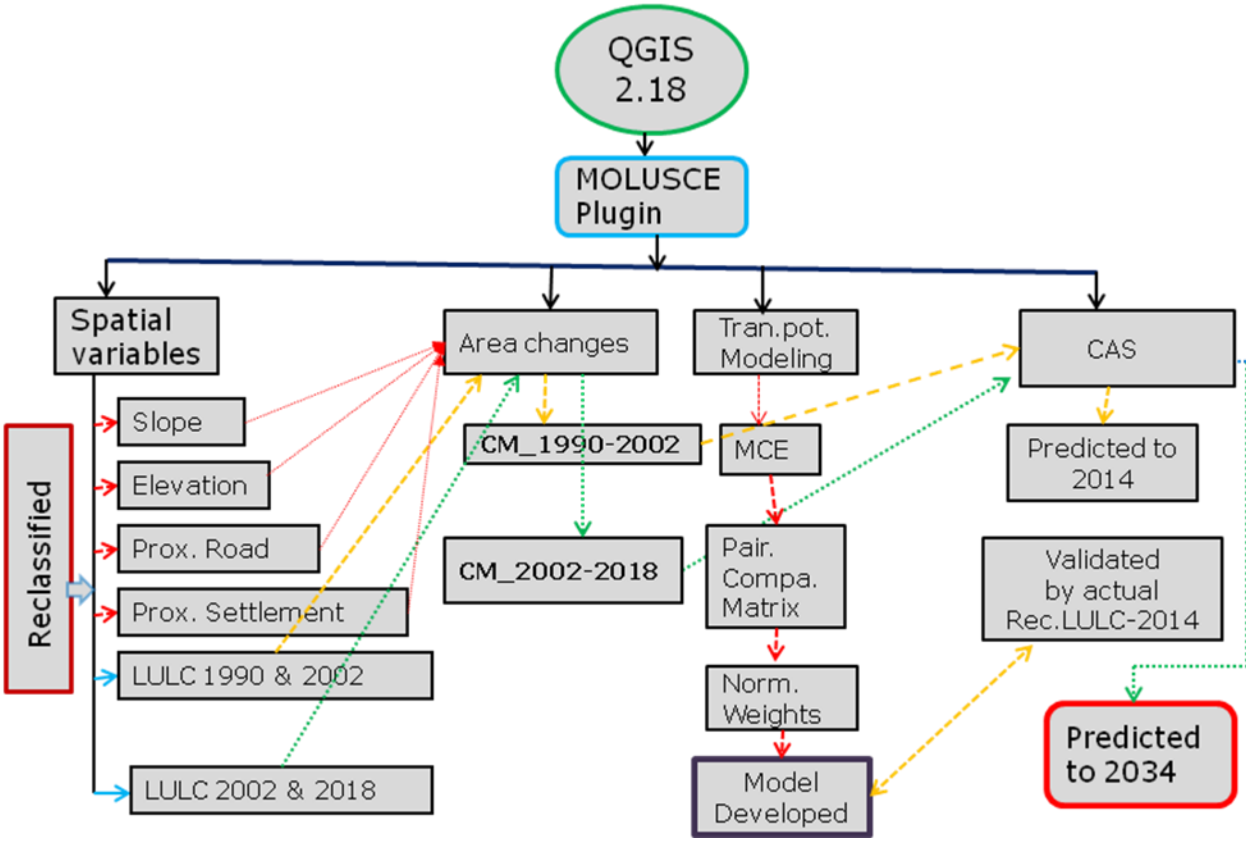


Figure: 3 Modeling and Prediction Flow Chart

Source: Author

4. RESULT AND DISCUSSION

4.1 CHANGE DETECTION RESULT

In the study area, five classes of land use and land cover were represented namely Forest land, (Shrub and Scrub) land, Agricultural land, Bare land and Built-up areas (Table 4).

Forest land was the most dominant land cover next to (Shrub and Scrub) land in the study area covers 6424.38 ha in 1990. In the first study period (1990-2002), it increased by 1815.30 ha. This is due to the demarcation of Hugumburda Grakahsu NFPA Boundary conducted in 1993 (Woldemichael et al., 2010) and decreased from the human and animal interference.

Whereas in the second study period (2002-2018) it decreased by 727.56 ha (Table 5; Figure 5 and 6). In the first study period Agricultural land, Bare land and Built-up areas increased by 822.60 ha, 497.34 ha and 197.10 ha, but Shrub & Scrub) land decreased by 332.34 ha. While in the second study period (Shrub & Scrub) land and Built-up area increased by 1114.65 ha and 998.91 ha respectively (Table5).

Built-up area was increased throughout the study period. Though Agricultural land decreased in the second study period, the net change throughout the study period shows increased. Therefore expansion of Built-up area and Agricultural land were the main drivers of deforestation in HGNFPA. This is due to high population growth in the study Weredas CSA (2013) demanded land for settlement and Agriculture.

This result is also supported by Zenebe and Sisay (1998) have conducted study at the area noted that, due to high population pressure and therefore increasing demand for agricultural land, the forest resource is on the verge of complete depletion. In addition to these, the encroachment of forest land and illegal cutting of trees are uncontrolled and as a result, the most valuable indigenous tree species, are becoming severely affected in the area.

A study by Solomon et *al*. (2018) carried out in Wujig Mahgo Waren forest, which is adjacent to Hugumburda Grakahsu NFPA show that; fuelwood collection, cultivated land expansion, population growth; free grazing, logging for income generation and drought were the major drivers of forest cover change. Another study by Bongers and Tennigkeit (2010) and Hailu et *al*. (2015) also indicated that Ethiopia has suffered extreme historical deforestation, principally due to agricultural expansion joined with population growth.

Table 5: LULC Change from year 1990 to 2002 and 2002 to 2018 top to bottom

	1990		2002		2018	
LULC Classes	Area (ha)	%	Area (ha)	%	Area (ha)	%
Forest land	6424.38	29.79	8239.68	38.21	7512.12	34.83
Shrub & Scrub land	9349.29	43.35	6016.95	27.9	7131.6	33.07
Agricultural land	1932.84	8.96	2755.44	12.78	2408.31	11.17
Bare land	3376.89	15.66	3874.23	17.96	2835.36	13.15
Built-up area	482.04	2.24	679.14	3.15	1678.05	7.78
Total	21,564.44	100	21,564.44	100	21,564.44	100

Source: Computed by Author

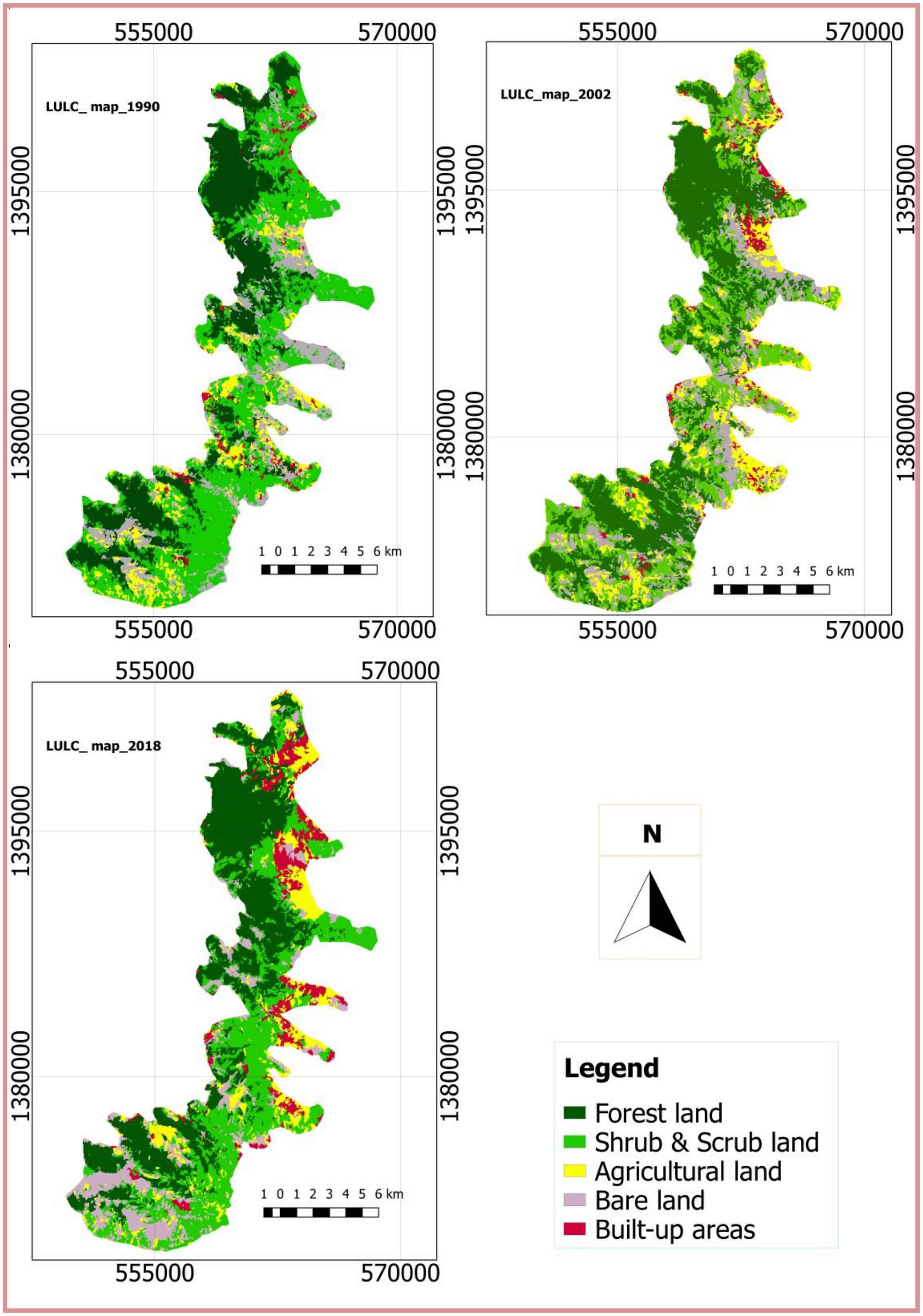


Figure 4: LULC Classes Map for the Years 1990, 2002 and 2018
Source: Author

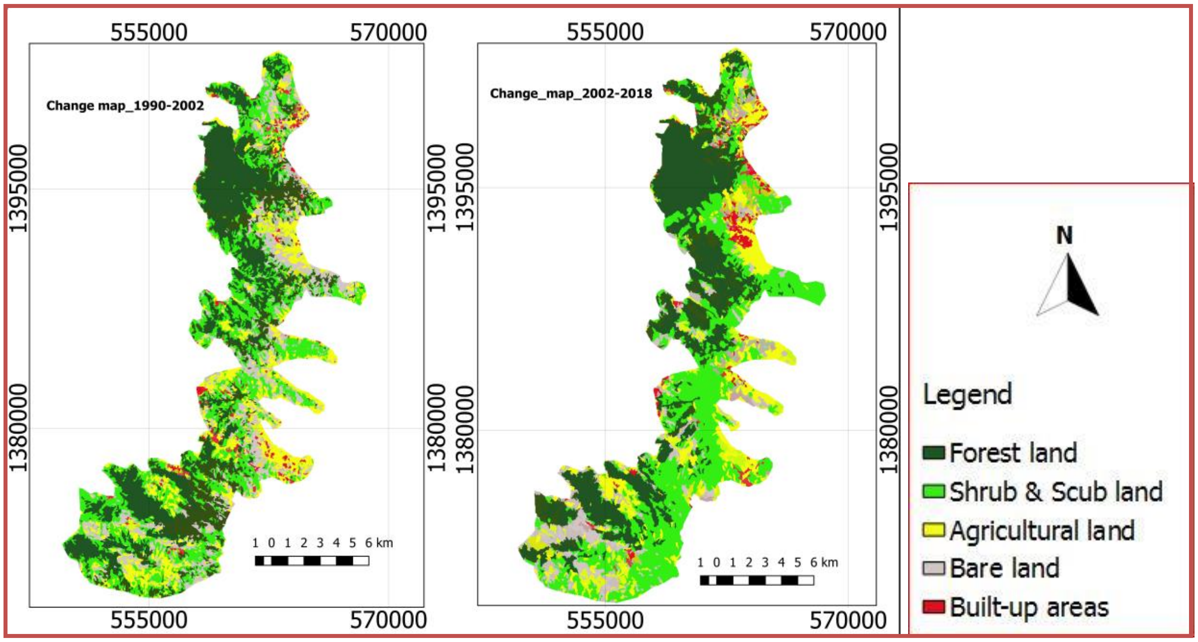


Figure 5: LULC Change Maps during 1990 - 2002 and 2002 - 2018 left to right
Source: Author

4.1.1 LAND USE LAND COVER CHANGE MATRIX

The conversion matrix was analyzed for each period to understand from which land use land cover class to which land use land cover class were converted. Results are presented in proportion (Appendix 2). The row of the table stand for the initial year and the column of the table stand for the final year of the change. The diagonal numbers showing the unchanged pixels. The result of change matrix during the first study period from 1990 to 2000, Out of 6424.38 ha forest 1531.57 ha (23.84 %) of the Forest land were converted into other LULCs; 19.6 %, 1.09 %, 2.69 %, and 0.46 % Forest land changed to Shrubland & Scrubland, to Agricultural land, to Bare land and Built-up area respectively (Appendix 2). Similarly forest cover change matrix result from second study period 2002 to 2018, Out of 8239.68 ha forest 2738.87 ha (33.24 %) Forest land converter into other LULCs; 22.46 %, 4.07 %, 3.19 %, and 3.51 % Forest land;

changed to Shrubland & Scrubland, to Agricultural land, to Bare land and Built-up area respectively (Appendix 2). There were also LULC conversion from the other land use land covers.

In (Appendix 2), Shows high percentage of change from Agricultural land and Built-up area to other LULC in the first and second study periods. This seems unusual, but it is due to the resettled of the dwellers outside of the NFPA because of voluntary and Government efforts. As the KIIs result voluntary dwellers were resettled every year out of the forest due to wild animals damaged their crops and attach their animals. In addition to this they were also resettled due to agreement done with Government from Ofla Woreda, Kebele Wenberet to Woreda Raya-Alamata, Kebele Selam-bikalsi, Adi-Moye village in the year 1991 which is outside of the HGNFPA.

The other reason may be the similarity of spectral reflection between Built-up area (scattered settlements), Bare land and Agricultural land (during fallow period) in coarse resolution of Landsat 5 TM and Landsat 8 OLI/TIRS. But to minimize such problem the classification was conducted via Object-based Image Segmentation through the latest and very advanced software (IMPACT Toolbox).

This result strengthens by FGDs & KIIs conducted in this study. The FGDs & KIIs result indicated the forest was changed from time to time to different land use such as; Shrubland, scrubland, agricultural land, bare land, and built-up area. The main reasons are increasing the price of wood in the market and the absence of electrification and alternative energy sources, overgrazing, expansion of cultivated land due to population increase, logging for income generation such as for agricultural instruments. This result is also highly related to the findings of the household survey (Figure 10).

The result indicated there were forest gain and loss in all study periods. In the study period between (1990-2002), 3346.83 ha, and between (2002-2018), 2011.68 ha forest had gained in addition to the demarcation of the NFPA, due to the continuous reforestation activities in the study area (Figure 7 & 8). As the report of KIIs, in addition to reforestation activities conducted by the government, the socio-culture of the local community has contributed to protecting the forest. They have the experience to conserve natural resources through 'Kire'. Kire is indigenous to the community used to set agenda to communicate and to make a decision in their social and political matters including forest issues.

However, there was also a high forest loss in the study area. 1531.53 ha and 2738.96 ha forest had lost between (1990-2002) and (2002-2018) respectively (Figure 7 & 8).

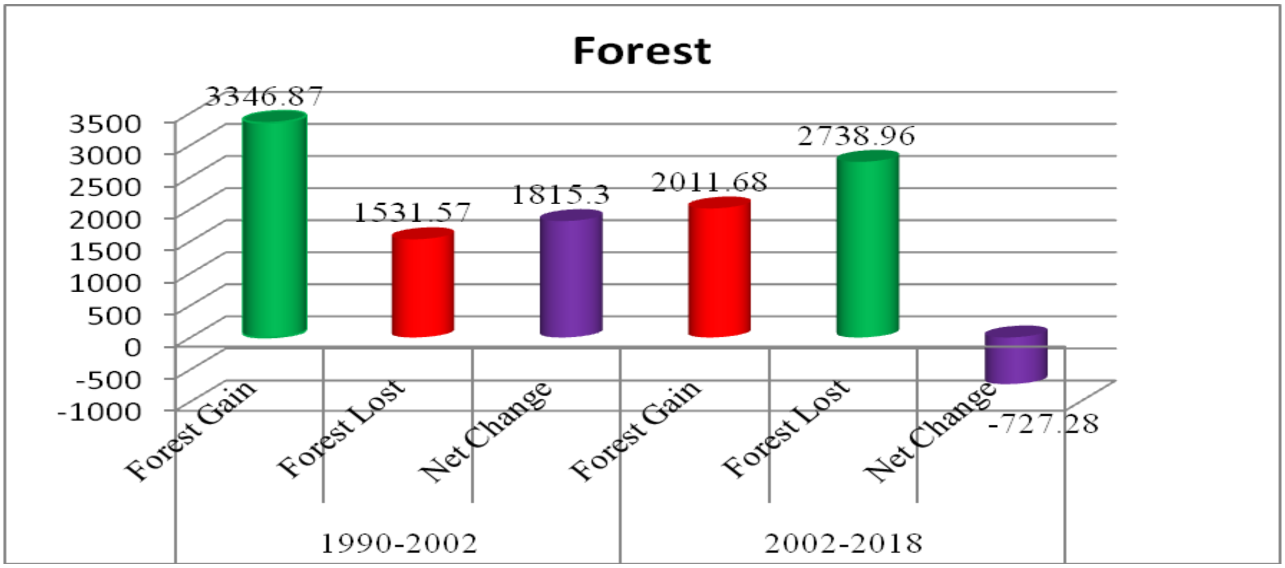


Figure 6: Forest gain and lost during1990 & 2002 and 2002 & 2018

Source: Author

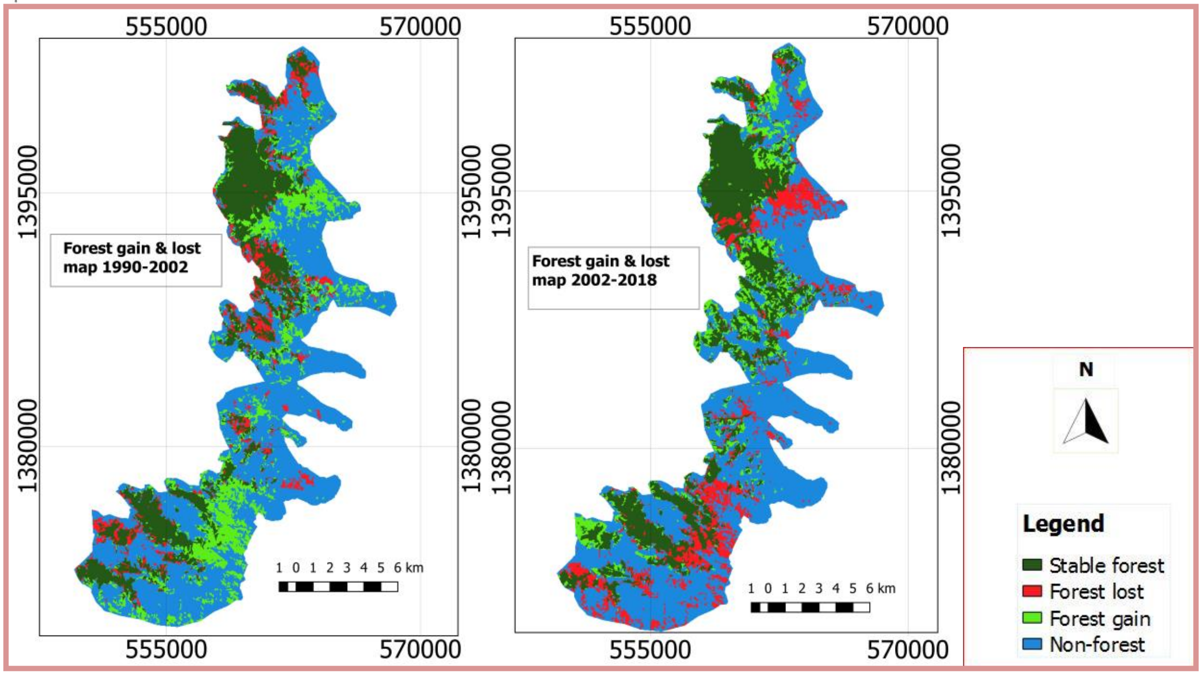


Figure 7: Forest gain and lost Map during 1990 - 2002 and 2002 - 2018 left to right

Source: Author

4.2 ACCURACY ASSESSMENT RESULT

The overall classification accuracy results of LULC of 1990, 2002 and 2018 are 82.0 %, 84.66 % and 91.33 % and the Kappa coefficient result 0.76, 0.79 and 0.88 respectively (Appendix 2). Hence the overall classification accuracy of 2018 LULC is 91.33 %, which is above the accepted limit Anderson (1976) stated 85% level of overall accuracy is an accepted benchmark. Even the overall accuracy of the historical period are approaching to the bench mark. Some literature indicated 80 % of accuracy assessment is accepted in their studies. And the Kappa value of the current LULC 2018 (0.88) laid in strong agreement, similarly Kappa value of the historical period (0.76 & 0.79) is approximate nearest to strong agreement (Congalton, 1998).

4.3 RATE AND TREND OF FOREST COVER CHANGES

Rate of forest cover change for the first study period (1990 - 2002) was increased by 151.28 ha yr $^{-1}$, whereas in the second study period (2002 - 2018) was decreased by 45.47 ha yr $^{-1}$ (Table 6). This result is supported by Abate & Abate, (2017) study. They have sated as that deforestation rates in East Africa are second highest of the continent, moreover it has the smallest portion of its forest area for conservation.

The forest land, agriculture and bare land was increased in the first period (1990-2002) and decreased in the second period (2002-2018), in contrast, Shrubland & Scrubland were decreased in the first period and increased in the second period. But built-up areas were continuously increased throughout the study period (Table 6).

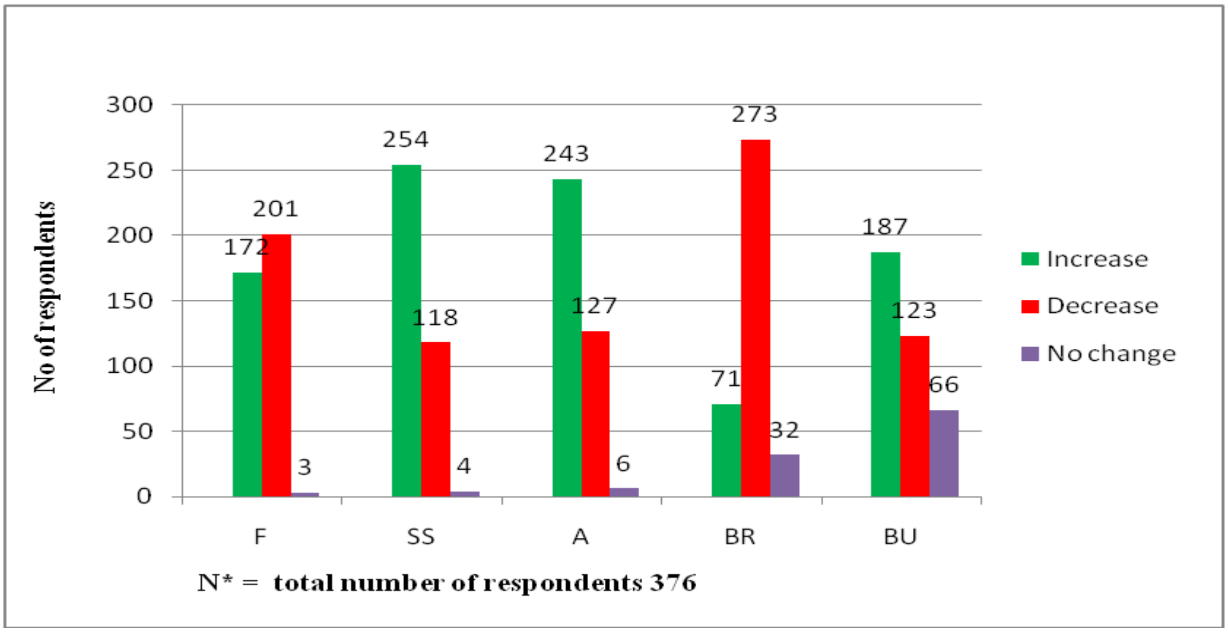
Table 6: Rate of Changes in LULC Classes in (1990-2018)

LULC Classes	1990 to 2002		2002 to 2018	
	Rate (ha/year)	(%)	Rate (ha/year)	(%)
Forest land	151.28	2.35	-45.47	-0.55
Shrub & Scrub land	-27.69	-0.29	69.67	1.16
Agricultural land	68.55	3.55	-21.69	-0.79
Bare land	41.45	1.23	-64.93	-1.68
Built-up area	16.43	3.41	62.43	9.19

Source: Author

4.4 THE SOCIO-ECONOMIC RESULT

The demographic characteristics of the household survey participants is presented in (Appendix 6). Out of the total 376 respondents 172 of them answered increased, 201 answered decreased and 3 answered no change for forest cover; 254 of them answered increased, 118 answered decreased, 4 answered no change for shrub and scrubland; 243 of them answered increased, 127 answered decreased, 6 answered no change for agriculture; 71 of them answered increased, 273 answered decreased, 32 answered no change for bare land and 187 of them answered increased, 123 answered decreased, 66 answered no change for built-up are (Figure 9). This result is more or less related to the result of the change detection using multi-temporal satellite images of years 1990, 2002 and 2018.



N* Number of respondents

Figure 8: Respondents' response for the status of LULCC from1990 to 2018

Source: Author

For the question have you observe FCC from the year 1990 to 2018 in HGNFPA?

Out of the total 376 respondents; 373 (99.2%) of them answered 'yes' and 3 of them answered 'no' (Table 7) below.

Table 7: Respondents' response for the question have you observe FCC in the last 29 years

Answer	Frequency	Percent
Yes	373	99.2
No	3	0.8
Total	376	100

Source: Author

Proximate drivers of FCC over the last 28 years in HGNFPA were Overgrazing, Wood extraction (domestic and market), Crop activities (agricultural expansion), Settlement expansion and others. Others are charcoal production, expansion of fire brake, exploit forest for house construction, mining, logging of forests for timber production,

Underlining drivers of FCC over the last 28 years in HGNFPA were weak policy implementation and lack of Strong institutional arrangement, Human population growth, Socio-Political and cultural factors (positively and negatively affected forest), Urbanization and others respectively (Figure 10). Others are; introduction of 'cochineal' insect (Opuntia ficus disease), insufficient forest gourd and low salary paid, sometimes conflict among forest guards and the local communities, even if the forest is demarcated the border of the forest is not clearly known by the local administrators and the community, absence of PFM, increasing the market value of the forest and forest product.

Similarly Melaku (2003) and Ayana et.*al*. (2013) researched Ethiopian NFPAs indicated that the lack of clear boundaries and weak on ground enforcement has meant that these state forests are in practice "open access". Tafere et. *al*., (2013) also indicated that, even if the Federal Forest Proclamation(No. 542/2007) provides the general framework for the sector and enforcement at the state level, detailed directives and regulations to in force the law at the ground are not yet developed 6 years after the proclamation.

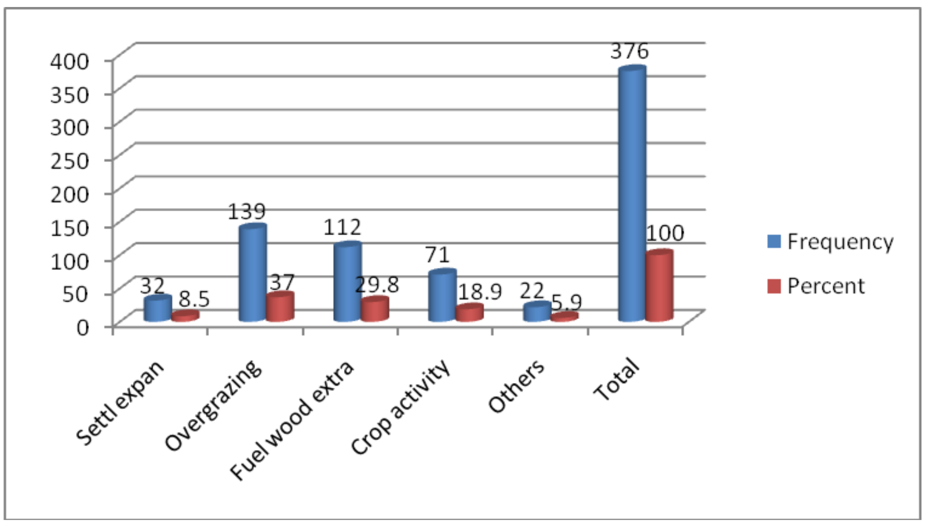
Zhu et *al*. (2016) also indicated in his findings, urban development and inappropriate administration of forests by a state actor are drivers of deforestation in Ethiopia. Bongers and Tennigkeit (2010) also concluded that, as the human population increased, the demand for arable land was inevitable and, gradually, agricultural activity started to dominate vast areas from a gentle slope to the steeper slopes of the high mountains of Eastern Africa. Hurni (1993) study conduct in Ethiopia indicated that the influence of humans, most of the high forests, particularly the dry evergreen montane forests as well as most of the moist evergreen montane forests, had been changed to farmlands.

Studies by Woldemichael e.t *al*, (2010) at Hugumburda Grakahsu NFPA, indicate that protection of the NFPA's has not been effective due the increasing human and livestock pressure on the resource base and lack of sustainable management and failure to fully recognize the rights and interests of local communities in forest products and forest lands.

Because of the introduction of Opuntia ficus disease (Belles) disease due to 'Cochineal' insect in the study area contributed to forest degradation and deforestation. The youth of Werebayen and Tahtay-haya Kebeles livelihood is directly shifted from the Cactus to the forest. As the information got from the FGD and KIIs Belles was played a vital role in the livelihood of the local community especially for the youth, animal feed, soil and water conservation, etc. After the destroying of the Belles, the youth trying to cut the forest for sale and the uncontrolled grazing become increase and increase.

This result is also supported by other studies such as Melaku (2003) and Ayana et.*al*. (2013) states that although several state forest areas have been identified, the lack of clear boundaries and weak on-the-ground enforcement has meant that these forests are in practice "open access". Birhanu (2014) also stated that forests in Ethiopia 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 an input for agricultural production and livestock grazing.

Similarly MEFCC (2016) reported that deforestation and forest degradation to be driven primarily by free livestock grazing, and fuelwood collection in all the regions followed by agricultural expansion, land fires, and construction wood harvesting and the underlying causes of deforestation and degradation were population growth, insecure land tenure, and poor law enforcement.



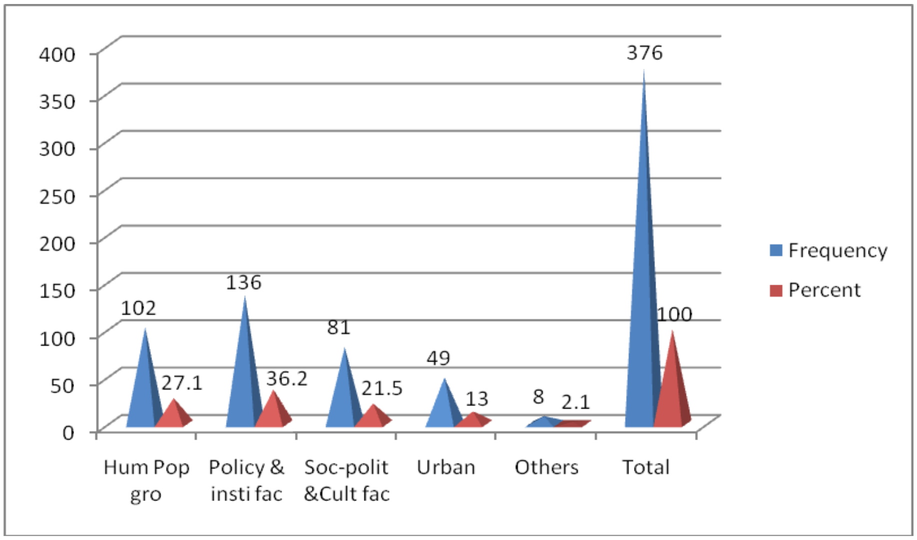


Figure 9: Respondents' response for the most Proximate and Underlining drivers of FCC over the last 28 years in the study area from top to bottom respectively.

Source: Author

According to the result of household survey 201 of the respondents answered the current status of the forest area is continuously decreases, 171 of them answered increases and 4 of them answered decreases (Figure 11). From this we can conclude the current status of the forest is decreased.

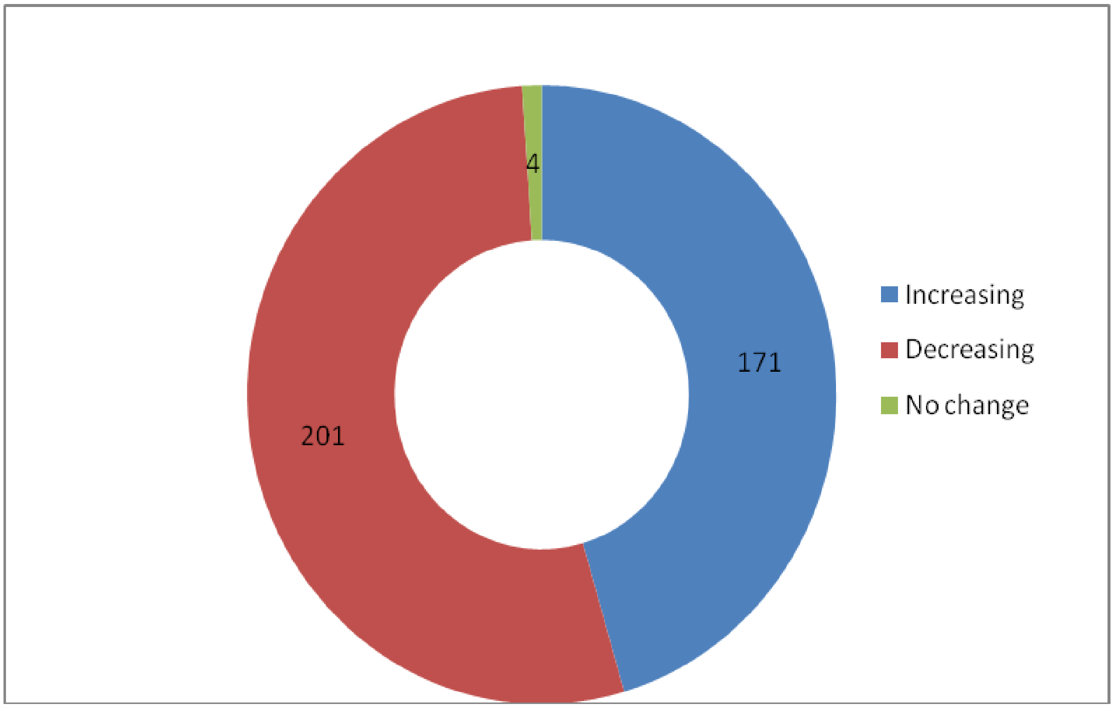


Figure 10: Respondents' response for the current status of forest in the study area
Source: Author

Out of the 376 total; 169 respondents answered forest degradation, 89 answered soil erosion, 99 answered plant diseases (Cupressus lusitanica) and 19 respondents answered drought respectively (Figure 12).

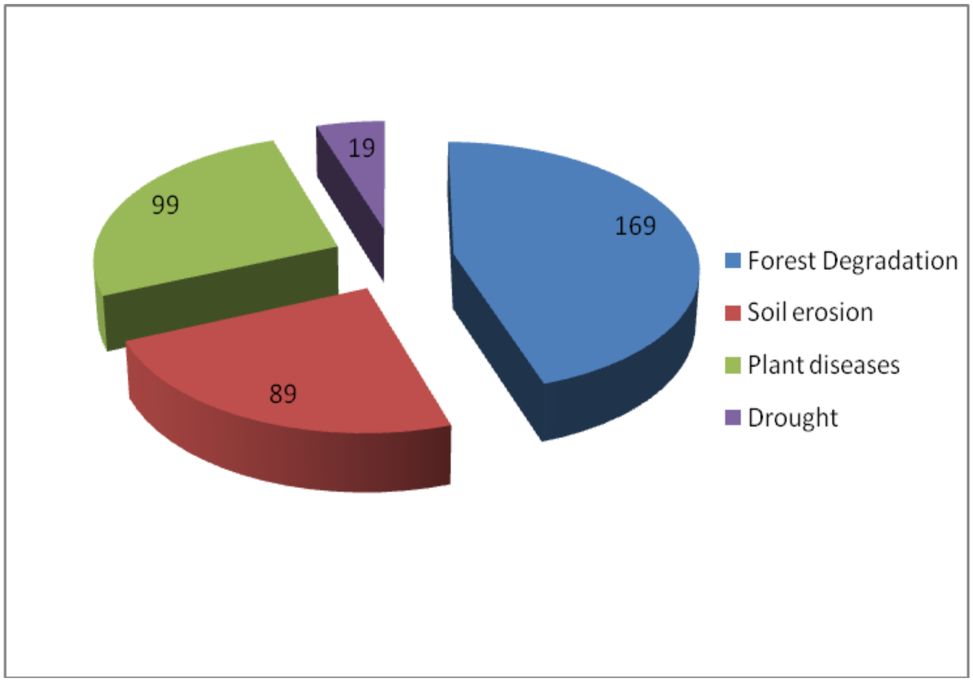


Figure 11: Respondents' response for events have occurred more frequently in the last 28 years in the study area.

Source: Author

The FGD participants and key informants identify four major Proximate driving forces of forest cover change in the study area. These are: 1) Overgrazing 2) Wood extraction (fuelwood extraction, commercial wood extraction), 3) Agricultural expansion (expansion of cropping activity, Shifting cultivation) and 4) Infrastructure extension (settlement expansion, transport extension respectively. Similarly The FGD participants and key informants identify four major Underling driving forces of forest cover change in the study area. These are: 1) Policy and institutional factor (Poor performance of and low policy implementation, property right), 2) Demographic factors (Human population growth), 3) Socio-political and Cultural factors (Public attitudes, values and believes at individual and public level) and 4) Economic factors (Urbanization, increase market accessibility, poverty and unemployment).

4.5 MODELING AND PREDICTING OF FUTURE FOREST COVER CHANGE

4.5.2 LULC DISTRIBUTION ACROSS DIFFERENT SPATIAL VARIABLES

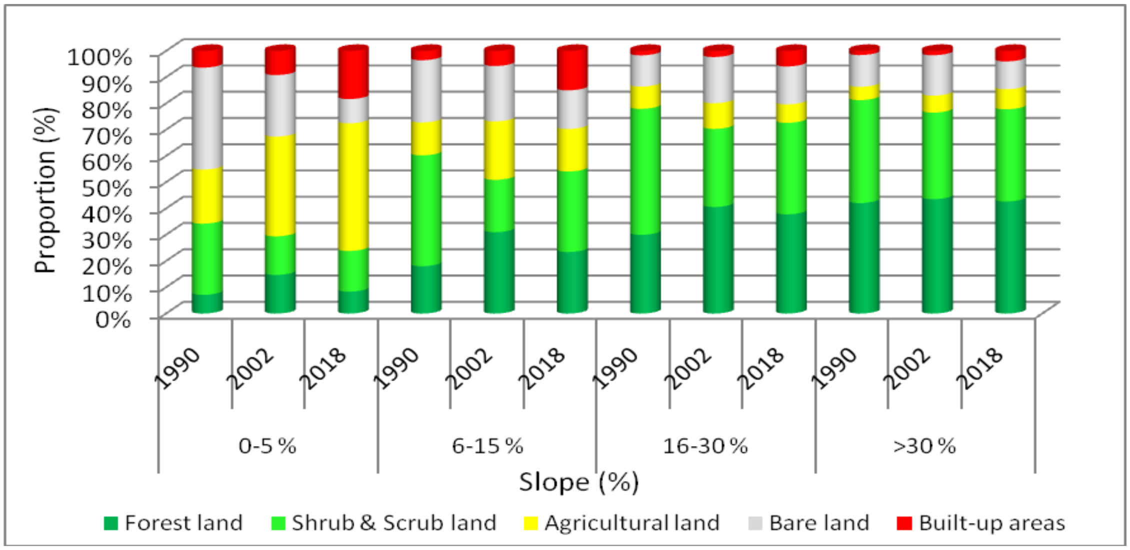
According to the overlay analysis out of the total area 5.26% laid in between 0-5 % slope, 19.38 % laid in between 6-15% slope, 47.98% laid in between 16-30 % slope and 27.38 % laid in between 30-90% slope; And 0.07% laid in between 1475-1500 m.a.s.l elevation, 69.12% laid in between 1500-2300 m.a.s.l elevation, 30.47% laid in 2300-3200 m.a.s.l elevation and 0.13% laid in between 3200-3284 m.a.s.l (Figure:13 and Appendix 3).

The study indicated, the proportion of forest became increased as the slope increased, whereas the proportion of built-up and agriculture decreased as the slope increased across the study periods (Figure 12). This result indicated that forest disturbance was decreased away from the relatively gentle slope gradient (0-5%) to the steep slope (30-90%). Gentler slopes were preferred to steep ones by a human for various agricultural uses because steep slopes are prone to erosion as compared to the gentler slopes. Based on this fact, gentle slopes were given highest values in terms of their influence on forest disturbance than steeper slopes (Table 8).

There is no forest land found in the elevation <1500 m.a.s.l, rather it was occupied by shrub and scrubland, agricultural land, bare land, and built-up area. But from the elevation 1500 to 3200 m.a.s.l the proportion of forest became increased whereas the proportion of agriculture and built-up areas decreased. In the elevation of (3200-3284 m.a.s.l) shrub and scrubland were the most dominant in the years 2002 and 2018, Whereas the proportion of forest became decreased (Figure 12). Similarly the lower elevation (1475-1500 m.a.s.l) of the study area was more important for crop cultivation and settlement than the elevation between (1500-3284 m.a.s.l). Hence, lower elevation was suitable for crop production, and settlements were more prone to forest disturbance than the higher elevation of the study area (Figure 12 & 13). Therefore, highest disturbance value was given to the lower elevation values than the higher elevation values (Table 8).

Proximity to settlements dataset also standardized to reclassify and to distinguish the future forest disturbance problem in the study area. Around the major settlement areas, croplands were expanding at the expense of natural forests. For this reason, proximity to settlements has been considered as one of the major factors in the forest disturbance analysis. The forest cover land near to settlement was highly prone to disturbance than the forest cover found far away from the settlement area (Figure 14).

Apart from the impact they have during their construction, roads provided access for a human to the forest. In the study area, the major road type was identified. From the reclassified asphalt road proximity dataset, forest cover areas having low distance value from road network location highly contributed to forest disturbance than those located far away from the road network, as it was more intensively used asphalt road contribute larger influence to forest disturbance by a human (Figure 14).



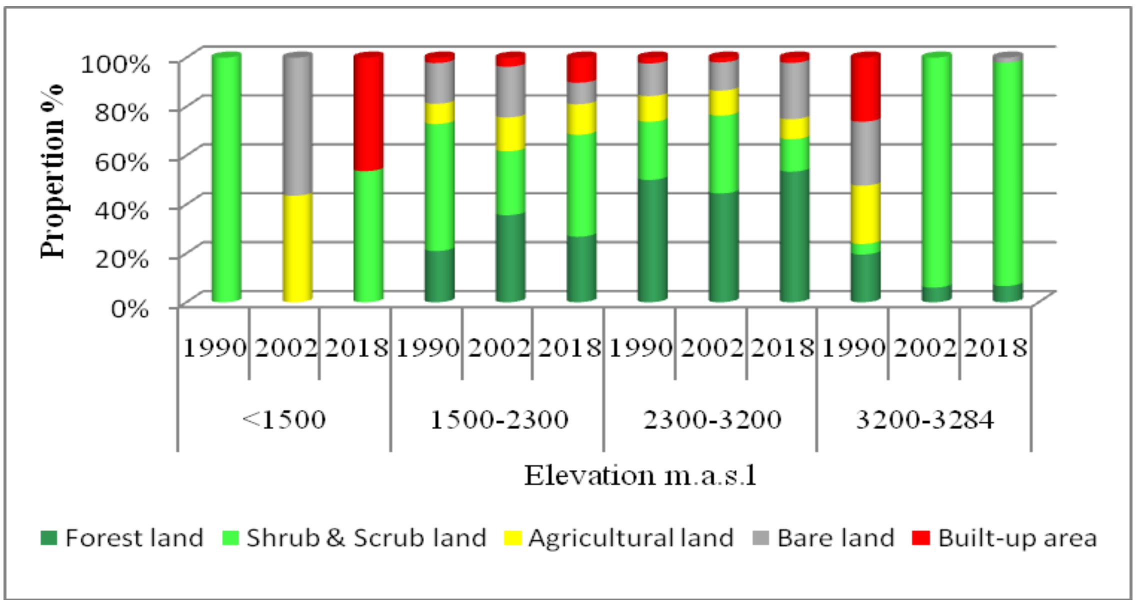
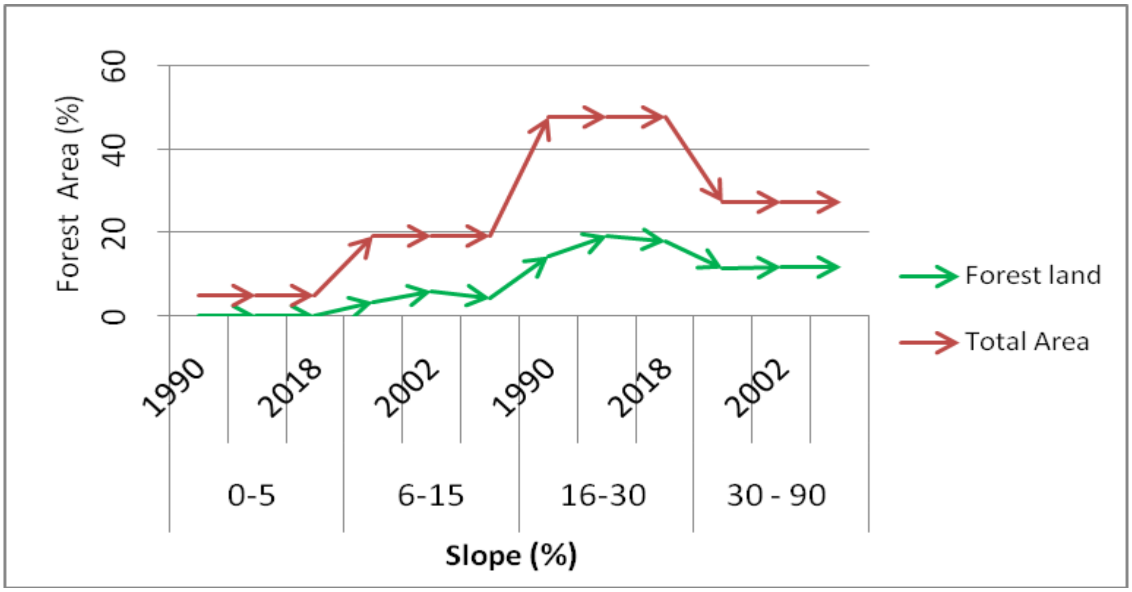


Figure 12: Proportion of LULC along the slope gradient and Elevation from top to bottom respectively

Source: Author



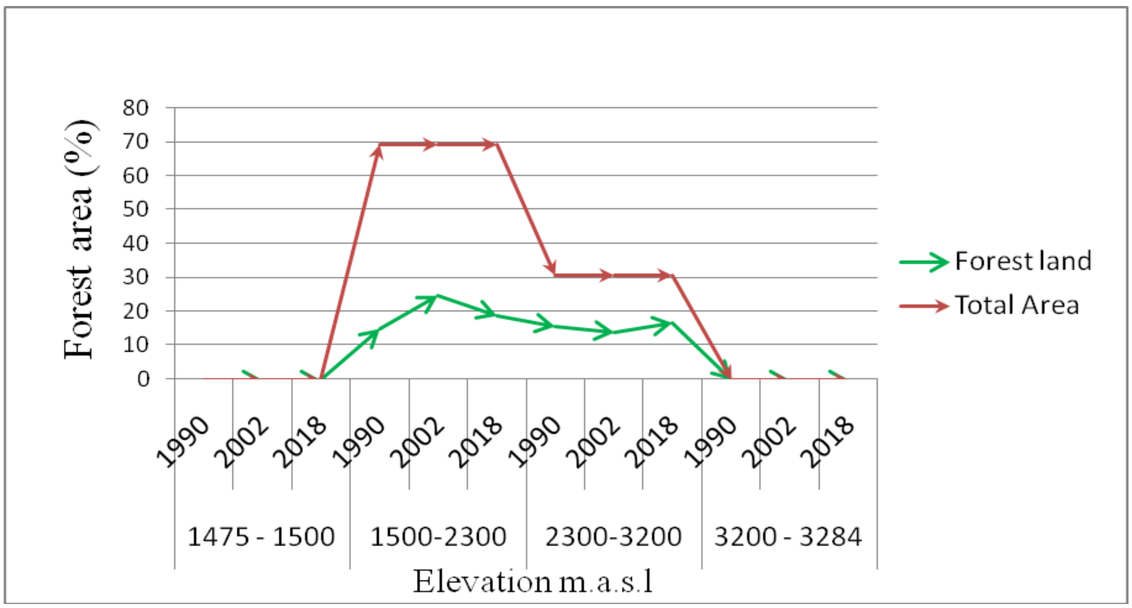


Figure 12: Area percentage of forest out of the total area along the slope gradient and Elevation from top to bottom respectively

Source: Author

Weights were given to each factor according to their influence on the forest-based on literature, expert opinion for settlement and road and according to their proportion to their area percentage for slope & elevation. Each reclassified factors and maps are presented in (Table:9 & Figure 14).

Table 8: Spatial variables with disturbance values

Spatial Variables	Classes	Rating
Elevation (m.a.s.l)	1475-1500, 1500 - 2300, 2300 -3200, 3200 - 3284	4, 3, 2, 1
Slope (%)	0-5, 5-15, 15-30, 30 - 90	4, 3, 2, 1
Proximity to settlement (m)	0 - 1000, 1000 - 2000, 2000 - 3000, 3000 - 4500	4, 3, 2, 1
Proximity to road (m)	0 - 500, 500-2000, 2000-5000, 5000 - 26,600	4, 3, 2, 1

Where; 4= Extreme, 3= high, 2= moderate, 1= low

Source: Author

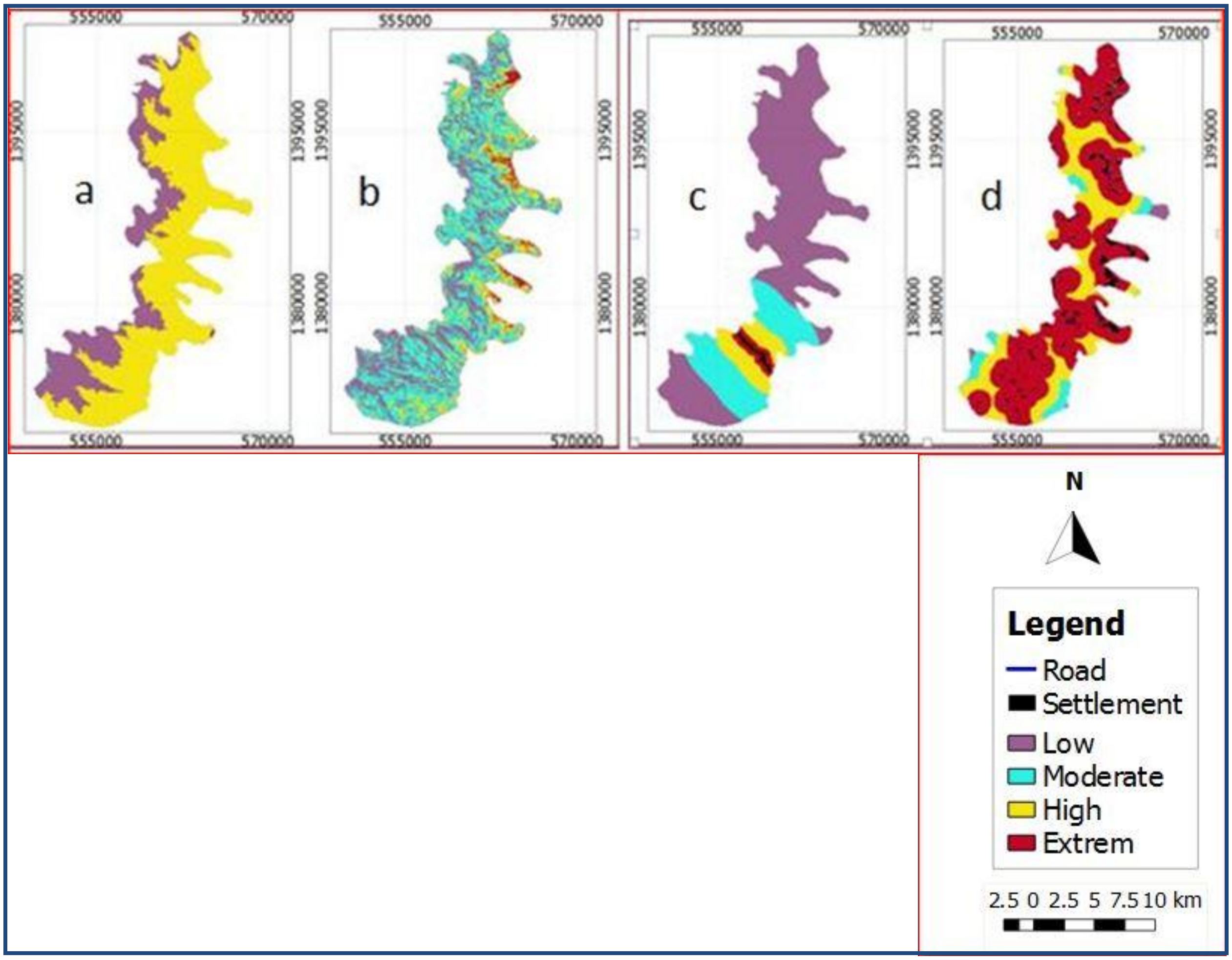


Figure 13: a, b, c & d are denote to reclassified maps of Elevation, Slope, Proximity to Road, Proximity to Settlement, respectively.

Source: Author

4.5.3 TRANSITION POTENTIAL MODELING

Weights were defining for each criterion based on their disturbance to the forest using MCE. The primary issue of Multi-criteria Evaluation (MCE) is how to join the information from different standards to form a single index of evaluation (Mideksa, 2009). Thus the first step to run MCE is producing proximity to forest cover area data stets or factor reclassified maps based on their disturbance to the forest. The MCE comparisons result indicated that the highest weight value is proximity to the settlement with value 0.487, followed by elevation value 0.352, slope value 0.120 and proximity to road value 0.041 (Table 9). The larger the weight indicates the more forest disturbance factor. MCE is an approach and a method to help decision-makers to describe, evaluate, sort, rank and select or reject based on evaluation based on several criteria (Sharifi, 2008).

Table 9: Pairwise Comparison Matrix between spatial variables.

	Proximity to Road	Proximity to Settlement	Slope	Elevation
Proximity to Road	**1**	0.111	0.2	0.143
Proximity to Settlement	9	**1**	7	1.0
Slope	5	0.143	**1**	0.333
Elevation	7	1.0	3	**1**
	Proximity to Road	Proximity to Settlement	Slope	Elevation
Weights	0.041	0.487	0.120	0.352

Source: Author

*Consistency Ratio (CR) is: 0.076230 < 0.1, Which is reasonable (Saaty 1980).

Where, CR = Consistency Index (CI) / Random index (RI)

Based on this the Forest Disturbance Risk Model (FDRM) for the study area is developed below.

Forest Disturbance Risk Model (FDRM) = ((0.041* Proximity to road) + (0.487* Proximity to settlement) + (0.12*Slope) + (0.352*Elevation))

4.6 VALIDATION OF MCE-CA MODEL

The value of predicted forest to the year 2014 based on forest and non-forest reclassified LULC of Years 1990 and 2002 was 6208.78 ha, which is closed to the actual value of reclassified to forest and non-forest LULC 2014. The predictive power of the model is 89.33 %, which is greater than the acceptable limit sated by (Araya and Cabral, (2010), greater than 80%. Then it was reasonable to make future projection. The percentage of correctness and kappa of the model is presented below in (Table:10).

Table 10: Validation result of CA Simulation Model

Model	**(%) of Correctness**	**Kappa**
CA Simulation	78.53	0.92

Source: Author

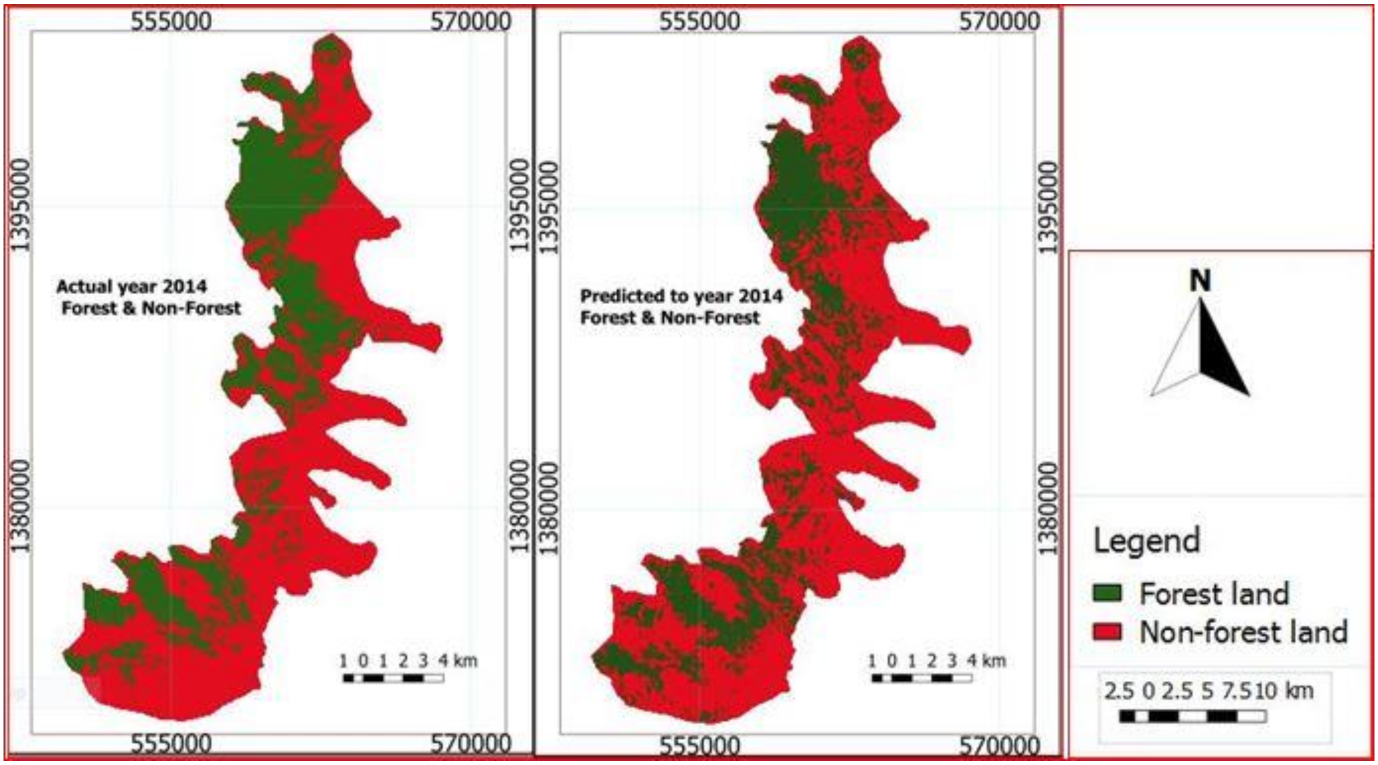


Figure 14: Reclassified to forest and non-forest year 2014 Actual vs. Simulated maps to validate the model left to right respectively.

Source: Author

4.7 CELLULAR AUTOMATA SIMULATION RESULT

After defining the parameters used for the calibration and modeling and assessing the validity, prediction of the forest cover change was conducted to year 2034 based on reclassified to forest and non-forest LULC classes of 2002 and 2018. The predicted forest to 2034 is 4772.88 ha. This result indicated 2,739.24 ha (36.46 %) of the existed forest in 2018 will be lost in 2034 (Figure 16).

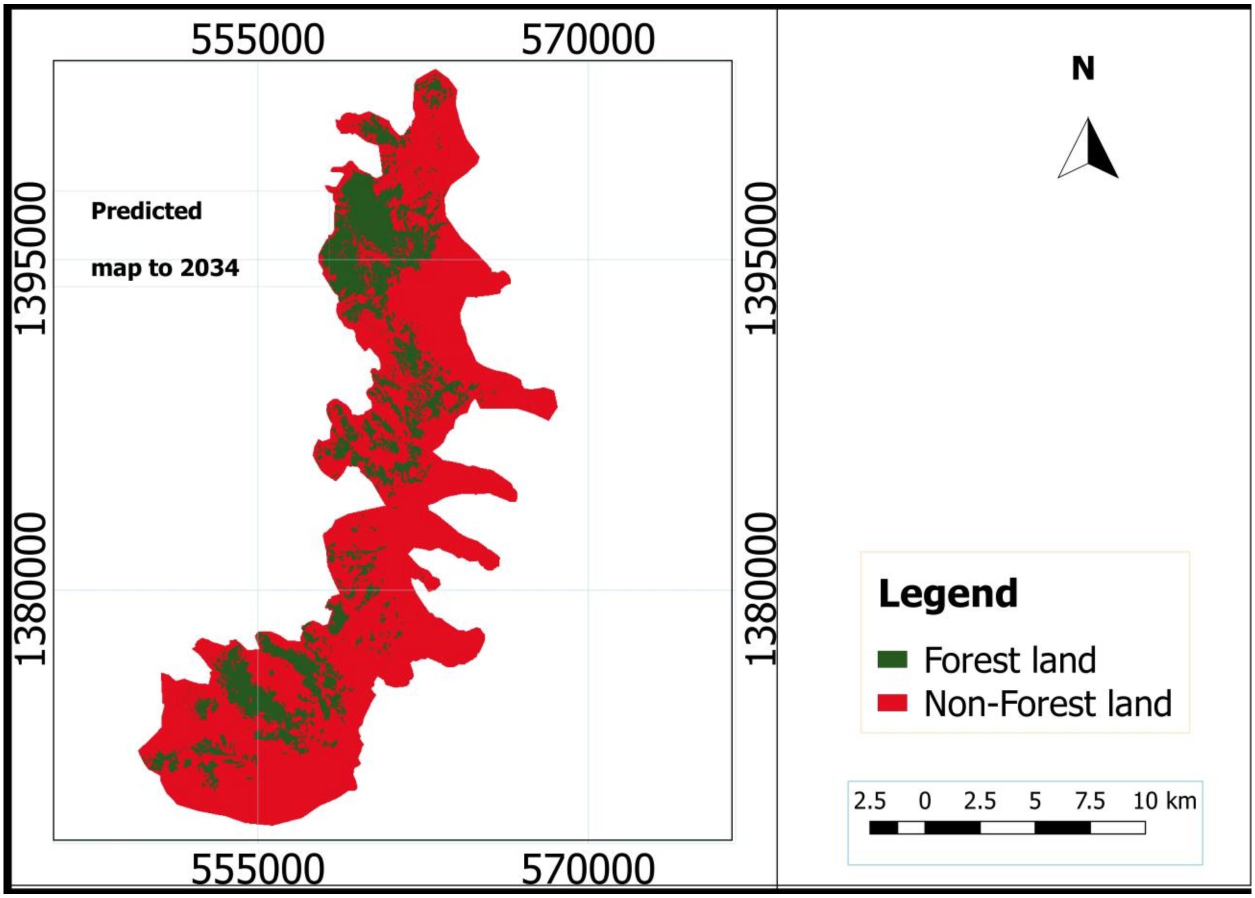


Figure 15: Forest and non-forest Predicted map for year 2034 via CA Simulation model

Source: Author

The future forest cover change trend is similar to the previous base year (2002-2018) trend of forest cover change. The rate of FCC will be -171.203 ha yr $^{-1}$ for (2018-2034), (Figure 16), which is more than triple from the rate of the base year (2002-2018), which was -45.47 ha yr $^{-1}$.

5. CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

Forest land, Shrub, and Scrubland, Agriculture, Bare land and Built-up areas were identified in the study. Different types of forest cover changes have been experienced throughout the study period in the study area. Land use land cover classification and change detection has been done through latest and advanced open software (IMPACT Toolbox). During the base year of the study 1990, forest land was the most dominant land cover in the study area holds 29.79 % (6424.38 ha) of the total land cover. And also it has increased by 1815.30 ha (8.42%) in the first period (1990-2002). Whereas in the second period (2002-2018), it decreased by 727.56 ha by (3.38 %).

Even thou the forest was increased in the historical period (1990-2002) by 1815.30 ha, it decreased by 727.56 ha from(2002-2018). The proximate drivers behind this FCC over the last 28 years in HGNFPA were Overgrazing, Wood extraction, Crop activities (agricultural) and Settlement expansions. Similarly, Weak policy implementation, lack of strong institutional arrangement, high human population growth, socio-political and cultural factors, urbanization were also the underlining drivers of FCC over the last 28 years in the study area.

A total of 150 Ground Control points were collected for accuracy assessment of the current and historical LULC classes. The overall classification accuracy of years 1990,2002 and 2018 are 82%, 84.66% and 91.33 %. Similarly Kappa's value of years 1990,200 and 2018 are 0.760.79 and 0.88.

The proportion of forest becomes increased as slope and elevation increased, in contrast the proportion of built-up and agriculture decreased as slope and elevation increased. The rate of forest cover change for the first period (1990 - 2002) was increased by 151.28 ha yr $^{-1}$, whereas in the second period (2002 - 2018) was decreased by -45.47 ha yr $^{-1}$ (deforestation). whereas the total rate of FCC throughout the study period (1990 - 2018) was increased by 37.51 ha yr $^{-1}$. The researcher tries to improve the accuracy of the model results by increasing the number of land-use attributes; that is, in addition to elevation and land use the researcher included slope, proximity to road and settlement in the simulations. The topography is an important factor for determining land-use change, especially for predicting the spread of permanent agriculture in the early stages (Hall et al., 2019).

The predictive power of the model is 89.33 %, which is greater than the acceptable limit sated by Araya & Cabral, (2010), The predictive power of a model is considered strong (i.e., greater than 80 %). The future FCC trend is similar to the base year of the prediction (2002-2018) trend of forest cover change, which will be -171.203 ha yr $^{-1}$ for (2018-2034), that is more than triple from the base year (2002-2018), which was -45.47 ha yr $^{-1}$.

5.2 RECOMMENDATION

This study proposes recommendation that will be helpful to farther planning and policy making. It is also helpful for government officials and planners to observe such development pattern as follow;

1. Federal, regional and local government should give enough attention and take appropriate measure to reduce the critical deforestation rate in HGNFPA, 2,739.24 ha (36.46 %) of the existed forest in 2018 will be lost in 2034 according to the result of MCE-CA Simulated Model,

2. Applied REED+ in HGNFPA will be best option to reduce the alarming rate of deforestation,

3. PFM should apply at HGNFPA, to develop sense of ownership and to use at least dead wood and grass by cut and carry,

4. Electrification and Energy saving stoves should introduced at least to the districts surround the HGNFPA,

5. Job opportunity should created for the jobless youths of the surround districts to decrease the pressure on the forest, and

6. The indigenous knowledge of the community towards natural resources conservation should be acknowledged and strengthened by government organizations.

7. It is better to resettle the dwellers outside the forest area.

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APPENDICES

Appendix 1: Error matrix (%) for image classification of 1990, 2002 and 2018 respectively from top to bottom

Error matrix for image classification 1990								
		Reference map						
Classification map		Forest	Shrub & Scrub land	Agriculture	Bare land	Built-up	Total	User's accuracy [%]
	Forest	**36**	1	0	0	0	37	97.29
	Shrub & Scrub land	5	**42**	3	2	1	53	79.24
	Agriculture	1	0	**18**	0	0	19	94.73
	Bare land	1	4	6	**23**	1	35	65.71
	Built-up	0	0	2	0	**4**	6	66.66
	Total	43	47	29	25	6		
	producer 's accuracy [%]	83.72	89.36	62.06	92.0	66.66	150	
Overall Classification Accuracy [%] = 82.0								
Kappa Coefficient = 0.76								

Error matrix for image classification 2002								
		Reference map						
Classification map		Forest	Shrub & Scrub land	Agriculture	Bare land	Built-up	Total	User's accuracy [%]
	Forest	**44**	2	0	1	0	47	93.61
	Shrub & Scrub land	2	**24**	2	2	1	31	77.41
	Agriculture	0	2	**30**	0	1	33	90.90
	Bare land	1	2	5	**23**	0	31	74.19
	Built-up	1	0	1	0	**6**	8	75.0
	Total	48	30	38	26	8	150	
	producer 's accuracy [%]	91.66	80.0	78.94	88.46	75.0		
Overall Classification Accuracy [%] = 84.66								

Kappa Coefficient = 0.79

Error matrix for image classification 2018								
Reference map								
Classification map		Forest	Shrub & Scrub land	Agriculture	Bare land	Built-up	Total	User's accuracy [%]
	Forest	**40**	2	0	0	0	42	95.23
	Shrub & Scrub land	1	**32**	0	2	1	36	88.88
	Agriculture	0	0	**25**	1	0	26	96.15
	Bare land	0	0	4	**28**	2	34	82.35
	Built-up	0	0	0	0	**12**	12	100.0
	Total	41	34	29	31	15	150	
	Producer's accuracy [%]	97.56	94.11	86.20	90.32	80.0		
Overall Classification Accuracy [%] = 91.33								
Kappa Coefficient = 0.88								

Source: Author

Appendix 2: Transition Matrix of 1990-2002 and 2002-2018 from top to bottom respectively

		2002				
1990		Forest land	Shrub & Scrub land	Agricultural land	Bare land	Built-up Area
	Forest land	**0.761607**	0.196030	0.010913	0.026884	0.004567
	Shrub & Scrub land	0.326730	**0.372830**	0.084000	0.181178	0.035262
	Agricultural land	0.041581	0.187698	**0.430853**	0.294561	0.045306
	Bare land	0.051358	0.244823	0.278004	**0.388076**	0.037739
	Built-up Area	0.079537	0.170836	0.266430	0.265123	**0.218073**

		2018				
		Forest land	Shrub & Scrub land	Agricultural land	Bare land	Built-up Area
2002	Forest land	**0.667555**	0.224648	0.040731	0.031971	0.035095
	Shrub & Scrub land	0.287727	**0.411876**	0.108204	0.139346	0.052846
	Agricultural land	0.016397	0.229749	**0.303305**	0.304481	0.146067
	Bare land	0.047971	0.526866	0.114154	**0.220991**	0.090018
	Built-up Area	0.072754	0.188577	0.211503	0.056454	**0.470713**

Source: Author

Appendix 3: Distribution of LULC in different elevation and slope gradient from top to bottom respectively

Elevation m.a.s.l	Years	Area of LULC classes					F_{Area} (%)
		F(ha)	SS (ha)	A (ha)	BR (ha)	BU (ha)	
1475 - 1500	1990	0	15.39	0	0	0	0
	2002	0	0	7.02	9.09	0	0
	2018	0	8.64	0	0	7.47	0
1500-2300	1990	3125.97	7741.17	1232.73	2482.02	324.18	14.53
	2002	5307.03	3893.67	2063.88	3090.15	550.62	24.68
	2018	3995.01	6217.02	1855.98	1312.56	1524.78	18.58
2300-3200	1990	3287.16	1563.3	689.4	874.8	155.97	15.28
	2002	2923.11	2093.22	669.42	760.41	124.47	13.59
	2018	3508.92	872.28	537.57	1511.73	140.13	16.326
3200 - 3284	1990	5.31	1.17	6.48	7.11	7.11	0.025
	2002	0.81	12.78	0	0	0	0.008
	2018	0.9	12.42	0	0.27	0	0.004

Slope (%)	Years	Area of LULC classes					F_{Area} (%)
		F (ha)	SS (ha)	A (ha)	BR (ha)	BU (ha)	
0-5	1990	81.09	307.35	233.55	440.55	71.91	0.376

	2002	166.77	166.5	430.56	265.68	103.95	0.773
	2018	93.96	175.05	547.56	104.31	206.37	0.436
	1990	755.28	1763.82	523.89	990.9	146.97	3.502
	2002	1296.27	832.68	930.96	880.74	239.85	6.011
6-15	2018	981.18	1281.51	677.07	614.34	627.03	4.550
	1990	3102.66	4962.87	877.77	1230.3	171.81	14.387
	2002	4200.12	3076.47	1012.05	1818.36	239.04	19.475
16-30	2018	3910.77	3607.38	725.13	1495.71	608.22	18.137
	1990	2485.35	2315.25	297.63	715.14	91.35	11.525
	2002	2573.91	1946.52	381.24	908.82	96.03	11.935
30 - 90	2018	2521.71	2072.97	451.26	624.96	235.35	11.695

Source: Author

Appendix 4: Ground Control Points

ID	X	Y	ID	X	Y	ID	X	Y	ID	X	Y
0	555414	1369646	39	563127	1402315	78	554781	1369483	117	552503	1372347
1	561644	1376163	40	560659	1392474	79	563329	1382323	118	562207	1384015
2	558957	1387950	41	559747	1379598	80	555451	1373320	119	562634	1378955
3	564116	1390042	42	563919	1377824	81	558985	1381194	120	558528	1393667
4	562106	1380637	43	553502	1373874	82	561708	1396141	121	562977	1400844
5	564133	1395696	44	563164	1401098	83	562179	1395785	122	560994	1376567
6	551621	1373172	45	555343	1370007	84	563829	1392197	123	556540	1374840
7	568418	1388805	46	563609	1385403	85	559832	1393196	124	556569	1372613
8	554618	1374137	47	560600	1379850	86	562400	1390974	125	555728	1374835
9	560870	1377543	48	560089	1387428	87	550987	1373280	126	552262	1371490
10	563380	1391564	49	563388	1400353	88	555141	1375364	127	560374	1385613
11	566292	1393860	50	560187	1393097	89	556739	1377099	128	559925	1400871
12	556446	1374055	51	559358	1400870	90	562763	1382760	129	561207	1395177
13	561179	1397524	52	556842	1371339	91	559767	1383466	130	562545	1402545
14	559573	1377794	53	560246	1388794	92	561508	1394923	131	561524	1394770
15	558926	1380838	54	562385	1386734	93	554021	1375730	132	558385	1381127
16	561059	1400295	55	563191	1382492	94	554386	1372842	133	552631	1372328
17	562468	1402341	56	564230	1385682	95	559358	1396893	134	554351	1372099
18	564107	1377299	57	552901	1370764	96	559310	1395784	135	559062	1374362

19	561082	1380984	58	554503	1377137	97	558264	1372227	136	561387	1393986
20	559968	1382030	59	561380	1387584	98	563011	1377888	137	567186	1388706
21	559009	1397372	60	560678	1390033	99	562560	1380707	138	560406	1377056
22	564507	1394866	61	551475	1373179	100	552884	1374026	139	561698	1378019
23	562815	1387068	62	561249	1375663	101	559810	1400605	140	558866	1375452
24	563213	1390873	63	562274	1390322	102	558190	1374668	141	557983	1378103
25	559577	1397408	64	563159	1399579	103	552688	1375541	142	561007	1390411
26	560035	1392791	65	563100	1377793	104	562909	1394345	143	549928	1372370
27	558412	1375266	66	561648	1397888	105	561837	1389710	144	556101	1373492
28	559090	1379180	67	562521	1402644	106	562428	1377438	145	559767	1374422
29	562469	1402017	68	561321	1398568	107	555559	1371741	146	554416	1373010
30	560097	1377936	69	558050	1375297	108	563813	1390510	147	555483	1369729
31	561222	1393700	70	557521	1377246	109	555793	1377324	148	561314	1399933
32	559812	1396237	71	556069	1371392	110	554512	1370877	149	554092	1376723
33	561297	1375926	72	561977	1399418	111	562995	1402884			
34	563625	1394048	73	561846	1380547	112	564184	1388430			
35	560485	1387304	74	559437	1379273	113	563407	1403214			
36	566775	1388801	75	560243	1379467	114	563254	1400270			
37	561020	1383637	76	554304	1370833	115	555638	1375112			
38	559490	1377242	77	560705	1391247	116	561123	1388795			

Source: Author

Appendix 5: Description of the Analytical Hierarchy Process (AHP)

Rank	Description
1	means that criteria **A** and **B** are equally important
3	means that **A** is thought to be moderately more important than **B**
5	means that **A** is thought to be strongly more important than **B**
7	means that **A** is thought to be, or has been demonstrated to be, much more important than **B**
9	**A** has been demonstrated to have much more importance than **B**

Source: Saaty, (1980)

Appendix 6: Demographic characteristics of respondents

	Frequency	Percent
Sex		
Male	241	64.1
Female	135	35.9
Total	376	100
Marital Status of Respondents		
Married	194	51.6
Unmarried	63	16.8
Divorced	17	4.5
Widow	102	27.1
Total	376	100
Age of Respondents		
30-35	109	29.0
36-60	208	55.3
>60	59	15.7
Total	376	100
Educational Status of Respondents		
Illiterate	145	38.6
Read	101	26.9
Read & Wright	55	14.6
Grade 1-8	45	12.0
Grade 9-12	22	5.9
> 12	8	2.1
Total	376	100

Appendix 7: Household sample size

No	Name of Sampled Kebeles	Total household (HH)	Sample size(nx)	%
1	Werebayen	2622	159	6.06
2	Thahtay Haya)	1521	92	6.04
3	Huguburda)	1135	69	6.07
4	Kulugize lemlem	930	56	6.02
Total		**6208**	**376**	**6.06**

Appendix 8: Questionnaire for HH interview

Part 1. Background information

1.1 Woreda ______________Kebele_____________ Sub-Kebele_____________

1.2 Respondent Full Name___________________________ Sex M__ F__ Age___

1.3 Respondent number_______ Date of interview_____________

Educational status:

1) Illiterate 2) Read only 3) Write only 4) Read and Write only 5) Primary (1-8)

6) Secondary (9-12) 7) Greater than secondary

Marital status: 1) Married 2) unmarried 3) Divorced 4) Widowed

Part 2: Drivers of forest cover change

2.1 What are the drivers of forest cover change in Hugumburda-Grakahsu National Forest

Priority Area (HGNFPA) in the last 28 years?

1) Education levels 2) Livestock activities 3) Population growth 4) weak land use laws

5) Type of crops grown 6) Property ownership 7) Lack of Proper Management

8) Expansion of infrastructure (market, social service) 9) Expansion of Towns

10) Others specify ________________________

2.2 Which environmental (biophysical) drivers are most common in the study area in the last 28 years? 1) Deforestation 2) Degradation 3) Soil erosion 4) Overgrazing 5) Others specify______________

2.3 Have you observe forest cover change in the study area in the last 28 years (1990-2018)?

A) yes B) No

2.4 If your answer to 2.3 is yes, what change do you observe?

A) forest cover increase B) forest cover decrease

2.5 What are the main drivers to increase or decrease the forest cover?

1) Direct causes 2) indirect causes

2.6 What are the existing forest cover types in the study area? __________________

2.7 Under the stated period on which period have you observe rapid forest cover change

the study area? why? _________________________

2.8 What are the direct/Proximate drivers of forest cover change over the last 28 years (1990 -

2018) the study area? (Urban expansion, illegal encroachment, overgrazing, agricultural expansion, wood extraction, expansion of infrastructure), Others specify__________________

2.9 What are the indirect/underlining drivers of forest cover change over the last 28 years (1990

- 2018) in the study area? (demographic factors, economic factors, technological factors, Policy and institutional factors, a complex of socio-political or cultural factors,) Others specify__________________________________

Appendix 9: Checklist for FGDs and KIIs

1. Deforestation / reforestation:

1.1 What are the forest cover fluctuations over the latest 29 years in (1990,2002 and 2018)?

1.2 What type of forest management systems has been applied in the study area?

1.3 What kind of change is it, e.g., what type of land use/cover has changed to what? Why?

1.4 what is the current status of the forest cover?

2. Driving forces:

2.1 What is the use or market of the products from a specific land use?

2.2 When farmers changed land use? what was their reason for doing that behind?

2.3 How do farmers perceive proximate& underline causes of forest cove change?

2.4 How has the observed land use/forest cover change been influenced by external and internal factors during the study periods (1990-2002 and 2002-2018) ?

3. Policy issues:

3.1 What are the policy issues to forest cover change?

3.2 What can the government and other actors do to support farmers toward more sustainable the forest and livelihood of the local communities?