LAND-USE LAND-COVER CHANGE AND VULNERABLE AREAS OF DEFORESTATION IN ANKASHA GUWAGUSA WOREDA, NORTH-WESTERN, ETHIOPIA

SAMSON TSEGAYE MEKASHA

A THESIS SUBMITTED TO DEPARTMENT OF GENERAL FORESTRY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF SCIENCE IN FOREST RESOURCE ASSESSMENT AND MONITORING

WONDO GENET NATURAL RESOURCE AND FORESTRY COLLEGE,

HAWASSA UNIVERSITY, ETHIOPIA

MARCH, 2020

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APPROVAL SHEET I

This is to certify that the thesis entitled "**Land-use Land-cover Change and Vulnerable Areas of Deforestation in Ankasha Guwagusa Woreda, North-western, Ethiopia**" submitted in partial fulfillment of the requirements for the degree of Master of Science with specialization in **Forest Resource Assessment and Monitoring** of the Graduate Program of the Department of General Forestry, Wondo Genet College of Forestry and Natural Resources, and is a record of original research carried out by **Samson Tsegaye Id. No MSC/FRAM/R016/10**, under my supervision, and no part of the thesis has been submitted for educational institutions for achieving any academic awards. The assistance and help received during the course of this investigation have been duly acknowledged. Therefore I recommend that it be accepted as fulfilling the thesis requirements.

Mersh Gebrehiwot (Ph.D.)	____________________	_________________
Name of Principal Advisor	Signature	Date

APPROVAL SHEET II

We, the undersigned, members of the Board of examiners of the final open defense by Samson Tsegaye have read and evaluated his thesis entitled "Land-use Land-cover Change and Vulnerable Areas of Deforestation in Ankasha Guwagusa Woreda, North-western, Ethiopia", and examined the candidate. This is therefore to certify that the thesis has been accepted in partial fulfillment of the requirements for the degree of Master of Science in Forestry with specialization in Forest Resource Assessment and Monitoring.

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Name of Chairman	Signature	Date
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Name of Principal Advisor	Signature	Date
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Name of External Examiner	Signature	Date

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DECLARATION

I, Samson Tsegaye, hereby declare to the school of graduate studies, Hawassa University that this is my original work and all sources of materials used are duly acknowledged. This work had not been submitted to any other educational institutions for achieving any academic awards.

Samson Tsegaye ______________________ ______________________

Signature Date

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List of Acronyms

AD	Activity Date
AHP	Analytic Hierarchy Process
AFOLU	Agriculture, Forestry and Land-Use
CCRS	Canada Centre for Remote Sensing
CSA	Central Statistics Agency
CRGE	Climate Resilient Green Economy
DEM	Digital Elevation Model
EF	Emission Factor
ETM+	Enhanced Thematic Mapper plus
FAO	Food and Agricultural Organization
FRL	Forest Reference Level
GFOI	Global Forests Observation Initiative
LULCC	Land-use Land-cover Change
MODIS	Moderate Resolution Imaging Spectro-radiometer
TM	Thematic Mapper
OLI-TIRS	Operational Land Imager and Thermal Infrared Sensor
QGIS	Quantum GIS
REDD+	Reducing emissions from deforestation and forest degradation
SCP	Semi-Automatic Classification Plugin
SRTM	Shuttle Radar Topography Mission
UNFCCC	United Nations Framework Convention on Climate Change
WGS	World Geodetic System

Abstract

In Ethiopia, population number was increasing continuously with agricultural land expansion for the last five decades. In this regard, it is essential to study the history of land-use/land-cover dynamics to make reliable and adequate information for future planning and management by using advanced technologies. This study is about the historical change of LULC since 1985 and identification of potential deforestation risk areas in Ankasha Guwagusa Woreda. Multi-temporal Landsat imageries (1985, 1996, 2006 and 2018) and SRTM Digital Elevation Model (DEM) were used combined with secondary data, Google Earth and field data for this study. Supervised classification method (Maximum Likelihood Algorithm) was used to produce LULC map. Also, five deforestation factors were selected based on literatures and considering infrastructure, topographic and socio-economic status of the area to identify the current deforestation risk area. These are slope, proximity to road, population density, proximity to river and proximity to town. Analytical Hierarchy Process (AHP) technique was used for weight assessment for each factor. Hence, the result from 1985 to 1996 show cropland, bare-land and built-up were increasing with 835 ha, 186.54 ha and 112. ha, respectively. In contrast, forest and water body was decreased. In the second period (1996–2006) forest, cropland and built-up increased with 1094 ha, 2185.7 ha and 346.78 ha, respectively. In final period (2006–2018,) cropland, bare-land and water body decreased by 1802.5 ha, 39.44 ha and 3.25 ha but forest and built-up increased by 772.91 ha and 1072.28 ha, respectively. The results from deforestation risk map show that 154.16 ha, 3064.37 ha, 4308.23 ha and 79.52 ha area of forest is identified as extreme, high, moderate and low risk zone, respectively. Accordingly, the result indicates the study area was under continually spontaneous LULCC for the last thirty three years. The most interesting result was the dynamics of forest cover that show a significant decrease in the first study period but increases in the second and third periods. However, the natural forest was decreasing continuously. The reason is probably recently appeared plantation forest expansion with two major species Eucalyptus spp. and Acacia decurrens or else uprising of the integrated watershed development campaign since 2000. In conclusion, the area was highly influenced by anthropogenic factors such as agricultural land expansion and urbanization. In the future, community-based land-use land-cover planning and sustainable forest management system is recommended to protect, conserve and rehabilitate the remaining natural environment.

Key words: Ankasha Guwagusa; Landsat; Land-use change; Modeling deforestation

1. INTRODUCTION

1.1. Background and Justification

Land-use and land-cover are different terms, however, land-cover is the observed bio-physical cover on the earth's surface and land-use refers to human interaction with the environment and is characterized by the interference of people on certain land-cover type (Anderson *et al.,* 1976; Tripathi and Kumar, 2012; Ayele *et al.*, 2014; Demeke and Afework, 2014 andFAO, 2016). For instance, the last few decades marked massive changes in land-use and land-cover in forest ecosystems of Ethiopia (Melakneh *et al.,* 2010; Misrak *et al.,* 2012). This change, human induced land-use and land-cover is considered as one of the most important factor for global environmental changes (Herold *et al.,* 2002; Ji *et al.,* 2005: Diallo *et al.*, 2009; FAO, 2016). Rapid replacements of land-cover by various land-use categories are observed globally (Ellis, 2015; Wu *et al.,* 2018).

The major reason for alteration of land-use land-cover is man-made (Helmut and Eric, 2001 and Turner *et al.,* 2009). Due to inappropriate use of natural resources such as unplanned agricultural land expansion; unplanned settlements; illegal logging; mining investment; building massive infrastructure construction like dams and road have a significant impact on the qualitative and quantitative decline of natural environment.

Forest is a very complex and constantly changing natural resource which contains different types of living and nonliving things having a strong integration (Joseph, 2005). Deforestation is the second largest source of greenhouse gas emissions following the burning of fossil fuels (Le *et al.*, 2009). In this context, forest degradation is defined as long term disturbances in forested areas

(Sasaki and Putz, 2009), mainly by selective logging and forest fires (Suryabhagavan *et al.*, 2016). Globally forest cover in 1990 was 2.5 million ha which was declined to 2.1 million ha in the year 2000 and 1.7 million ha in the year 2010, with decreasing rate of 1.6% per year and 2.0% per year in first and second decade respectively (FAO, 2011; Mannan *et al.*,2019). In Africa a continent with an estimated forest area of 675 million ha, corresponding to 17% of globally that lost about4 million ha of forest between1990 and 2000, and this number declined to 3.4 million between the years 2000−2010 (FAO, 2011 and UNECA, 2011). The forest environment gives an opportunity for ecotourism, which includes hiking, camping, bird watching and other outdoor adventures or nature study activities. Similar research reported that these changes to agricultural expansion, uncontrolled and illegal logging with a significant impact on natural and artificial forest regeneration (Misrak *et al.*, 2012; Suryabhagavan *et al.*, 2016).Therefore, deforestation and forest degradation in Ethiopia become serious environmental issues that need attention to stop a rapid decrease of the natural forest cover. To assess and monitor natural resources it is necessary to support by recent technological approach for detecting the dynamic change (GFOI, 2016; Pucha-cofrep *et al.*, 2018).

Remote Sensing and GIS techniques play a vital role for monitoring natural resources in areas with difficult access, such as rainforest regions (Hansen *et al.*, 2009; Mengistie *et al.*, 2013; Obang*et al.*, 2017). In this context, remote sensing data from several satellite sensors such as Landsat, ASTER, Sentinel-2A, MODIS continual global coverage at moderate to high resolution which is now available free and provides temporal datasets for few decades, has become increasingly used to identify the forest cover types and their relative changes (Helmer *et al.*,2000; Lu and Weng, 2007; Gao and Zhang, 2009; Gumma *et al.*,2011; Lu *et al.*,2012; Jia *et al.*,2014; Dinku and Suryabhagavan, 2019). In recent years, fine and high resolution imageries (i.e. from

GeoEye, IKONOS,Quick Bird, WorldView) enable LULC change detection and mapping with high accuracy (80–90%) but they are expensive. Several studies have proven the effectiveness of space-borne imagery to monitor LULC changes and forest degradation specifically in Africa (Muller *et al.,* 2011; Misrak *et al.,* 2012; Brown *et al.,* 2014; Abyot *et al.,* 2014; Belete and Suryabhagavan, 2019). Therefore, this study was conducted to analyze land-use/land-cover dynamics and mapping deforestation risk area in Ankasha Guwagusa Woreda over three decades using remote sensing and GIS approach.

1.2.Statement of the Problem

Land-use land-cover; mostly social and economic importance for humans globally includes cultivation in various forms, livestock grazing, urbanization and construction, reserves and protected lands, and timber extraction. These and other land-uses have cumulatively altered land-cover at a global level. Hence, land-cover is altered dramatically because of those and other land-use, the impact has been significant not only for land-cover but also for local, regional, and global environments (Turner *et al.*, 2009).

In Ethiopia, land-use land-cover conversion is a common problem due to increase in population growth, expansion of agriculture, overgrazing, illegal agricultural investment, urbanization, etc. Many research papers indicate that most of the reason for this conversion is man-made (Mengistie *et al.*, 2013; Obang *et al.*, 2017).

According to FRL (Forest Reference Level), in Ethiopia, the annual forest loss was around 92 thousand hayr^{-1}and annual forest gain of around 19 thousand hayr^{-1}from year 2000 to 2013(MEFCC, 2017).This report indicates that the country lost a vast amount of forest cover every year and if this trend continuous loss of biodiversity, soil erosion, flood, desertification, and shortage of timber, dam and lake sediment problem, climate variability and other social, political and economic challenge will increase in the future.

Currently, north-western Ethiopia is the area that is vulnerable for land-use land-cover change including deforestation due to expansion of small and large scale agriculture investment and urbanization (REDD+, 2015). Accordingly, Ankasha Guwagusa is one of the Woreda in this region which face the problem of dramatic conversion of LULC particularly a significant number of endemic and other species and natural forest areas were threatened(Abiyot, 2017; Stévart *et al.*,2019).However, without clear and advanced information about the past and present LULC dynamics, it remains difficult or almost impossible to take the measure of integrated and sustainable land resource management actions(Abyot *et al.*,2014).

Hence, the present paper aims to investigate the amount of land-use land-cover conversion for the past thirty three years and identifying the most vulnerable areas for deforestation by using updated and advanced remote sensing and GIS technology. The study is provided timely and scientifically backed information for policy and decision makers and also will be used as information for future resource management.

1.3. Objective

1.3.1. General Objective

The overall objective of this research is to generate information on the land-use land-cover change and investigating susceptible areas for deforestation in Ankasha Guwagusa Woreda using remote sensing and GIS approach.

1.3.2. Specific Objectives

The specific objectives of the study are:

- To investigate the rate of land-use land-cover change for the past thirty three years since 1985.
- To quantify the amount of forest cover change for the last thirty three years.
- To identify forest areas under risk of deforestation.

1.4.Research Question

- What is the rate and amount of land-use land-cover change occurred for the last thirty three years?
- How much is forest cover change for the past thirty three years?
- Which part of the forest area is under a potential risk of deforestation?

1.5. Significant of the Study

Land-use land-cover dynamics in northwestern Ethiopia remain spontaneous which needs detail scientific research for present and future land-use planning and management. This study provides data and information about the rate and trained of land-use land-cover change for the past three decades and identifies forest areas vulnerable for deforestation in Ankasha Guwagusa Woreda. Therefore, the result of this study can be used by policy and decision makers, natural resource managers, environmental experts, development agents, foresters, researchers and other stakeholders.

1.6. Scope of the Study

The scope of this research paper was spatially limited only in Ankasha Guwagusa Woreda, Awi Zone, Amhara Regional State of Ethiopia. The study focused on investigating the rate of land-use land-cover change and quantifies the amount of forest cover dynamics for the past thirty three years. Besides, it was also focused on identification of potential risk of deforestation for present year.

2. LITERATURESREVIEW

2.1. Land-Use Land-Cover Change and its Drivers

Land-use and land-cover is a vigorous constituent in the interfaces of human activities with environmental understanding. Human activities on land to fulfill different needs can be defined as land-use (Obang *et al.*, 2017). Whereas land-cover is observer (bio)physical cover on the earth's surface(FAO, 2016). A quantitative and qualitative alteration of LULC mostly with the interference of humans is called land-use and land-cover changes. It is a prime environmental issue at local, regional and global level(Letchumy *et al.,* 2012).Human beings modifies the structure and functioning of ecosystems at a different levels by activities like farming expansion, and influence the interaction between ecosystem and its surrounding environment(Asmamaw, 2013; Dinku and Suryabhagavan, 2019).Globally, land-use and land-cover changes play a major role in controlling fundamental aspects of earth system functioning such as influence biotic diversity worldwide and contribute to local and regional climate variability and change (Chase *et al.*,2000; Sala *et al.,* 2000).Also, soil degradation, desertification, deforestation, global warming, flooding, landslide collectively affect climatic, economic or socio-political integration.

Ethiopia is endowed with various biodiversity resources due to different agro-ecological patterns. The country can be classified into 15 land-use patterns, 19 livestock patterns, 48 cropping patterns and at least six farming systems. The dominant land-use patterns are grazing land, browsing, agriculture land, forest land and woodlands. In AFOLU (Agriculture, Forestry and Land-Use) release of CO_2 is estimated from the land-use change as a result of deforestation, expansion of cultivation land, forest fires and biomass burning in grasslands(MEF, 2015).However, around 85% of the population and 75 % of the livestock of Ethiopia live in the highlands which is greater than 1500 m elevation, covers 43% of the overall territory (Aklilu and De Graaff,2006).Many research papers shows LULC change is mainly driven by uncontrolled high population growth, the rapid expansion of urbanization, high demand for production, land shortage. Land-use land-cover change respond to social, demographic, political, cultural, economic and environmental status and forces which are highly characterized by high human populations (Masek *et al.,* 2000 and Ayele *et al.,* 2014)

In north-western part of Ethiopia, natural resource is influenced by human intervention mainly by agricultural expansion and illegal settlements. More recent evidence (Abiyot, 2017)which studies in forest patches of Guangua-Illala and Kahtasa forests in Awi Zone shows that for the last four decades forest cover experienced significant negative change. As a result, more than 80% of the primary forest was dramatically converted into other lands with a high rate of deforestation. Hence, this change threatened the remaining forest patches and a significant number of endemic and other species in the study area. He recommends that reversing the change by using integrated land-use planning and restoration measures using priority species is very critical. Likewise, Asmamaw (2013) the land-use and land-cover of the Gilgel Abbay watershed area were changed considerably from 1986 to 2001. Agricultural land significantly changed from 9% in 1986 to 55% in 2001 which create redaction of the amount of forest cover. The dynamic shift within LULCs on the area was due to uncontrolled population growth which creates high pressure on the forest and other lands to expand cultivated land.

Similarly, Mengistie *et al.*(2013) have been performed on LULC change analysis in Munessa Sheshemene district. The study shows a continuous increase of croplands observed but natural forests, grasslands and woodlands were declining as the result of deforestation and grassland decline. Besides, increases in tree patches along the study landscape show the fast forest fragmentation over the last four decades and the significant transformation into monoculture agricultural systems. The result shows that about 60% of the land-use land-cover is changing dramatically from 1974 to 2013. About 75% of the plantation forest land was altered from natural forest. In developing countries like Ethiopia, a rapid increase in population which causes high demand forraw materials and production (food, fuel-wood, cloth, shelter, forage) leads us continuous change of land-use land-cover pattern of our natural environment.

The population of Ethiopia has increased for the last few decades; from 42.6 million in the 1984 census to 53.5 million in the 1994 census and 73.8 million in the 2007 census, and to a projected 91 million in 2013 (CSA, 2013). More than 80% lives in rural areas and about 16 percent of the population living in urban areas. Rapid population growth in the county for the last decades, therefore turns out to be deterioration and over-exploitation on the natural resources (MEF, 2015).Due to high percent of the population depends on agriculture for their livelihood well-being the problems became serious.

2.2. Deforestation

A forest is ‘land spanning more than 0.5 ha with trees higher than 2 meter and a canopy cover of more than 10%, or trees able to reach these thresholds in situ (MEFCC, 2017). Definition of forest remains ambiguous across countries. Forestry sector plays a significant role in social, economic and cultural development of a country. In Ethiopia, about 4% of total GDP (9% of agricultural GDP) is obtained from forestry sector. Forest and woodlands have a significant national economic value for the country. Informal forest based activities estimated to contribute more than 30% of per capita income in some areas (CRGE, 2011). Therefore, for Ethiopia protecting and conserving the forest is a very important task through sustainable forest management plan.

Deforestation is a total conversion of forest land into other land-use such as agriculture or infrastructure. This conversion of forest land is mainly due to human activities. Natural disasters like volcano and forest fire may cause deforestation and when the area is unable to regenerate naturally; it is converted to other land (MEFCC, 2017). According to Bregman (2015), the impact of deforestation on the ecosystem is very high for the 20th and 21st centuries. The report indicates that about half of the world tropical rainforest has been lost within the last 50 years. From the total annual global greenhouse gas emissions, 16-19% is caused by deforestation on tropical forest. Furthermore, forests are used for environmental and social values including biodiversity reserve, water reservoir, climate regulation, pollination, seed dispersal, natural pest control, cultural values and tourism. Hence, deforestation brings the imbalance within and between environmental and social integration.

Ethiopia proposes a forest reference level MEFCC (2017) based on average annual emissions and removals over the period 2000 to 2013 assessed by AD x EF nationally. The result shows 17.9 mln $tCO_2e\,yr^{-1}$ wasemitted from deforestation and 4.8 mln $tCO_2e\,yr^{-1}$ was removed from the atmosphere in afforestation. The prime reason for climate change is the uprising of global temperature due to the release of carbon dioxide into the atmosphere. In tropical regions, deforestation has a long term impact on soil resources. When the vegetation cover is removed from the land, the soil is exposed to splash erosion and expands into gully erosion through time. Also, increase its compaction, deterioration of organic material, leaching out its few nutrients available, aluminum toxicity of soils increase and reduction of organic material are other impacts of deforestation and forest degradation on soil(FAO, 2007).

Deforestation has been attributed to socio-demographic factors, which include population growth and the structure class of political economy, and specific exploitation activities like commercial logging, fuel-wood gathering, and pasture clearance for cattle production (FAO, 2007).Causes of deforestation can be divided into two categories: proximate (direct) causes and underlying (indirect) causes.

Proximate or direct drivers of deforestation and forest degradation are anthropogenic and actions that directly impact the forest cover and result in quantitative and qualitative loss of biomass. In Africa, (sub) tropical Asia and Latin America, agriculture remains the dominant proximate cause of deforestation and forest degradation. Urbanization, mining investment, infrastructure, (commercial) timber extraction and logging activities, Fuel-wood collection, charcoal production, and livestock grazing in forests are the most important proximate or direct drivers of deforestation and forest degradation around the world. Underlying or indirect drivers are complex interactions of economic, social, political, cultural and technological processes that affect the proximate drivers to cause deforestation and forest degradation. Population growth, domestic markets, national policies, governance are some of the indirect causes at national and subsistence and poverty at local a level(Kissinger *et al.*, 2012).

In Ethiopia, deforestation and forest degradation to be driven mainly by free livestock grazing, fodder use and fuel-wood collection (charcoal production) in all the regions followed by farmland expansion, land fires and construction wood harvesting. The underlying causes of deforestation and degradation based on framework analysis were identified to be population growth, insecure land tenure and poor law enforcement. South-eastern woodland areas of the county are affected by free grazing. In Gambella, Benishangul-Gumuz and Afarregional states, large-scale agricultural investment remain a significant driver of deforestation (MEFCC, 2017).

Some of the driving factors of deforestation which are essential to be studied for a country like Ethiopia slope, proximity to river, proximity to road, proximity to town, and population density.

Slope: According to many studies when the area is steep slope the deforestation rate or extents of the forest remain very slow or near to zero. This is because it became hard to cut the tree or conversion of the forest land to other land-use types to become very difficult for humans. Gentle slope areas are comfortable for many activities such as agricultural and infrastructure expansion whereas mostly steep slopes are not preferred (Broothaerts *et al.*, 2012).

Proximity to river: The probability of deforestation near rivers, streams, lakes and artificial water holes becomes high because human beings and wild animals need regular access to water (Workaferahu, 2015; Sanchayeeta *et al.*, 2017).

Proximity to road: Many studies confirm that as the forest cover is closer to the road it has a very high possibility to be affected by humans as a result of accessibility to transport, easiness for illegal logging activities, market availability and so on. Agricultural expansion is increasing because it becomes easy for market for selling their product. Large scale agricultural investments also attracted because of its access to transport products (Geist and Lambin, 2002; Mo *et al.*, 2017; Sanchayeeta *et al.*, 2017). This is true in most tropical forests in Africa and Latin America. In Amazonian, nearly 90% of deforestation occurred within a 100 km radius from major roads (Alves, 2002; Barber *et al.*, 2014).

Proximity to town: Settlements also play a critical role in the degradation of the forest resources. Forest destruction to obtain the agricultural productive land requirement of the increasingly growing population is perhaps the most vital deforestation threat in the developing countries (Getahun, 2013; Forson and Gavu, 2016). This variable is very important variable because all the wood material which is used for construction, furniture, and fuel-wood and other purpose is extracted easily from the neighboring forest. Therefore, the closer the forest to the town the more it is disturbed by humans.

Population density: Population density is often stated as a major factor that has pressure on natural resources, especially forests. In developing countries endowed with forest resources, rural population migrants when access to land is improved, and convert forest into cropland, harvest trees for fuel-wood, timber, and other forest products (Getahun, 2013; Leblois *et al.,* 2016). According to the study which was conducted in population dynamics and LULC change in Dera Woreda, as population density was increased from the year 1984 to 2011 the need to people's food, shelter and other basic necessities also increase which cause LULC change (Temesgen *et al.,* 2014).

Therefore, population density is very critical for a country like Ethiopian which has high population growth rate. As the population density is very high in a given area the pressure on the surrounding natural resource becomes very high.

2.3. Role of Remote Sensing and GIS for LULC Dynamics and Deforestation

'Remote sensing defined as data on the characteristics of the earth's surface is acquired by a device that is not in contact with the objects being measure'(Bakker *et al.,* 2001). Remote sensing helps to detect the extent and magnitude of deforestation and forest degradation problem. Multi-temporal data which is very important to study LULC change analysis is provided remote sensing technology. Advanced relevant information about the LULC dynamics could be extracted from different sources of remote sensing. It serves as a monitoring tool to ensure companies are following cut guidelines and specifications(CCRS,2000).

Remote Sensing provides a spatial opportunity to assess and monitor deforestation and forest degradation for several reasons. First, with remote sensing we can work at multiple scales ranging from specific to large area forest cover. This included detailed study at local level to global forest resources assessment and monitoring purposes. Second, remotely sensed data can be acquired repeatedly (temporal resolution) that services us to monitor and detect forest resources on a regular basis. Third, these measurements can be made on a near real time basis which is very useful for monitoring each and every event such as wildfire. Fourth, remote sensing data has synoptic coverage and information can be acquired inaccessible areas. Fifth, we could use wavelengths that are not visible to human eye then remotely sensed data is collected. Thus, remote sensing is the most effective means of assessing and monitoring natural resources such as forest and water. However, It is important to understand that remote sensing does not replace field survey but provides very important and advanced information(FAO, 2007).

2.4. Modeling Deforestation

Modeling is used in a variety of fields, including land-use land-cover change science, to understand the dynamics of systems, to develop and improve hypotheses that can be tested empirically, and to make forecasts and/or evaluate scenarios for use in assessment activities(Lallo *et al.*, 2017; Sanchayeeta *et al.*, 2017; Sahana *et al.*, 2018).

Important environmental problems such as desertification, sedimentation of lakes and rivers, biodiversity loss, and climate change caused by greenhouse gasses, are just a sample of local and global phenomena brought about or exacerbated by human activities. These problems have concerned the attention of many disciplines. In particular, ecologists, economists, and geographers have engaged in the specification of models that attempt to capture the causes and consequences of land-cover and land-use change (Brown *et al.*, 2014). Applications of these models range across temperate and tropical ecosystems. Some of these models use spatially-explicit data in the sense that the dependent variable and most or all the independent variables are geographically identified through a system of coordinates. These modeling efforts are also characterized by the use of data derived from remote sensing applications, and handled and manipulated with geographic information system software(Muller *et al.,* 2011; Megersa, 2016; Sahana *et al.*, 2018).Modeling deforestation is important to identify which area of the forest is susceptible to present and future deforestation.

3. MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Location

Ankasha Guwagusa Woreda is located in Awi Zone Amhara National Regional State, north-western Ethiopia, about 120 km south-west of Bahir Dar, the capital town of Amhara Regional State of Ethiopia. Ankasha Guwagusa is bordered on the south by newly created Woreda in 2016 Yayu Guwagusa, in the west by Guangua, on the north by Banja Shekudad and on the east by Guwagusa Shekudad. The study area is geographically bounded by latitude 1179940−1213886 N and longitude 242774−278197 E, covering a total area of 47038ha (Figure 1)(Dessalew, 2014).

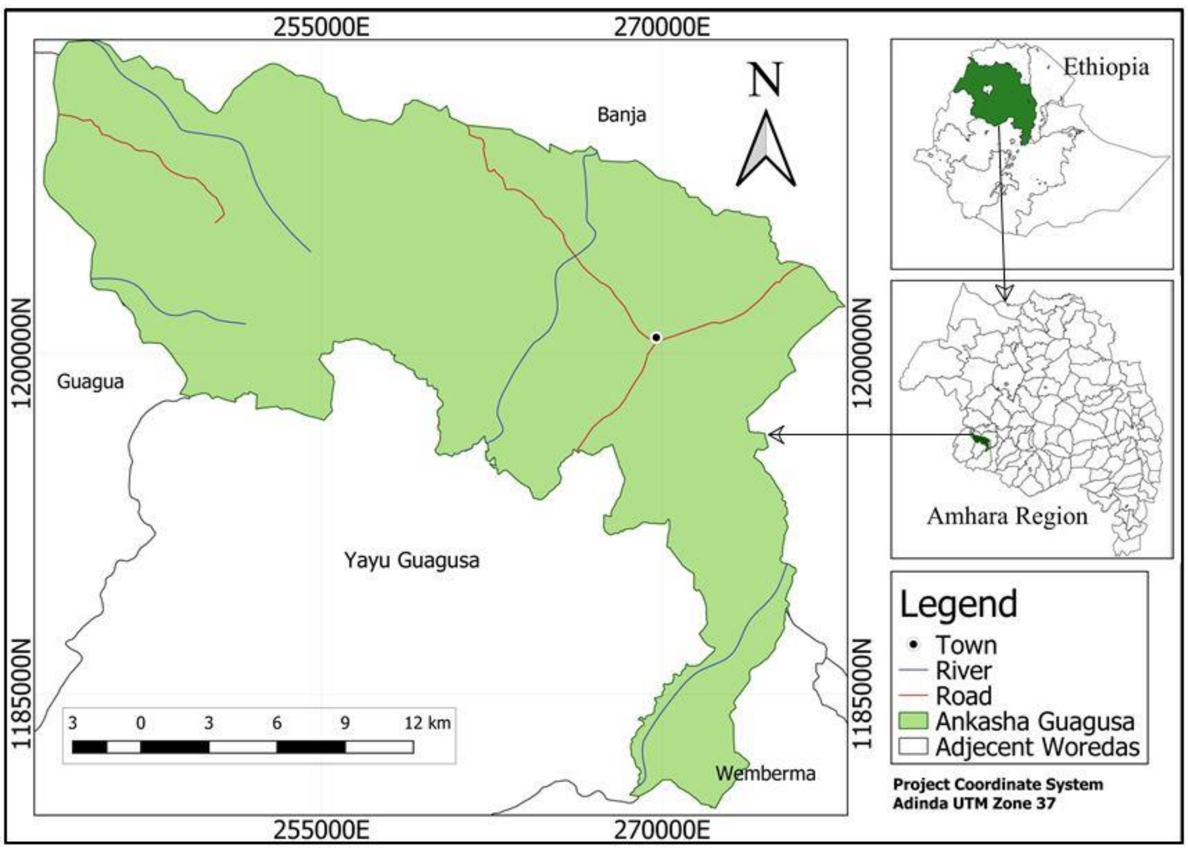

Figure 1: Location map of the study area.

3.1.2. Topography

The topography of the study area is mountainous, undulating plains, hilly, gullies and valleys. The elevation varies from 1849 meter above sea level in eastern and western part to 2883 meters above sea level in the north western of the study area (Figure 2). The three dominant soil types of the district are nitosol, fluvisols (at gentler slopes and river banks) and vertisols, locally walhi (covers the major lower slope positions of the area). Varied topography of the area resulted in diverse climatic patterns (Assaye, 2016).

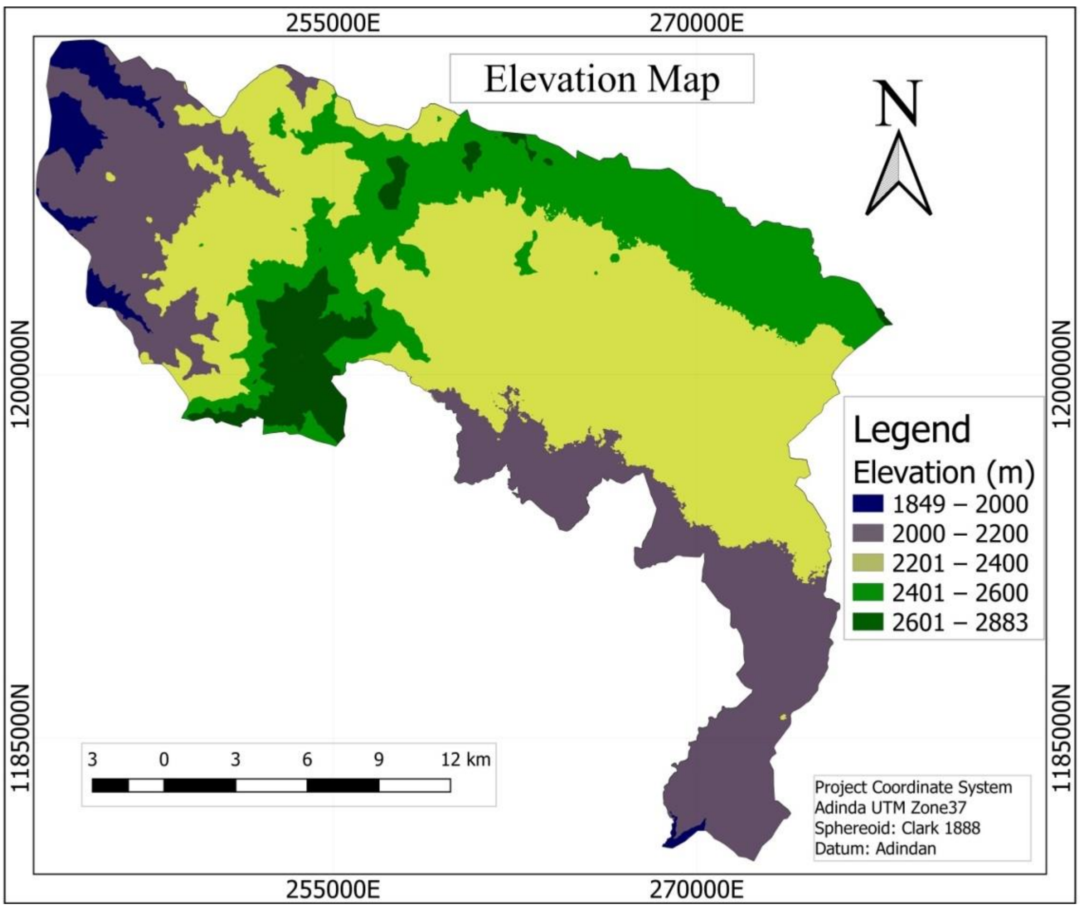

Figure 2: Elevation map.

3.1.3. Climate

According to the metrological stations of NMA (national metrology agency), the study area receives erratic average rainfall from 1305.4 mm to 3055.75 mm of rainfall per year. The months of July and August receive the highest amount of rainfall that reaches above 595 mm per month at the peak periods (Figure 3).Land surface temperature (LST)of the study area varies between the mean annual minimum of 24.3°C in 2014and a mean annual maximum of 35.5°C in 2012 (Figure 4).

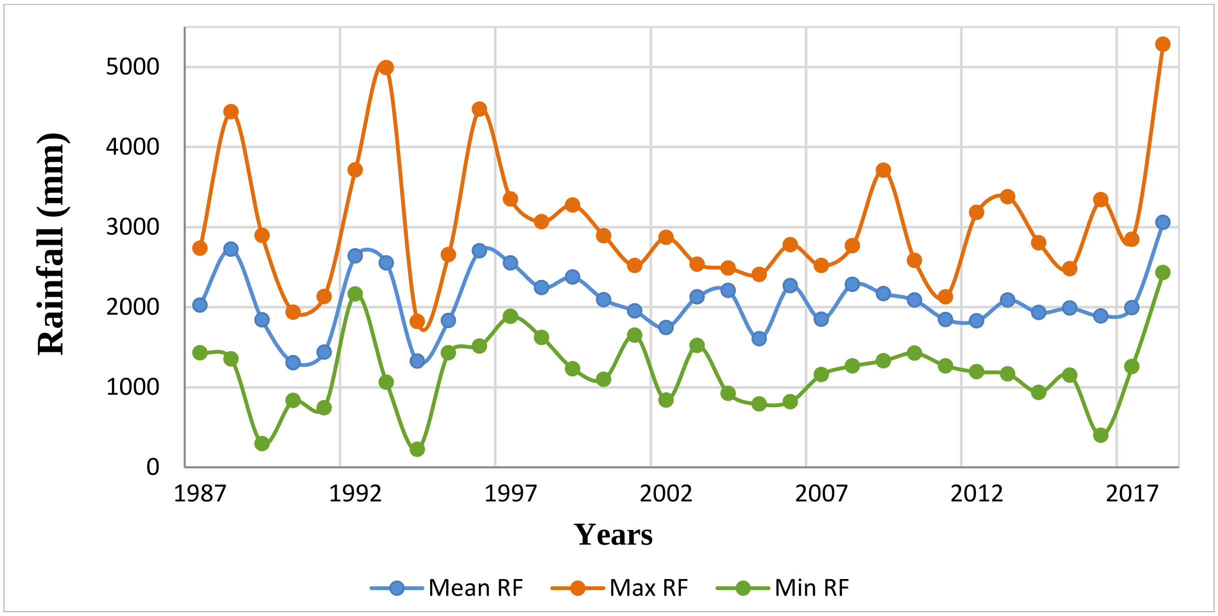

Figure 3: Annual Rainfall of the study area (1987–2018) (Source: NMA)

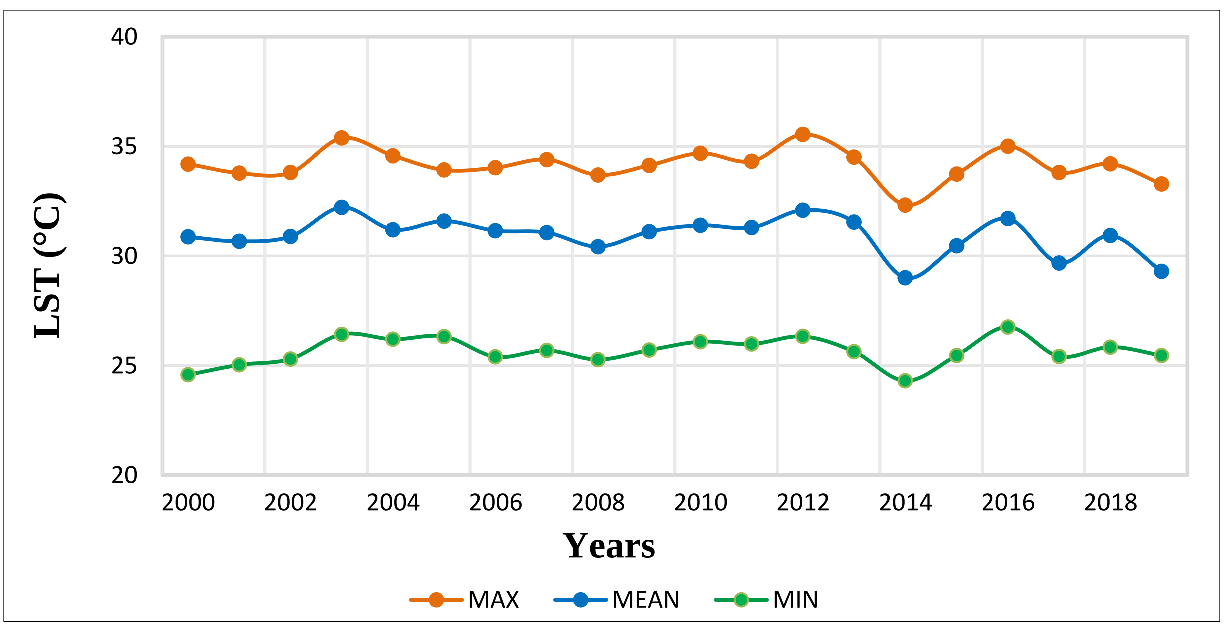

Figure 4: LST of the study area (dry season) (2000–2018) (Source: USGS, MODIS LST)

3.1.4. Vegetation

Ankasha Guwagusa Woreda predominantly covered by Dry evergreen Afromontane forest and grassland complex. The forest containsdifferent species like *Olea europaea*sub-spp. *Celtis africana, Euphorbia ampliphylla, Juniperus procera, Dracaena spp., Carrisa edulis, Mimusops kummel, Rosa abyssinica (Mawordi), Ekebergia capensis,* etc. The area is also associated with *Arundinaria alpine* (Anini) highland bamboo and extensive areas of grassland rich in species including legumes. The most essential genera are *Hyparrhenia*, *Eragrostis*, *Panicm*, *Trifolium*, *Eleusine*, *Pennisetum*, *Eriosaema Sporobolus*, and *Crotalaria* (Temesgen *et al.*, 2015).

3.1.5. Population and Farming System

According to Ankasha Guwagusaaddministrative office, the district has a total population of 111,164 of which 49.62% are males and 50.38% are females in 2018. The farming system of the area is predominantly subsistence farming based on mixed crop-livestock production. Major crops grown in the area are maize, teff finger millet, barley, potato, wheat, and other vegetables, mainly with one harvest per year. Besides, barley, wheat, potatoes and other vegetables are also produced twice per year with a traditional irrigation system (Assaye, 2016).

3.2. Data Acquisition

3.2.1. Satellite Imagery

Primary and secondary data were collected and used from different data sources to generate the required information. Remote sensing and Geographic Information System were used in this study to generate information on the trend and the amount of change taking place for the last thirty three years. Free RS data sources (Landsat TM, ETM+ and OLI-TIRS) from USGS Earth Resources Observation Systems (http://www.earthexplorer.usgs.gov) of the year 1985, 1996, 2006 and 2018 were used to produce adequate information to meet the major issues and objectives of the research. The RS data sources were selected as much as possible in the same vegetation season which was January and February. All the RS data sources were referenced and projected to Universal Transverse Mercator (UTM) projection system Zone 37N and datum of World Geodetic System 84 (WGS84). The Landsat image has a spatial resolution of 30m (Table1) which is commonly used for land-use land-cover change detection and spatial analysis purpose. In addition to Landsat data, Digital Elevation Model (DEM) of the study area was obtained from the same data source with 30 m resolution Shuttle Radar Topography Mission (SRTM) to extract slope. Google Earth was used to generate road, river and town of the study area by using digitizing method.

The software used in this study was QGIS (Quantum GIS) open-source GIS software to make the LULC change detection, mapping and modeling deforestation. In addition, R Studio and Microsoft Excel were used to process, analyze and interpret the data.

Table 1: Description of used satellite imageries.

Image Type	Path and Row	Resolution (meter)	Acquisition Date
Landsat TM	170/52 and 170/53	30m	02/17/1985
Landsat TM	170/52 and 170/53	30m	01/31/1996
Landsat +ETM	170/52 and 170/53	30m	01/18/2002
Landsat OLI	170/52 and 170/53	30m	01/11/2018
DEM	ASTGTM2_N10E036 ASTGTM2_N11E036	30m	02/12/2018

3.2.2. Ground Truth Data

Data acquired from satellite sensors should be supported and checked with reality by using solid ground truth information. Hence, ground truth data were collected from the field using handheld global positioning system GPS for training data (Region of Interest), accuracy assessment and model validation. Training data that was used to produce land-use land-cover map was collected from the field to have a correct spectral value for each class. However, Google Earth (high resolution image) also used to collect information from areas where impossible to accesses.

3.2.3. Demographic Data

Demographic data for 2018 was obtained from the Ankasha Guwagusa Woreda administrative office for every Kebele to create the population density factor map for every 17Kebeles (Appendix 2).The population density was one of the explanatory variables for spatial data analysis.

3.3. Methodology

3.3.1. Image Pre-processing

Digital image pre-processing is the improvement of digital image for human interpretation (Bakker *et al.*, 2001).After downloading and extracting the satellite image, pre-processing activities have taken place. These include atmospheric correction, layer stacking/merging, gap-filling(Landsat 7), image mosaic, clipping and other image enhancement pre-processing activities that were applied to improve the quality, interpretability of the image so that the images become appropriate and ready for further analysis.

3.3.2. Image classification

Image classification is the process used to produce thematic maps from the satellite image. The themes can vary from general categories to detail descriptions of specific classes (Robert and Schowengerdt, 2007).Hence, different classes from a pre-processed image were identified through supervised classification (Maximum Likelihood Algorithm) to produce primary LULC map. This map was used to collect training data to have a clear understanding of the features and locations of classes during fieldwork. Subsequently, 270 ground training point (GTP) training data was collected from the field with the help of local experts and elder peoples who live in the area over the last thirty three years.

In the present study, a total of 210 training data (cropland, forest and bare-land collected 50 points for each class and 30 for built-up and water body each) were collected from the ground. Of the total GTPs collected during fieldwork around 30% were used for accuracy assessment. The final supervised classification was performed using maximum likelihood algorithm in QGIS Semi-Automatic Classification Plugin (SCP). The Semi-Automatic Classification Plugin (SCP) is used to make supervised classification for remote sensing images, providing tools for the preprocessing and post-processing of images. The description of land-use land-cover classes are as follows (Table 2).

Table 2: Land-use land-cover types.

LULC Class	Description
Forest	Represents both natural and plantation forest areas that are stoked with tree capable of making timber or other wood product.
Crop land	Lands covered with agricultural activities.
Built-up	Areas composed of intensive use with much of the land by towns, rural villages and roads.
Bare-land	represents an areas under degraded grassland and with some area that are bare grounded (rocky).
Water body	Land which is covered with lake, rivers, dams etc.

Based on the result of the classified land-use land-cover data the rate of LULC change was calculated and analyzed based on the formula of (Suleiman *et al.*, 2017) as follows:

$$R = \frac{(a_2 - a_1)}{t} \quad (1)$$

Where R is rate of change, $a_2$is recent year land-use land-cover in ha, a_1 is initial year land-use land-cover in ha and *t*is interval year between initial year and recent year.

To compute percentage changes in each land-use land-cover for the study area, targeted land-use land-cover was segmented into two change periods of image analysis. From Eq. (1), a relationship for estimating percentage change of targeted land-use land-cover for the change detection periods under study was established (Suleiman *et al.*, 2017) Eq. (2).

$$\%\Delta inl = \frac{(a_2 - a_1)}{A} \times 100 \qquad (2)$$

where Δinl is change in the targeted land-use land cover under study, $a_1$and a_2 are the areas (image-based estimated areas) of the targeted land-use land cover at the beginning and end of the change detection analysis and A is the sum total area.

3.3.3. Image reclassification

One of the objectives of the present study was to quantify the amount of forest cover change for the last thirty three years. Therefore, the raster map which was produced as five LULC classes were reclassified into forest and non-forest. Forest was already classified as a forest but non-forest contains built-up, water body, bare-lands and cropland. Those two thematic maps were used to assess and analyze the extent and amount of forest cover dynamics in the study area.

3.3.4. Accuracy Assessment

Accuracy assessment was conducted to obtain better data from sample points (ground control points) using Global positioning system (GPS) and comparing this data with the map classification to improve the uncertainty. The importance of accuracy assessment using GCP for improving the uncertainty of classification is emphasized (FAO, 2016). Stratified random sampling was used to determine the GCP for each LULC class. This sampling technique is selected because to sample each LULC individually, each pixel element is assigned only in one particular class and no pixel element is left to assign(FAO, 2016 and GFOI, 2016).The sample was distributed in proportional allocation technique; the number of samples was allocated based on the size of area within the classes. The smallest number of samples was 5 per class. Overall accuracy is the proportion of area classified, and thus refers to the probability that randomly selected samples on the LULC map is classified correctly Eq. (3). User's accuracy is the proportion of the area classified as class i that is also class i in the reference data (ground data) Eq. (4). It provides users with the probability that a specific area of the map of class i is also that class on the ground. Producer's accuracy is the proportion of area that is reference class j and is also class j in the LULC map Eq. (5). It is the probability that class j on the ground is mapped as the similar class (FAO, 2016).

$$A = \sum_{j=1}^{q} P\mathrm{jj} \tag{3}$$

$$Ui = \frac{Pii}{Pi.} \tag{4}$$

$$Pj = \frac{Pjj}{P.j} \tag{5}$$

Where, A is overall accuracy, P*jj* and P*ii* diagonal values, U*i* is users accuracy, P*j* is producers accuracy, P.*j* is column total and P*i*. is row total. In addition to overall accuracy, kappa coefficient was also computed as follows:

$$\mathrm{k} = \frac{N\sum_{i}^{r} Xii - \sum_{i}^{r}(Xi*X+i)}{N^2 - \sum_{i}^{r}(Xi+*X+i)} \tag{6}$$

where, N is the total number of samples in the matrix, $r$is number of rows in the matrix, x_{ii} is the number in row i and column i, x_{+i} represent the total for row i, and x_{i+} represent the total for column i.

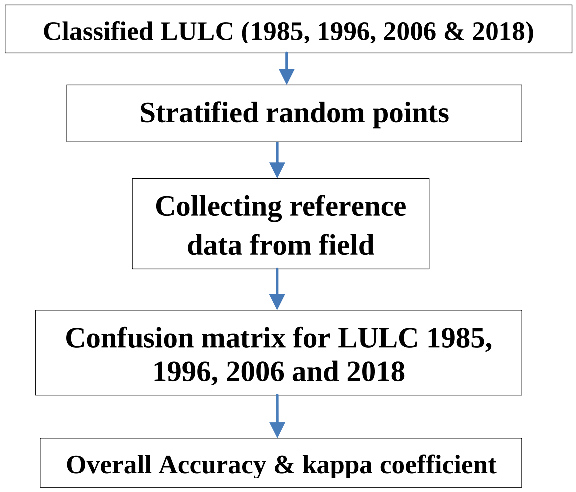

Figure 5: Accuracy assessment work flow.

3.3.5. Modeling and Mapping

Deforestation is driven by bio-physical and socio-economic factors which need to be studied to conserve and protect the forest cover (REDD+, 2015). In this study, the most influential factors were selected as an independent variable based on literature reviews and the considering infrastructure, topographic and socio-economic status of the study area. Forest and non-forest map of 2018 was used to identify the existing area of the current forest. Graphical modeler (QGIS) was used to produce deforestation risk zone map.

3.3.5.1Deforestation Risk Map Analysis

Model parameters

Deforestation risk model was developed based on five parameters which are slope in percent, proximity to river, population density, proximity to road and proximity to town(Muller *et al.*, 2011; Lallo *et al.*, 2017 and Sanchayeeta *et al.*, 2017). The last four parameters were rasterized and all are reclassified. In this study, the level of risk for deforestation is classified into four. **1** is assigned as low risk while**2** and **3** areas moderate and high risk and**4** is extreme risk for deforestation (Table 3).Then, by using pairwise comparison technique weighted overlay analysis was computed to give the appropriate value for each parameter.

a) Slope

Slope of the study area was one parameter to analyze the level of vulnerability to deforestation. Forest on a steeper slope is less vulnerable to being cleared than forest on lower gradient, because the soil at steeper slope is more exposed for soil erosion and unsuitable for agriculture (Broothaerts *et al.*, 2012; Megersa,2016).Gentle slope is comfortable for agricultural activities whereas mostly steep slopes are not preferred. Therefore, the steppers the slope the disturbance of the forest becomes very low whereas in gentle or flat slope anthropogenic and animal intervention occurrence is high. Based on that, the scale value for high slope percentage is low and for gentle slope percentage is high. The slope gradient of the study area was extracted from the DEM. It was classified into four based on the risk value which is indicated in Table 3 and Figure6&7.

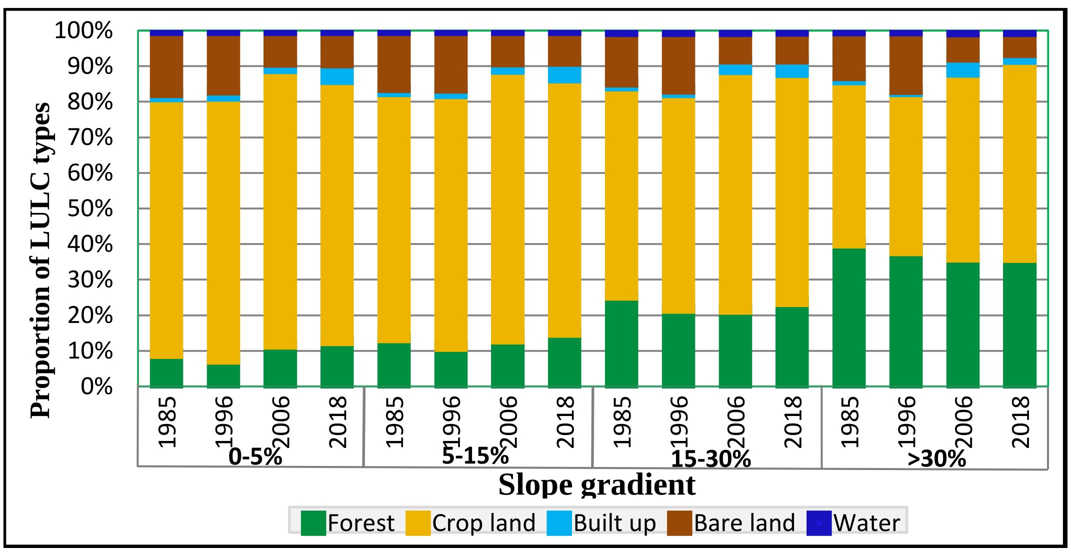

Figure 6: Proportion of LULC types with slope gradient.

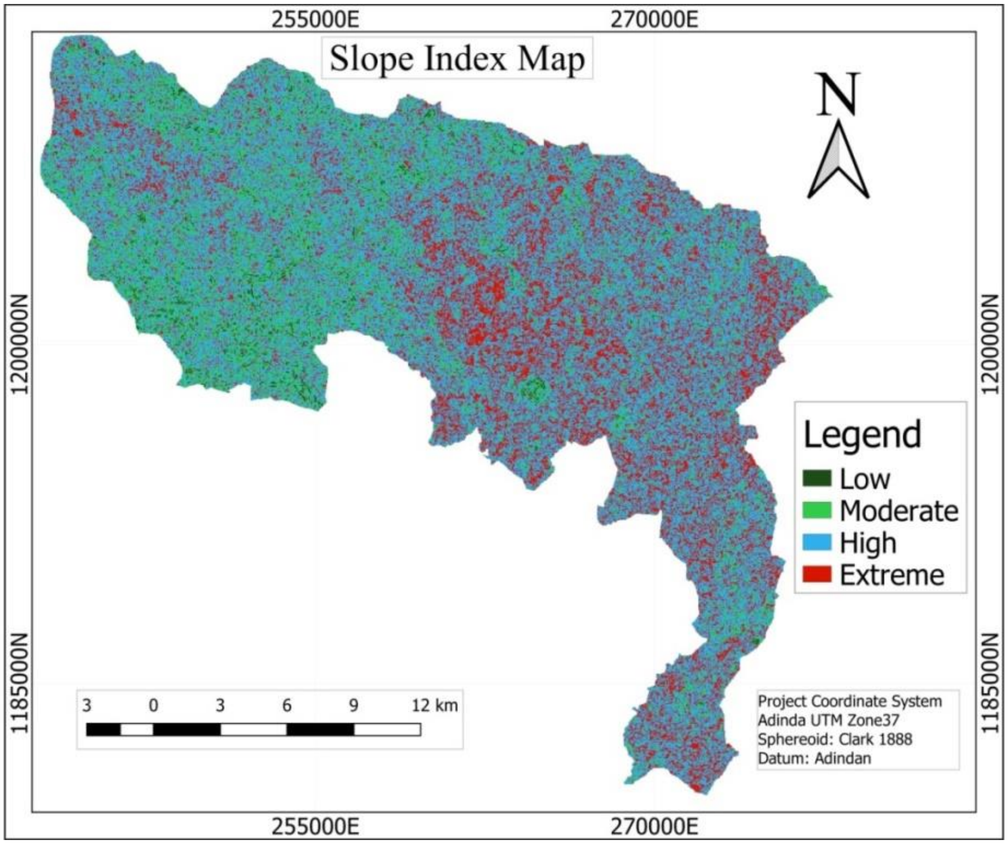

Figure 7: Slope index map.

b)Proximity to River

Water is a vital element for existence of life on earth. Therefore, the probability of deforestation near to rivers, streams, lakes and artificial water holes becomes high because of human beings and wild animals need regular access to water (Workaferahu, 2015; Sanchayeeta *et al.*,2017). Based on that, river is considered as one factor for modeling of deforestation for this study. The closer the river to the forest the risk of deforestation became high whereas as the forest is far from the rivers its risk became lower. The river factor value and index map which was rasterized and reclassified is shown in Table 3 and Figure8.

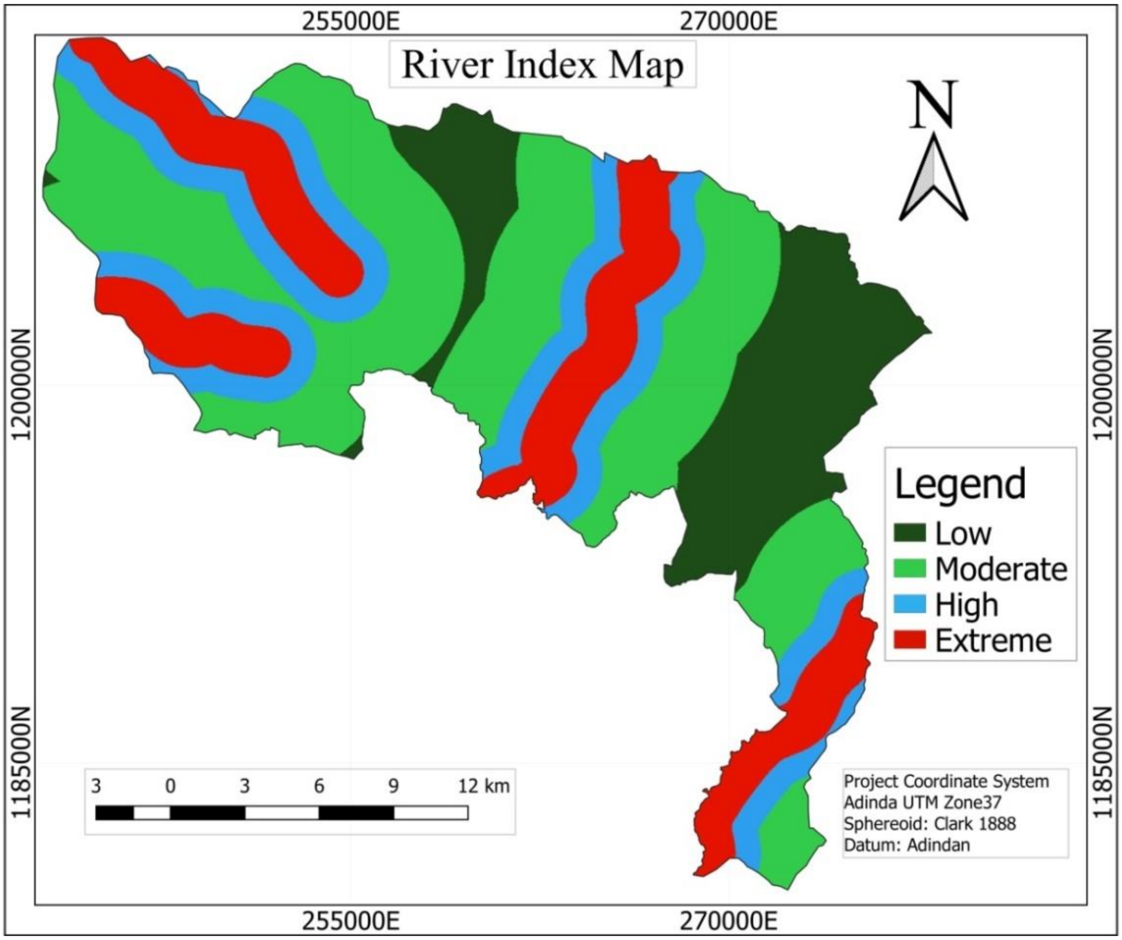

Figure 8: River index map.

c) Proximity to Road

Road is a very critical parameter to evaluate the influence of human beings on the natural ecosystem (Geist and Lambin, 2002; Mo *et al.*, 2017; Sahana *et al.*, 2018). Proximity to road was considered as one factor to develop the model in this study. Many studies confirm that as the forest cover is closer to the road it has a very high possibility of the forest to be affected by humans. This is because of the accessibility to transport, easiness for illegal logging activities, market availability and so on. Agricultural expansion is increasing because it becomes easy for the market for selling their product. Large scale agricultural investments also attracted. For this reason, the road index map was produced with risk scale value using buffer analysis by rasterized and reclassifies it as shown in Table 3 and Figure9.

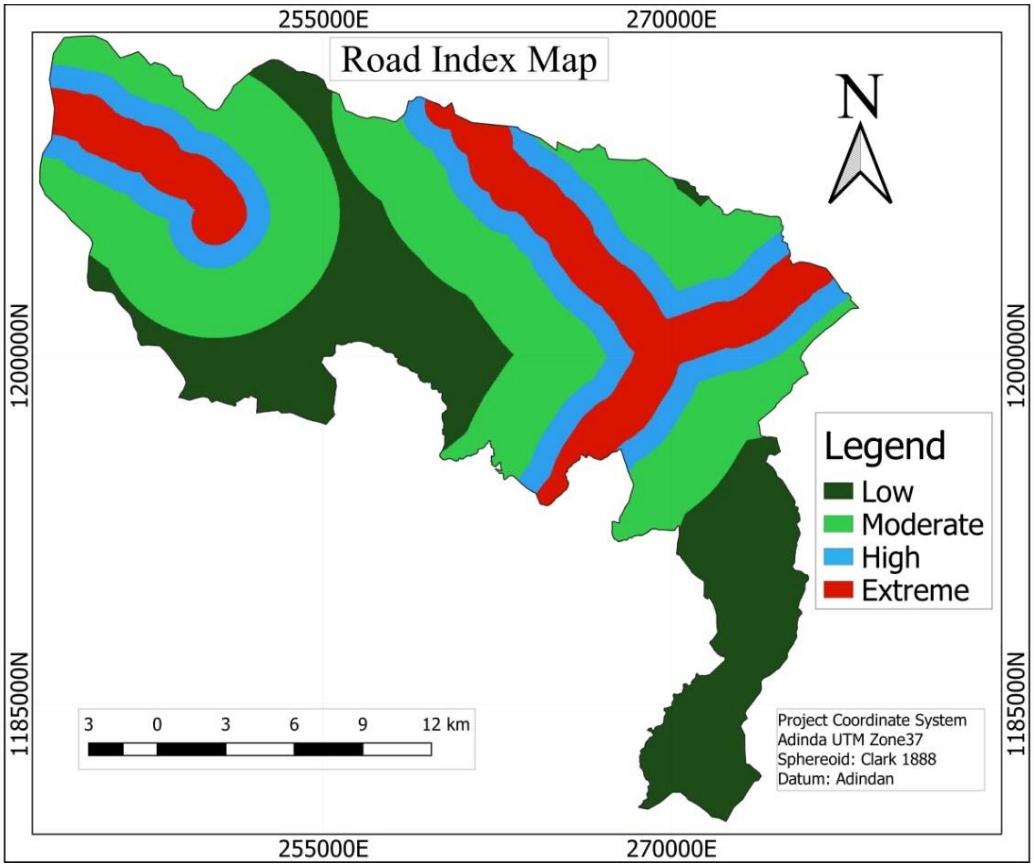

Figure 9: Road index map.

d)Proximity to Town

Natural resource which is found around urban areas/towns is largely affected by human intervention. In urban areas, most of the wood material which is used for construction, furniture, and fuel-wood is obtained from the nearest forest (Getahun, 2013; Forson and Gavu, 2016). In addition, major towns are used as a deposit for logged trees and then export to other locations. Therefore, the closer the forest to the town the more it is disturbed by humans. Similar to the above factor maps, an index map for town was produced with risk scale value using buffer analysis by rasterized and reclassifies (Table 3 and Figure10).

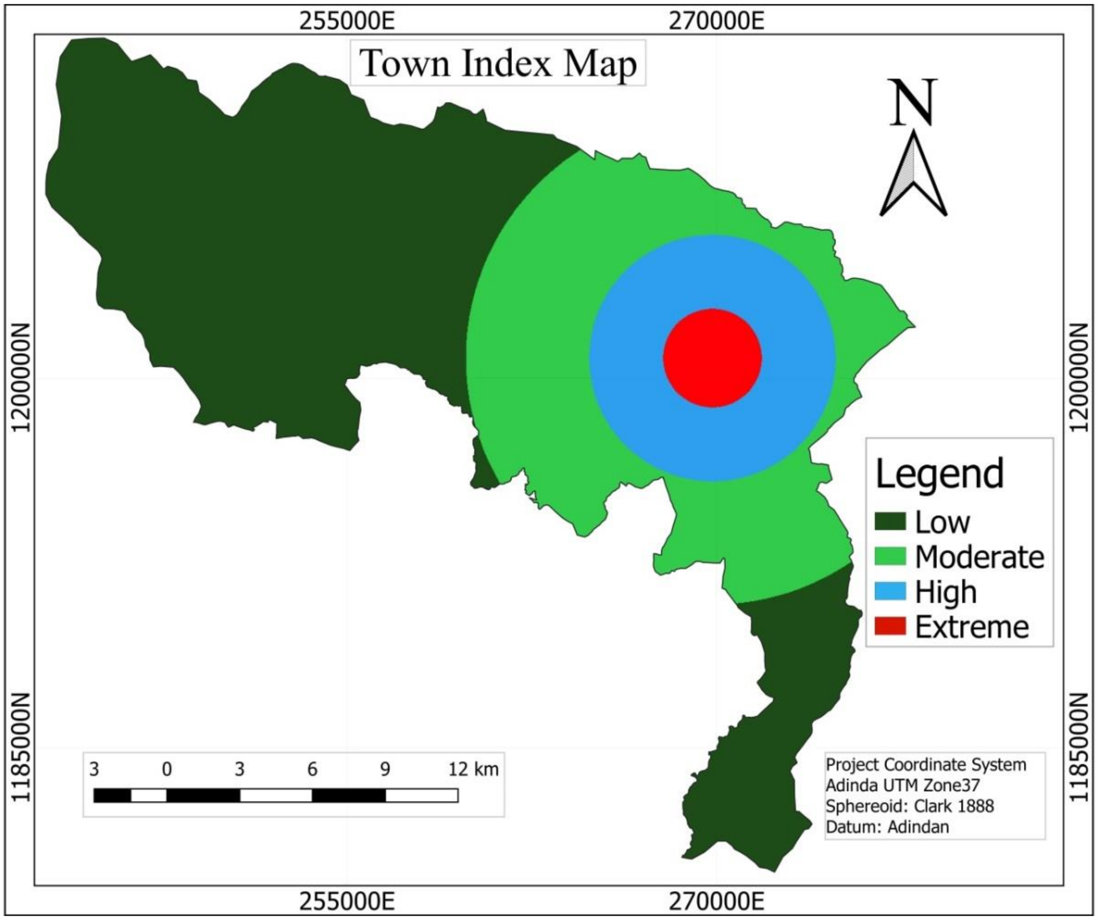

Figure 10: Town index map.

e) Population Density

Population density is one factor considered to make modeling deforestation in the study area. As the population density is increases in a given area the pressure on the surrounding natural resource also increases (Getahun, 2013; Leblois *et al.*, 2016).The population density data per Kebele for 2018 was collected from Ankasha Guwagusa Woreda administration office (Appendix 2) then rasterized and reclassify to produce population density index map by using scale value(Table 3 and Figure11).

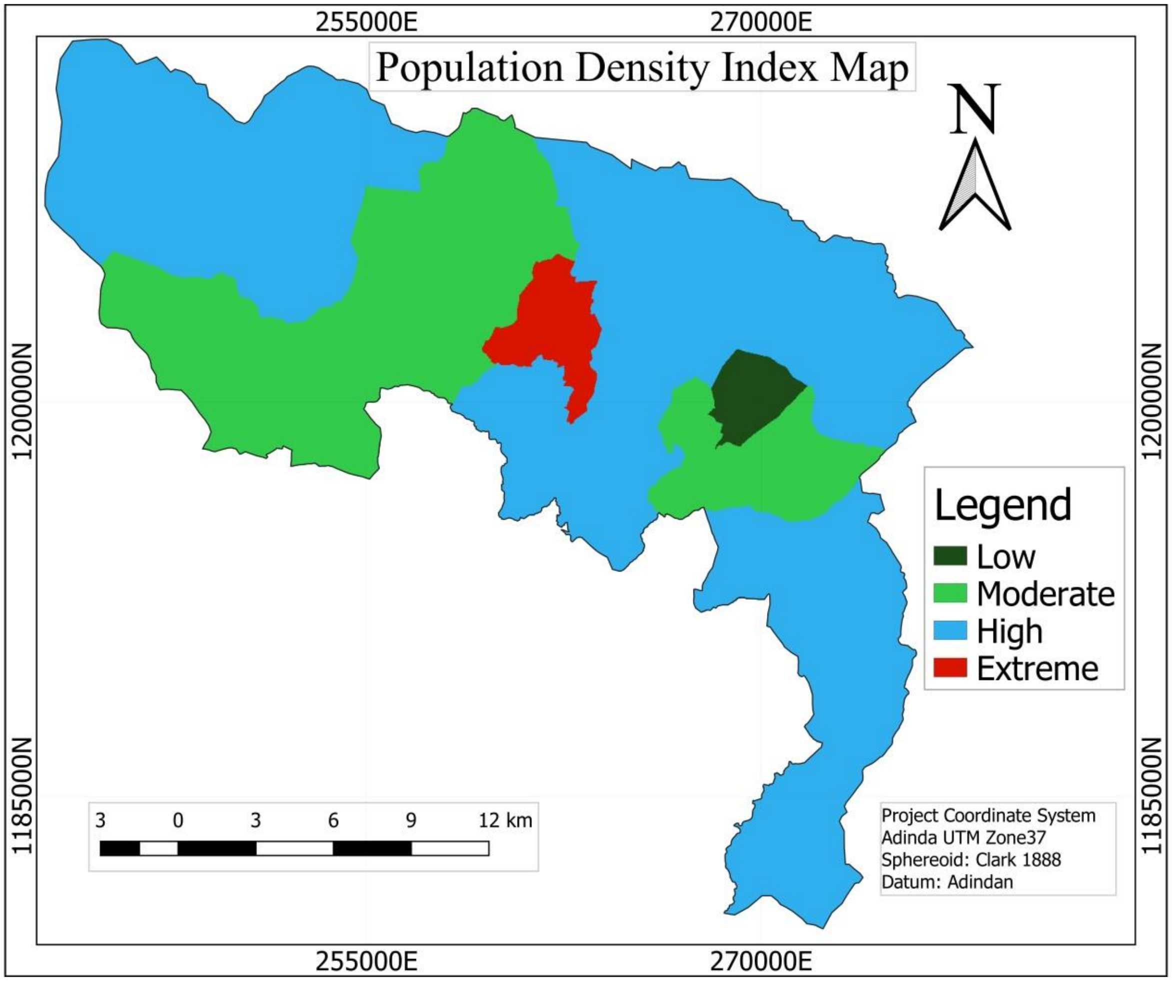

Figure 11: Population Density index map.

Table 3: Model parameters with risk values

Variables	Classes	Ratings
Slope in Percent	<5, 5-15, 15-30, >30	4,3,2,1
Distance from road in meter	<1000, 1000-2000, 2000-5000, >5000	4,3,2,1
Distance from river in meter	<1000, 1000-2000, 2000-5000, >5000	4,3,2,1
Distance from town in meter	<2000, 2000-5000, 5000-10000, >10000	4,3,2,1
Population density per ha	>3.5, 2.5-3.5, 2.5-1.5, <1.5	4,3,2,1

where, 4 is Extreme, 3is high, 2 is moderate, and 1is low.

3.3.5.2. Weighting Overlay Analysis

After producing the dataset, weights were assigned for each factor and combining based on their weight was the critical step to conduct MCE (Multi Criteria Evaluation). By using Analytic Hierarchy Process (AHP)method calculated in Pairwise Comparison Matrix was prepared by comparing two factors at a time using a scale with values from 9 to 1/9as introduced by (Saaty, 1980) (Table 4).

Table 4: Nine points of continuous rating.

1/9	1/7	1/5	1/3	1	3	5	7	9
Extremely	Very strong	Strongly	Moderately	Equally	Moderately	Strongly	Very strong	Extremely
Less important							More Important	

Pairwise Comparison Matrix developed by comparing/computing two variables to decide the degree of their importance value symmetrically. Therefore, the lower triangular half was filled then remaining cells are reciprocals of the lower triangular half. A consistency ratio (CR) was calculated to evaluate the success of the weight criteria matrix. The formula to calculate the CI is as follows:

$$\boldsymbol{CI = \lambda\,\mathrm{max} - \frac{n}{n-1}} \quad (7)$$

where, CI is Consistency index, n is the matrix size and λ=5.3055 calculated by weighted dot product average. Based on Equation6below, the consistency ration result was 0.0682. According to (Saaty, 1980), if the value of CR is less than 0.1 then the consistency is good (Table5).

$$\boldsymbol{CR = \frac{CI}{RI}} \quad (8)$$

where, CR is consistency ratio, CI is Consistency index and RI is Random index of n.

Table 5: Pairwise comparison and weighted matrix.

Factors	Slope	Road	River	Town	Population density	Weight
Slope	1.00	2.00	5.00	5.00	1/2	**0.23**
Road	1/2	1.00	7.00	5.00	1/2	**0.28**
River	1/5	1/7	1.00	1/3	1/7	**0.04**
Town	1/5	1/5	3.00	1.00	1/3	**0.08**
Population density	2.00	2.00	7.00	3.00	1.00	**0.36**
Total	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

CR is 0.068.

As it is indicated on equation below, the parameters of the model have been multiplied by their individual weight to generate deforestation risk zone map for the study area.

DRZ=0.23*Slope +0.28*Road +0.04 *River +0.08*Town +0.36*Population density (9)

where, DRZ= Deforestation risk zone.

GPS data was collected from the field to evaluate accuracy of the model by comparing with the real world (Appendix 3). Therefore, it is used to check incidence for deforestation occurrence in the study area by GPS was a model validation method (Megersa, 2016).

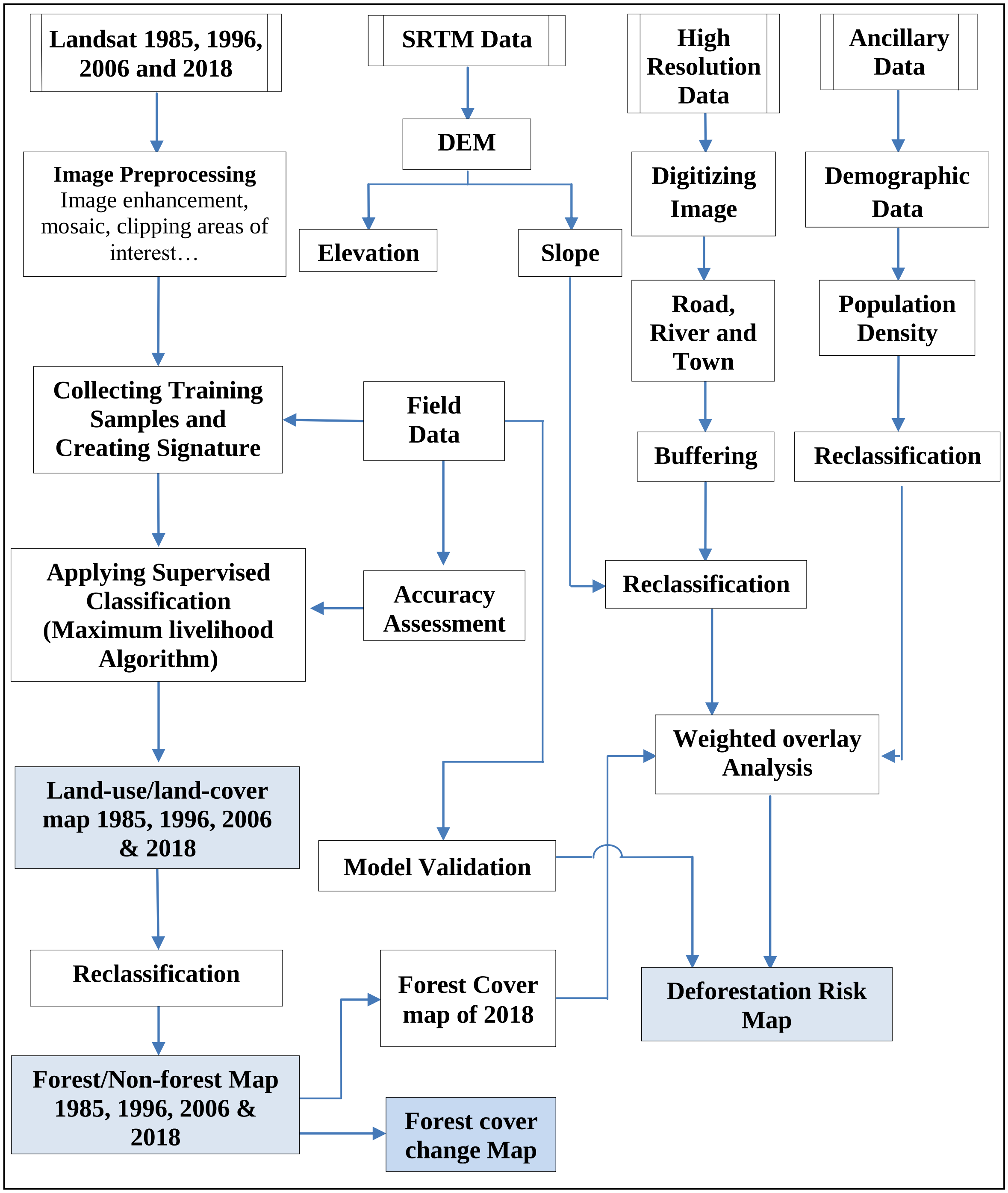

Figure 12: Methodological Workflow

4. RESULTS AND DISCUSSION

4.1. Land-Use Land-Cover Class

The results of the land cover classification showed that most of the forest area found in northwest part was6858.09 ha (14.58 %) and the cropland was32015 ha (68 %). Built-up, bare-land and water body covered relatively small areas which has only 564.84 ha (1.2 %), 7537.16ha (16 %) and 62.72 ha (0.13 %) in 1985, respectively (Figure 13 and Table 6).The forest area was not fragmented but continuous dense natural forest with very less human and natural disturbance and the cropland was found typically in the eastern and middle part of the study area with higher percentage. In this year, built-up coverage was very small compared to other study years because number of urban population was relatively lesser as the study area recorded an incessant increase (CSA, 2013).

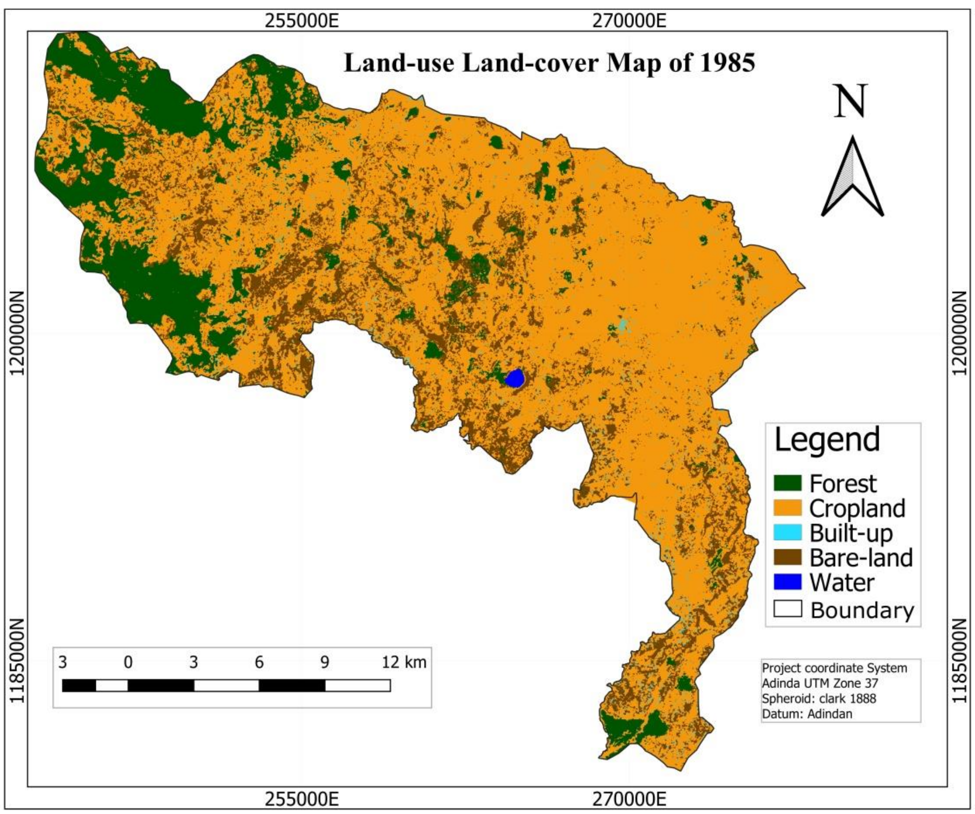

Figure 13**: Land-use Land-cover Map of 1985.**

The result of the LULC classification of 1996 revealed that from the total land coverage, cropland accounted about 32850.21 ha (69.84%) in the year 1996.Forest, built-up and bare-land take the share of 5738ha (12.2%), 676.95 ha (1.44%) and 7723.7 ha (16.42%), respectively. The remaining area was covered with water body which covers48.78 ha (0.1%) (Figure 14 and Table 6) . Like the previous year, cropland still covers most of the study area as compared to other LULC types. This result indicates that expansion of agricultural land was the major activities carried by local people. This was clearly elaborated by (Obang *et al.*, 2017) that the surrounding natural resource highly influences by anthropogenic factor.

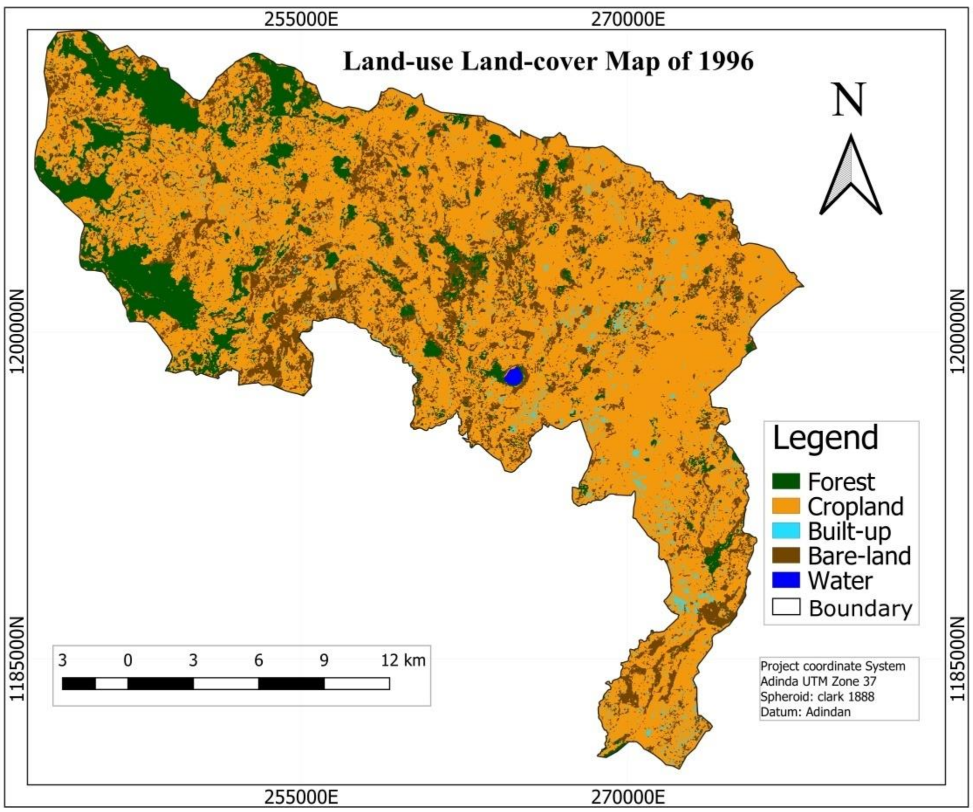

Figure 14: Land-use Land-cover Map of 1996.

The result of the land cover classification showed that cropland coverage units were about 35035.91 ha or 74.48% of the total area whereas the remaining classes took only 25.52%. Built-up, bare-land and water body was 1023.73 ha (2.2%), 4097.9 ha (8.7%) and 48 ha (0.1%), respectively (Figure 15 and Table 6). This result shows that the cropland increasing significantly as the demand for agricultural area increasing parallel to continuous population growth. The second largest class was forest areas which cover about 6832.35 ha (14.53%). In this year the new forest patches emerged in the eastern and middle area whereas the north-western area of compound wide natural forest starts to shrink down. However, forest coverage was significantly increasing in 2006. The reason for this was the area of newly arisen small patches of forest in the middle and eastern parts was greater than deforested natural forest in north-western areas. As a result of deforestation and forest degradation, the whole forest ecosystem disturbed. This result is similar to De Mûelenaere *et al.* (2014)that afforestation and deforestation were in balance in northern Ethiopia from the first phase (1917–1965) to the second phase (1965–1982).Likewise, Jacob *et al.*(2015) also reported there was significant evidence that *Eucalyptus arborea* tree line show increase from the year 1965 to 2010 due to anthropogenic factors.

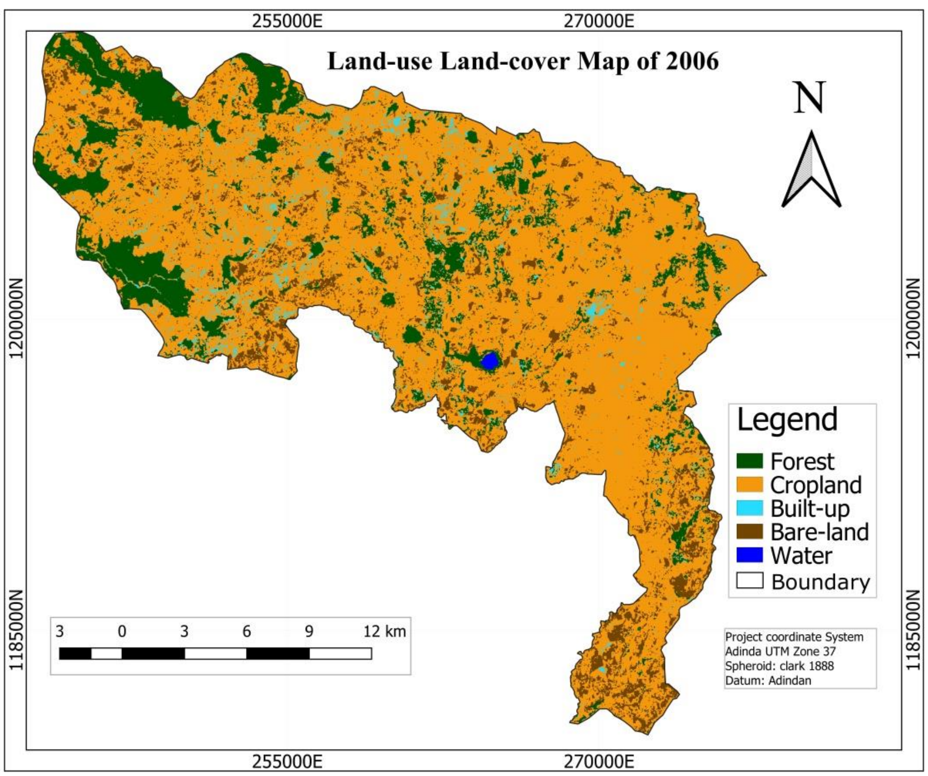

Figure 15: Land-use Land-cover Map of 2006.

The last LULC Class map produced was the year 2018 which shows cropland covers around 33233.41 ha (70.6%) and the forest area accounted 7605.3 ha (16.2%).Cropland and forest areas still cover more than 85% of the study area. Like previous years water body covers relatively small part which is 44.81 ha (0.1%). Built-up and bare-land are covering 2096 ha(8.6%) and 4058.46 ha (4.5%) respectively. In 2018, built-up area expansion was showed in most of the study area. This indicates that due to continuous population growth, urbanization was the main activity in recent years. Similarly, a dramatic uprising of forest coverage is showed in most middle part of the study area (Table 6). In this year the forest percentage is higher but distributed in the study area. A similar pattern of results was obtained by Abiyot (2017) that the forest cover show increase cropland decreasing in resent years.

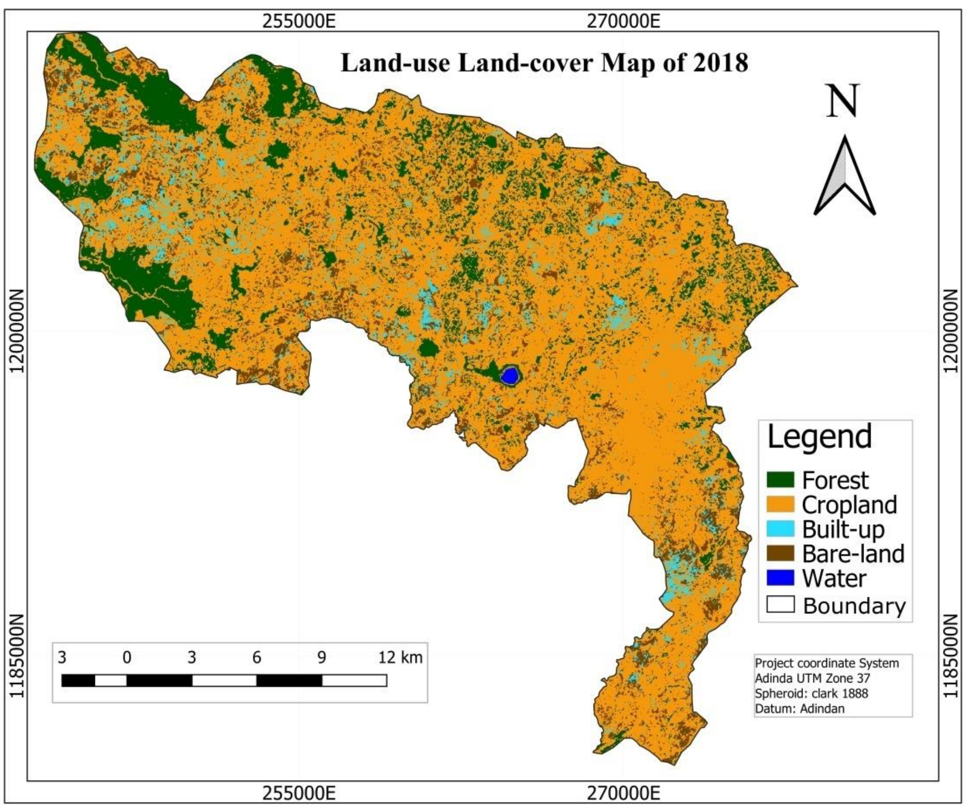

Figure 16: Land-use Land-cover Map of 2018.

Table 6: Land-use/land-covers areas during 1985–2018.

LU/LC	1985		1996		2006		2018	
	Area (ha)	**Area (%)**	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**
Forest	6858.09	14.58	5738.31	12.20	6832.35	14.53	7605.26	16.17
Cropland	32015.14	68.06	32850.21	69.84	35035.91	74.48	33233.41	70.65
Built up	564.84	1.20	676.95	1.44	1023.73	2.18	2096.01	8.63
Bare land	7537.16	16.02	7723.7	16.42	4097.9	8.71	4058.46	4.46
Water body	62.72	0.13	48.78	0.10	48.06	0.10	44.81	0.10
Total	47038	100	47038	100	47038	100	47038	100

4.2. Land-Use Land-Cover change

4.2.1. Extent and trend of land-use land-cover changes

Land-use land-cover trend of the study area shows a significant change from 1985 up to 2018. According to the result, forest lands and water body from the year 1985 to 1996 have decreased by 1119.78ha (2.38%) and 14ha (0.03%), respectively. In contrast, built-up, bare-land and Cropland increased by 112ha (0.24%), 186.54 ha (0.4%) and 835 ha (1.78%) during the first period, respectively. During the periods of 1996 to 2006, the extents of forest, cropland and built-up areas have increased by 1094ha (2.3%), 2185.7ha (4.65%) and 346.78ha (0.74%), respectively, whereas bare-land and water body have decreased by 3625.8 ha (7.7%) and 0.72ha (0.001%), respectively. In the final period (2006–2018), built-up and forest land have increased with 1072.3 ha (2.3%) and 772.9 ha (1.64%), respectively. Cropland, bare-land and water body have decreased by 1802.5 ha (3.83%), 39.44 ha (0.08%) and 3.25 ha (0.01%) respectively. In recent period built-up shows a dramatic increase compared to the others.

Land-use land-cover trend from the baseline up to the final year shows increase in cropland, built-up and forest by 1218.3 ha (2.6%), 1531.2 ha (3.3%) and 747.2 ha (1.6%), respectively. Bare-land and water body have decreased by 3478.7 ha (7.4%) and 17.9 ha (0.04%). The summary of land-use land-cover dynamics during periods of 1985–1996, 1996–2006, 2006–2018 and the whole year's period from 1985 to 2018 elaborated in Table7 and Figure 17.

These results are in good agreement with Letchumy *et al.* (2012); Asmamaw (2013) and De Mûelenaere *et al.* (2014) which have shown that the land-use land-cover trend was multi-directional. Hence, one LULC type (e.g. bare-land) was changed into other LULC types (e.g. cropland) and vice versa. This is due to lack of appropriate land-use land-cover planning, which is very important for protecting and conserving the surrounding natural environment. Mengistie *et al.* (2013) reported continuous increase in agricultural lands was observed at the expense of decreasing natural forests, grasslands and woodlands. The study implies increasing land-use land-cover types were the result of grassland conversion and deforestation. Likewise, agricultural land was increased by nearly50%, while bare-land shows high decline in Holeta watershed, central Oromia from 1984 to 2006 (Ayele *et al.*, 2014). Mekonen and Muluberhan (2019) conducted a research in Eritrean refugee settlements in the north-western Tigray that land-use land-cover has changed dramatically with Farmlands and settlements were increasing at the expense of the forest land.

Table 7: Trend of Land-use/land-cover change during 1985–1996, 1996–2006, 2006–2018 and 1985–2018 (net change).

LULC	1985–1996		1996–2006		2006–2018		1985–2018	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area(ha)	Area (%)	Area(ha)	Area (%)
Forest	-1119.78	-2.38	1094.04	2.33	772.91	1.64	747.17	1.59
Cropland	835.07	1.78	2185.7	4.65	-1802.5	-3.83	1218.27	2.59
Built-up	112.11	0.24	346.78	0.74	1072.28	2.28	1531.17	7.43
Bare-land	186.54	0.40	-3625.8	-7.71	-39.44	-0.08	-3478.7	-11.56
Water body	-13.94	-0.03	-0.72	0.001	-3.25	-0.01	-17.91	-0.03

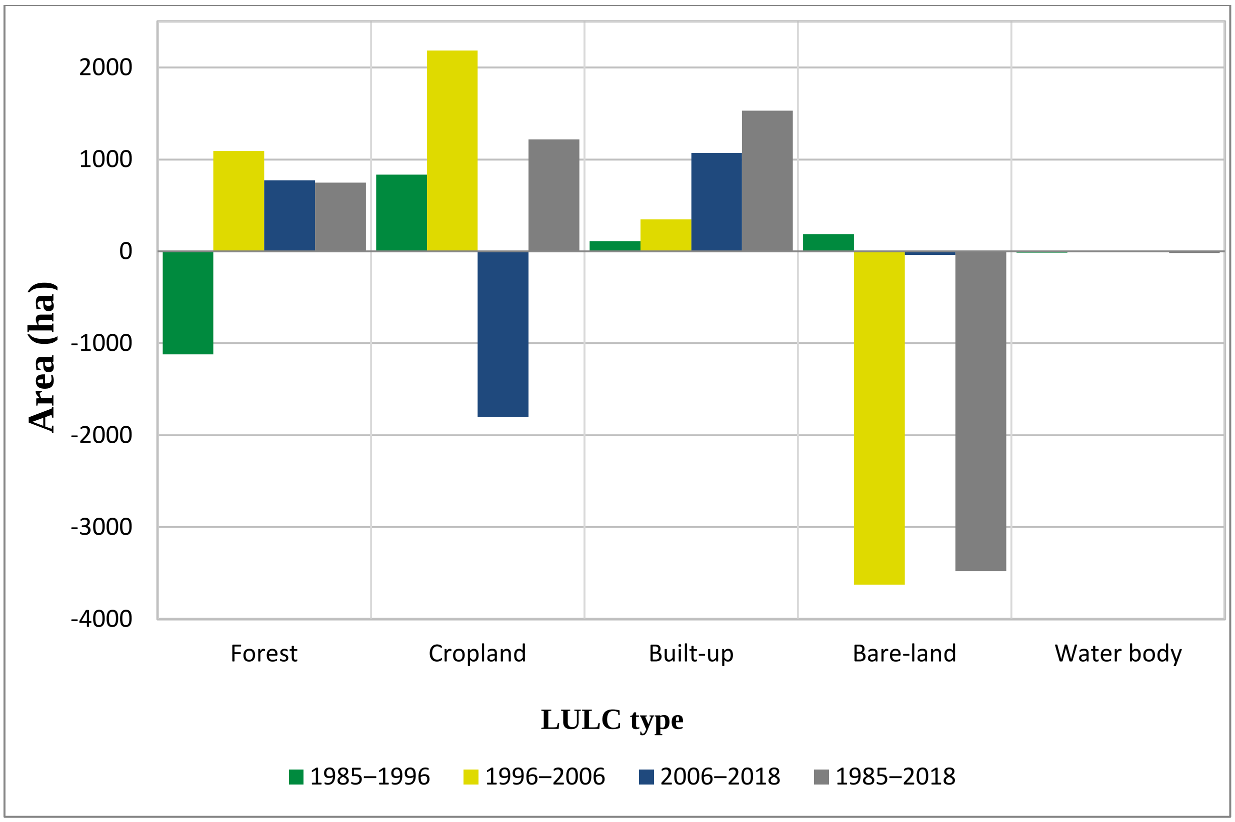

Figure 17: Extent and trend of land-use/land-cover changes.

4.2.2.Rate and Dynamics of Land-use Land-cover Change

The rate of land-use land-cover change was continually spontaneous for the last thirty three years since 1985. As shows in Figure 18 below, the cropland in the first and second period's show a significant increase with 75.92 ha yr^{-1} and 218.57 ha $y\bar{r}^{1}$ but in the final period, it decreases with

150.2 ha yr^{-1}. This result indicates the demand for agricultural land was very high in 1996–2006. Contrary to expectations cropland was replaced by newly emerged small patches of forest in most middle part of the study area (Figure 16). Built-up shows increasing rate throughout all periods with 10.2 ha yr^{-1}, 34.68 ha yr^{-1} and 89.4 ha yr^{-1}. Obviously, like most areas in Ethiopia the expansion of urban areas was expected due to population growth (CSA, 2013).The results are directly in line with Dinku and Suryabhagava (2019) that the built-up area was increasing continuously in Harenna Buluk Woreda, Bale Zone, Ethiopia from1995 to 2016.Similarly, Melakneh *et al.* (2010) also reported an increasing trend of built-up areas due to an increase in human population and related pressure for land and resources conducted in Holeta-Berga watershed for thirty three years (1973–2006).However, cropland shows uniformly continuous increasing rate in their report which is in contrast with the present study. In the future, the demand for urban areas will be increasing from year to year and it seems continuous.

A decreases rate was recorded in bare-land and water body. Bare-land shows a small increase in the first period with 16.96 ha yr^{-1}, but for the second and third periods it declined with 362.58 ha yr^{-1} and 3.29 ha yr^{-1}, respectively. Specifically, in the second period bare-land was decreasing with extreme amount. This result indicates during 1996–2006 bare-land has been shifting to cropland and small patches of forest in addition to small built-up area. Also, water body decreases in 1.27 ha yr^{-1}, 0.07 ha yr^{-1} and 0.27 ha yr^{-1} for the three period respectively. A similar pattern of results was obtained by Mengistie *et al.* (2013) that bare-land replaced by other land-use land-cover types and water body showed a slight reduction in the study period. Liyew (2019) argued a similar decreasing bare-land and water body. In contrast, Mekonen and Muluberhan (2019) reported that bare-land was dramatically increasing in May-Kuhili and Wuwhdet refugee camps occupied by Eritrean refugees in North-western Tigray. According to the research, sudden increase in population number crates a negative impact on the surrounding natural environment with unexpected land-use land-cover dynamics during the study period (2000–2010–2017).

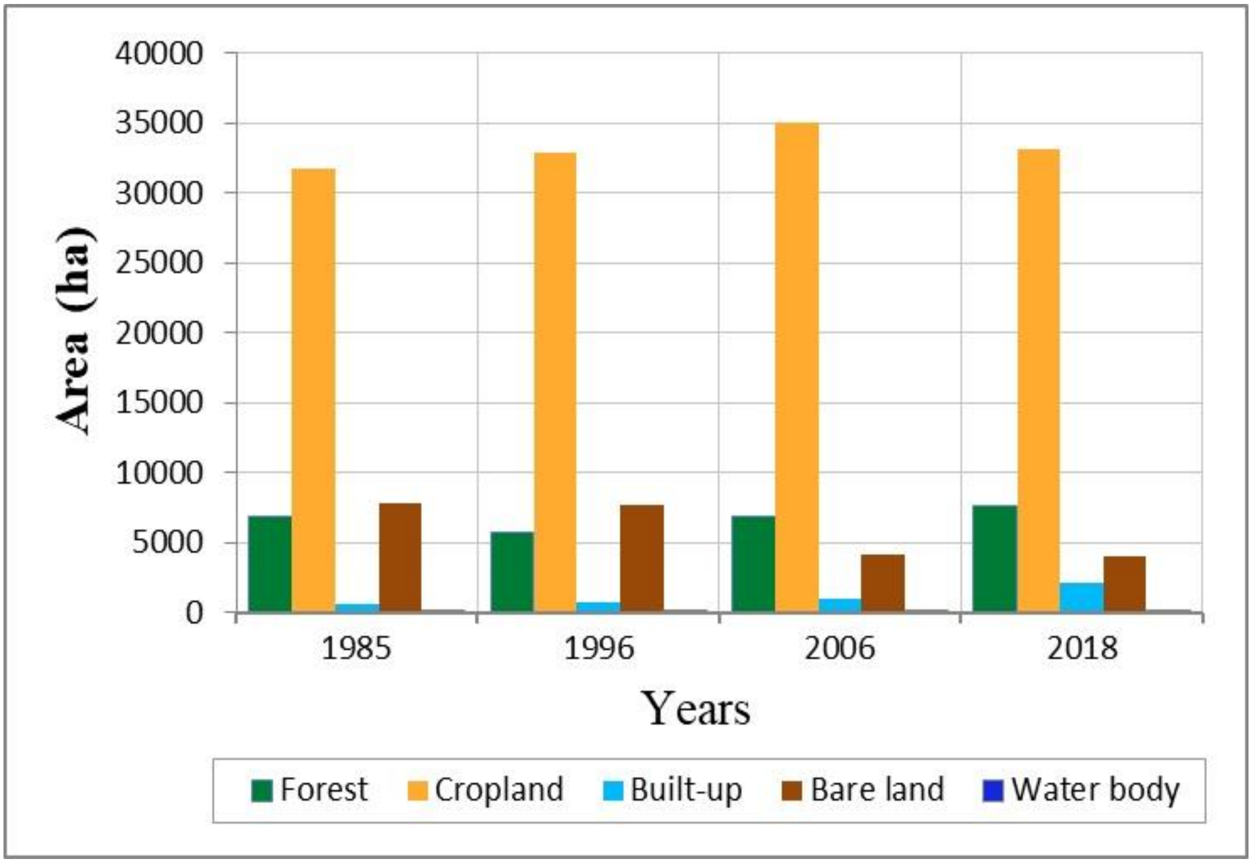

Figure 18: Rate of LULC change from the year 1985 to 2018.

4.2.3. Land-use Land-cover Change Matrix

There was a significant transitional change that happened between LULCs during the initial year (1985) to final year (2018) of the study. As shown in (Table 8), around 16513.88 ha (35%) was transferred from one LULC type to other whereas 30524.12ha (65%) was stable for the net change transition. Hence, bare-land has dramatically decreased from 7537.2 ha in the initial year to 4058.46 ha (by 3478.7 ha) in the final year. This result indicates that a high amount of bare-land was shifting into other land-use land-cover types. The findings are directly in line with Ayele *et al.* (2014) that the high percentage of decreasing land-use land-cover type was observed in bare-land (1984–2006).Likewise, water body also decreased from 62.7 ha in 1985 to 44.81 ha in 2018 with a 17.9 ha difference. Forest land have increased from 6858.1 ha in the initial year to 7605.26 ha (by 747.2 ha) in a final year respectively. The highest amount of gain was recorded for built-up and cropland which increased from 564.84 ha in 1985 into 2096 ha (by 1531.2 ha) in 2018 and from 32015.14 ha in 1985 into 33233.4 ha (by 1218 ha) in 2018, respectively. Accordingly, a probable reason for cropland and built-up increase at the expense of bare-land could be high demand for land for small scale agriculture and settlement. Many research findings from elsewhere also showed that such changes are common in other areas in a similar manner. Overall these findings are in accordance with findings reported by Melakneh *et al.* (2010); Ayele *et al.* (2014) and Tesfa *et al.* (2016) that cropland and built-up areas were increasing with the expense of other LULC types, as a result of continuous increase of population number.

In the present study, the main land-use land cover change is the surrounding local community mostly for cropland and urban area expansion. Similarly, Asmamaw (2013) had stated that in Gilgel-Abbay watershed, lake Tana basin cropland significantly increased from 9% in 1986 to 55% in 2001 which creates a reduction for other land-use land-cover classes. Also, Mengistie *et al.* (2013) result reported that about 60% of the land-use land-cover is changing dramatically from 1974 to 2013. The study reported a continuous increase of croplands observed but natural forests, grasslands and woodlands were declining as the result of deforestation and grassland decline. The study also revealed that plantation forests were created at the expense of natural forest.

Table 8: Matrix of Land-use/land-cover Changes between 1985 and 2018.

Land-Use Land-Cover (1985)		Land-Use Land-Cover (2018)						Class Change
		Water body	Forest	Cropland	Built-up	Bare-land	Grand	
	Water body	**44.81**	3.78	14.13	0	0	**62.72**	**-17.91**
	Forest	0	**4096.71**	2544.51	58.85	158.02	**6858.09**	**747.17**
	Cropland	0	2830.76	**24993.45**	1679.63	2511.3	**32015.14**	**1218.27**
	Built-up	0	40.04	406.75	**59.03**	59.02	**564.84**	**1531.17**
	Bare-land	0	633.97	5274.57	298.5	**1330.12**	**7537.16**	**-3478.7**
	Grand Total	**44.81**	**7605.26**	**33233.41**	**2096.01**	**4058.46**	**47038**	

4.3. Forest cover change Analysis

4.3.1. Forest and Non-forest Class

Forest non-forest result of this study revealed that, a high amount of forest cover was observed in 2018 with 7605.3 ha (16.2%) and the smallest coverage was in 1996 with 5738.3 ha (12.2%). However, in the initial year 1985 and 2006 relatively similar forest cover was shown with 6865.47 ha (14.58%) and 6832.35ha (14.52%) (Figure 19 and Table 9). The percentage area of 1985 and 2006 was almost similar but the position of the forest cover relocated (distributed). This result is in line with Bireda (2015) which indicates the percentage of forest cover in the initial study year (1973) and final year (2015) was higher than the middle study year (1987). According to the study, the major reason for this result was due to a decline in the productivity of cultivated land which opened the way for the introduction and expansion of *Acacia decurrens*. However, it is contrary to the work of Obang *et al.* (2017) that the forest cover declined highly in similar manner due to several explanations of which unsustainable large and small scale agriculture, forest fire, illegal logging, charcoal and fuel-wood.

Table 9: Forest Cover for the year 1985, 1996, 2006 and 2018.

Years	Forest coverage	
	Area in ha	Forest area (%)
1985	6858.09	14.58
1996	5738.31	12.20
2006	6832.35	14.53
2018	7605.26	16.17

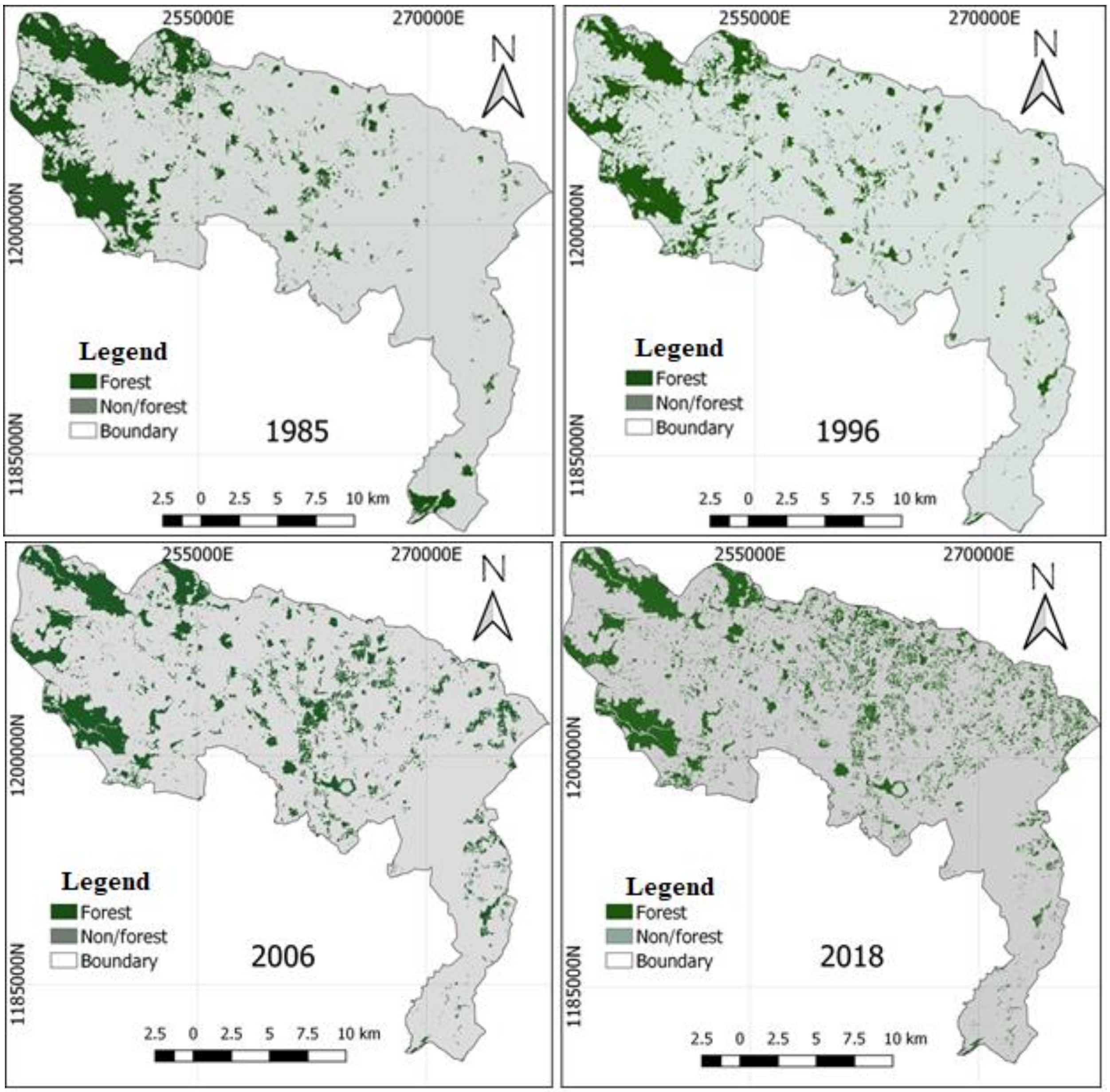

Figure 19: Forest / Non-forest map.

4.3.2. Rate of Forest Cover Change

The rate of forest cover change result shows that during the first period (1985–1996) the forest cover has decreased by 101.8 ha yr^{-1}(0.22%) but increasing in the second period (1996–2006) by 109.4 ha yr^{-1}(0.23%). Remarkably, the first period decreasing rate and the second period increasing rate shows almost reverse pattern which show "V shape" (Figure 12).A similar pattern of results was obtained by Tesfa *et al.* (2016), which was conducted in Beressa watershed northern central highland of Ethiopia. However, forest gain was mostly concentrated in the middle part of the study area by replacing bare-land and cropland. This transition of forest gain is continuous for the last period (2006–2018) increased by 64.4ha yr^{-1}(0.14%). From the starting to the end year of the study rate of forest cover change has increased by22.64 ha yr^{-1} (0.0476 %)(Table 10and Figure 20).

Table 10: Rate of forest cover change per year for the period 1985–1996, 1996–2006, 2006–2018 and for the whole year 1985–2018.

Period	Rate of forest cover change per year	
	Area in ha	percentage
1985–1996	-101.79	-0.22
1996–2006	109.4	0.23
2006–2018	64.4	0.13
1985–2018	22.64	0.04

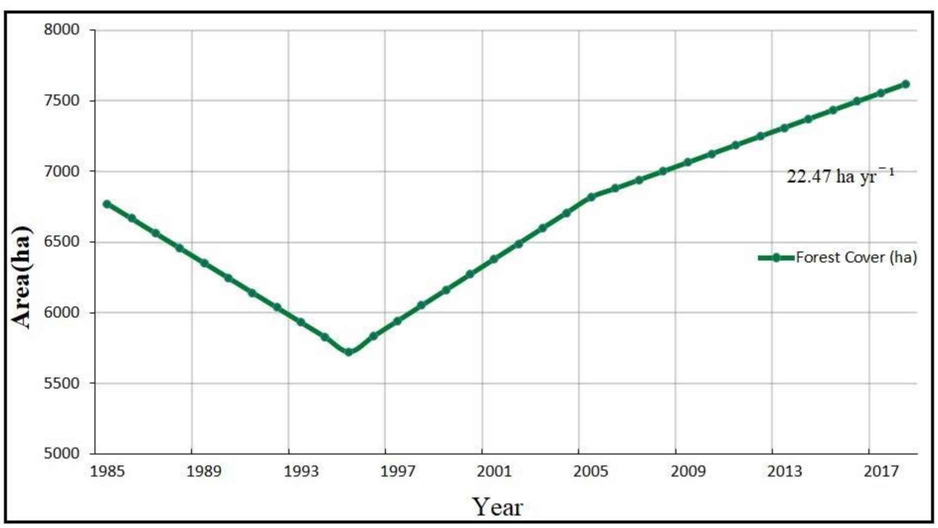

Figure 20: Rate of forest cover change from 1985 to 2018.

4.3.3 Forest Cover Change Transition

The result of forest/non-forest change statistics and map shows in the first period 2326 ha (4.9%) of forest area was changed into non-forest while 4531.8 ha (9.64%) stay unchanged. Likewise, in the same period 1206.4 ha (2.56%) non-forest areas were changed to the forest and 38973.4 ha (82.86%) stay unchanged. In the second period (1996 to 2006) 1220.6 ha (2.6%) of forest was changed into non-forest area which shows a significant decrease compared with the previous one. In contrast, the change from non-forest to forest show increase by covering 2314 ha (4.9%) while stable forest and stable non-forest cover 4517 ha (9.6%) and 38985 ha (82.9%), respectively. Furthermore, the amount of change from forest to non-forest was 1884 ha (4%) and from non-forest to forest covers 2657ha (5.65%) in the final period (2006–2018). In this period stable non-forest show a significant decrease by covering 37548.6 ha (79.8%) while the stable forest was 4948.3 ha (10.5%)(Figure 21 and Table 11).

As clearly observed in Figure below, the forest cover shows dramatic transition from one period to other. Hence, most of the forest to non-forest (deforestation) was recorded in the north-western part edges of the natural forest and its surrounding area is shrinking with fragmented. Whereas, the non-forest to forest (reforestation and/or plantation) transition occurred in the central and most eastern part with several smaller patch of forest**.** Therefore, the level of forest cover change and degradation reported in this study was analyzed in terms of anthropogenic factors as reveled in earlier studies (Berhanu and Suryabhagavan, 2014; Qamer *et al.*, 2016). Deforestation and forest degradation is triggered by various factors that undermine forest cover potential and its productivity, which might lead to irreversible deterioration of the habitat. Ethiopia is one of the four regions in Africa that are highlighted with a high proportion (greater than 40%) of potentially threatened species existed (Stévart *et al.*, 2019)

Significant differences were found from the result of rate of forest cover change during three study periods. The major finding of the present study is the alarming rate of reduction of natural habitats during the period 1985 to 1996. Almost 1119.78 ha of the forest area decreased by other land-use classes during the period. This result is consistent with De Mûelenaere *et al.* (2014); Jacob *et al.* (2015); Abiyot (2017) which shows the most significant decline of primary forest whereas secondary forest was increasing. One question still unanswered is the exact reason for reforestation/plantation.The first possible reason could be an opening of integrated watershed management and natural resource protection as a nationwide campaign by the government since 2000. In the early 2000s, community based integrated watershed development was introduced to achieve wider integrated natural resource management and livelihood improvement (Gebrehaweria *et al.*, 2016).

The second reason could be the recent findings of a large plantation forest potential by the local community with two major species *Eucalyptus spp.* and *Acacia decurrens* established in the study area. Moreover, cropland decreasing trend only during the period from the year 2006–2018 with 1802.5 ha (3.9%). This is probably the spread of plantation by converting from other land into forest land in recent days. Tesfa *et al.* (2016) reported the major reasons have been positively contributed to the increase of the share of forest coverage such afforestation, community and private level tree plantation of *Sesbania susban*, tree *Lucerne* and *Eucalyptus* trees.

In contrast, the bamboo dominated natural forest which is found in the western part of the district seems to decrease dramatically. The causes of deforestation might be due to the habits of the local community and their extreme poverty, which led them too dependent on forest resources and despite attempts to implement a management transfer system, the illegal exploitation remained considerable (Dinku and Suryabhagavan, 2019).

Furthermore, weak on implementation of national forest policy and utilization and conservation of forest resources would have contributed to extensive human encroachment into forests. Moreover, non-coherent decisions, weak land-use policies and governmental institutions and agencies led to the transformation of natural habitats to the other land-use and land-cover classes.

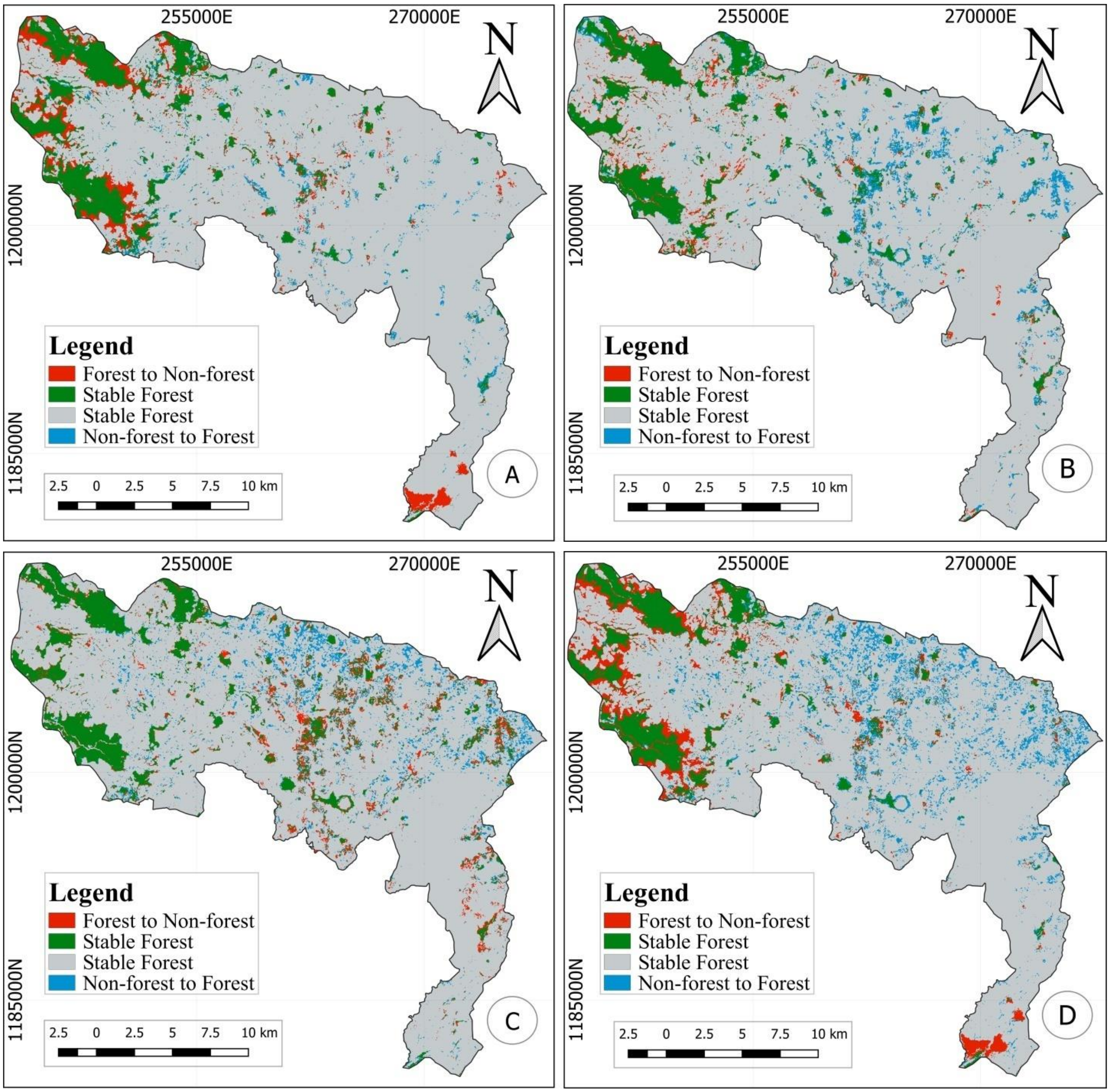

Figure 19: Forest cover change ***A***(1985-1996), ***B***(1996-2006), ***C***(2006-2018) and ***D***(1985-2018).

Table 11: Forest/non-forest change statistics (1985 to 2018).

	1985 to 1996		1996 to 2006		2006 to 2018	
	Area(ha)	Area(%)	Area(ha)	Area(%)	Area(ha)	Area(%)
Forest to Non-forest	2326.24	4.94	1220.59	2.59	1884.10	4.01
Non-forest to Forest	1206.46	2.56	2314.63	4.92	2657.01	5.65
Stable Forest	4531.85	9.64	4517.72	9.60	4948.25	10.52
Stable Non-forest	38973.4	82.86	38985.01	82.88	37548.59	79.83
	47038	**100**	**47038**	**100**	**47038**	**100**

4.4. Classification Accuracy Assessment

Accuracy assessment result for land-use and land-cover shows that, for 1985, overall accuracy was 88.34% with Kappa equal to 0.81. For 1996, Overall accuracy 88.24%, Kappa equal to 0.84. In 2006, the overall accuracy was 90%, Kappa equal to 0.79. Overall accuracy result of 2018 was 90.90% with Kappa equal to 0.76, respectively (Appendix 1). According to (Anderson *et al.*, 1976), the result of overall accuracy is 85% and above the map accuracy is acceptable.

4.5. Modeling Risk of Deforestation

Deforestation risk map result shows that extreme (deep red color) which is found in the central part of study area covers154.16ha(2.03%) and high (blue color) which is found in mostly in central with few eastern part of the study area which covers 3064.37ha (40.28%). This result indicates that the higher population density, closer to infrastructure and topographic condition makes the area vulnerable for deforestation and forest degradation. In other cases, moderate (light green color) and low (dark green color) cover most western and northern border part of the study area with 4309.83 ha (56.65 %) and 79.52 ha (1.05 %) of coverage respectively(Figure 22 and Table 12). This result indicates that the risk of deforestation is low for areas with unsuitable for agricultural land (steeper slope), very far from the infrastructure with low population density. The results have a number of similarities with Suryabhagavan *et al.* (2016). According to the study conducted in Harenna Forest, South Western Ethiopia, locations found closer to infrastructure like road and towns found to be higher deforestation risk. Likewise, Megersa (2016) reported in Bale mountains national park the risk of forest disturbance chance closer to settlement and towns is higher.

Overall, forest resource in the study area is highly influenced by topographic and man-made factors. This result is in line with Wyman and Stein (2009) and Sahana *et al.* (2018)that anthropogenic factors such as distance from road, nearness of forest to the settlement and agricultural proximity to forest and physical factors like slope and elevation have directly accelerated deforestation.

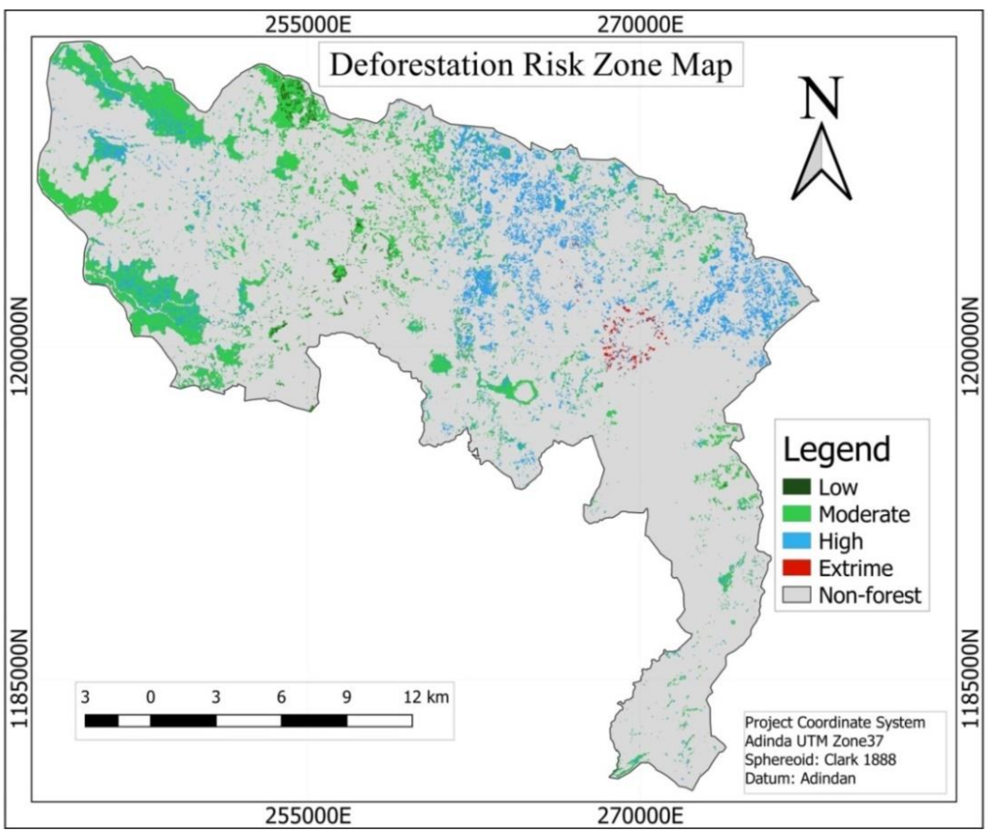

Figure 20: Deforestation Risk map.

Table 12: Summary of Deforestation risk model map.

Risk zone	Degree of deforestation Risk	Area(ha)	Percentage	Description of Deforestation Risk
4	Extreme	154.16	2.03	Very low slope percentage (flat/gentle), very high population density and very close to town, road and river
3	High	3063.35	40.28	Low slope percentage, high population density and close to town, road and river
2	Moderate	4308.23	56.65	Moderate slope percentage and population density and moderately far from town, road and river
1	Low	79.52	1.05	Very high slope percentage (steep), very low population density and very far town, road and river

The results also show that more than half of the forests cover categorized in the extreme and high degree of deforestation risk zone which is found in eastern and some western parts. This is because the area described as a higher population density, gentle slope and very closer to road, river and town compared to other areas. Moderate and low deforestation risk areas found mostly around in western and eastern parts as a result having lower population density, higher slope percentage and far from road, river and town.

4.6. Model Validation

Model validation result revealed that the level of accuracy of the final deforestation risk map is presented in Figure 21 below with overlaying the GPS points (Appendix 3). Hence, more than 97 % of the points are overlapping under high and moderate deforestation risk zone of the final map. Based on that performance of the model reliable that represents the reality (Megersa, 2016).

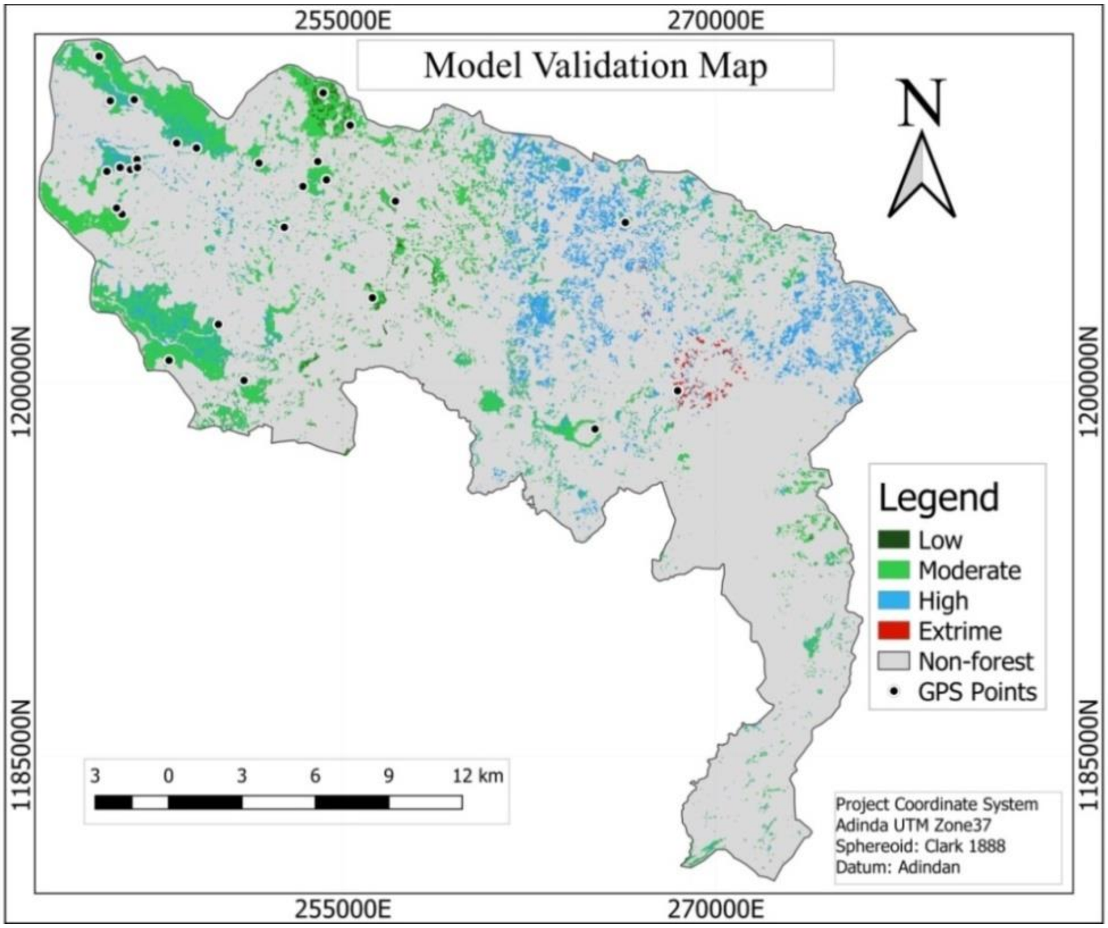

Figure 21**: Model validation map.**

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusion

North-western part of the country has been under continual LULC changes for the last fifty years. The finding of this study showed that there is a substantial transition of LULC types in the study area since 1985. Expansion of agricultural land and urban/settlements due to high rate of population growth has been shifting bare-land, forest land and slightly water body. This alteration has its own positive or negative impact on the biophysical and socioeconomic aspects. Therefore, it is possible to conclude that the reason for the alteration of the land-use land-cover was anthropogenic because the result shows a high amount of increment in cropland and built-up in the study area. This result shows there was a high demand for agricultural land, fuel-wood and shelter. In conclusion, it is evident that this study has shown there was a poor land management system. As a result, decline of biodiversity (fauna and flora) resource, forest degradation, deforestation, susceptibility for soil erosion and also qualitative and quantitative decrease of surface and groundwater incident become a common problem which might be led to drought and food insecurity.

The forest coverage shows unpredicted change throughout the study period. As indicated in the result, decreased in the first and second period but in the third period sharp increases recorded since 2006. However, in the western part large area of compound forest reduction was found in the year 1985 which downsize in the year 2018. Whereas, the forest areas indicated in the last period since 2006 was small in size and dispersed mostly in the eastern and middle part of the study area. It is possible to conclude that the existence of forest change implies that there was a high amount of natural forest resource decline followed by social, environmental and economic problems in the study area. In contrast, a recent year's expansion of plantation and/or reforestation indicates there is a chance to minimize anthropogenic pressure for the remaining natural forest. Further experimental investigations are needed to understand the reason for this change and the opportunity potential behind it.

Identification of forest areas with extreme, high, moderate and low risk for deforestation was an important output of the present study based on five factors slope, population density and proximity to road, river and town. Therefore, based on the weight overlay analysis result the about 3217 ha of the remaining forest area falls under extreme and high risk area. Hence, decisions and policymakers should develop and implement integrated sustainable forest management system for the future.

5.2. Recommendation

- As the population number is increasing obviously scarcity of natural resources occurred. As a result, people always explore the natural resources found in their surroundings to survive which causes damage. Thus, it is highly recommended to implement sustainable land-use land-cover planning, promoting agricultural intensification systems with irrigation and applying integrated watershed management system should carry out to control the decline and deterioration of entire natural resource in the study area.
- Most of Awi Zone areas including Ankasha Guwagusa have a very wide potential of bamboo forest the so-called the new green gold. Hence, it is recommended to introduce participatory forest management (PFM) that the community can be economically benefited as well as the natural environment will be conserved.
- Areas which are identified as extreme and high deforestation risk needs community based conservation and management measures. Therefore, creating buffer zone area around the

forest, delineating protected natural forest areas and promoting awareness on forest ecosystem services are highly recommended.

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Appendices

Appendix 1.

Statistical information of accuracy assessment for the year 1985, 1996, 2006 and 2018.

LULC Type	1985		1996		2006		2018	
	Producers Accuracy (%)	User's accuracy (%)	Producers Accuracy (%)	User's accuracy (%)	Producers Accuracy (%)	User's accuracy (%)	Producers Accuracy (%)	User's accuracy (%)
Forest	85.7	85.72	80	80	66.67	85.7	77.78	77.78
Cropland	93.84	88.57	92.86	89.65	97.23	92.1	97.5	92.85
Built-up	83.33	100	66.65	80	83.33	100	80	80
Bare-land	70	87.5	85.71	85.72	80	80	71.43	100
Water	100	80	100	100	100	80	100	100
Overall accuracy (%)	**88.34**		**88.24**		**90**		**90.90**	
kappa statistics	**0.8136**		**0.8414**		**0.7994**		**0.7605**	

Confusion matrix for LULC map of 1985.

Map data	Reference data						User accuracy
	Bare-land	**Built-land**	**Cropland**	**Forest**	**Water**	**Grand Total**	
Bare-land	**7**	0	1	0	0	**8**	**87.5**
Built-land	0	**5**	0	0	0	**5**	**100**
Cropland	3	1	**31**	0	0	**35**	**88.57**
Forest	0	0	1	**6**	0	**7**	**85.71**
Water	0	0	0	1	**4**	**5**	**80**
Grand Total	**10**	**6**	**33**	**7**	**4**	**60**	
Producer accuracy	**70**	**83.33**	**93.94**	**85.7**	**100**	**88.33**	

Confusion matrix for LULC map of 1996.

Map data	Reference data						User accuracy
	Bare-land	**Built-up**	**Cropland**	**Forest**	**Water**	**Grand Total**	
Bare-land	**6**	1	0	0	0	**7**	**85.71**
Built-up	0	**4**	1	0	0	**5**	**80**
Cropland	1	1	**26**	1	0	**29**	**89.65**
Forest	0	0	1	**4**	0	**5**	**80**
Water	0	0	0	0	**5**	**5**	**100**
Grand Total	**7**	**6**	**28**	**5**	**5**	**51**	
Producer accuracy	**85.71**	**66.66**	**92.857**	**80**	**100**	**88.23**	

Confusion matrix for LULC map of 2006.

Map data	Reference data						User accuracy
	Bare-land	Built-up	Cropland	Forest	Water	Grand Total	
Bare-land	**4**	0	1	0	0	**5**	**80**
Built-up	0	**5**	0	0	0	**5**	**100**
Cropland	0	0	**35**	3	0	**38**	**92.10**
Forest	0	1	0	**6**	0	**7**	**85.71**
Water	1	0	0	0	**4**	**5**	**80**
Grand Total	**5**	**6**	**36**	**9**	**4**	**60**	
Producer accuracy	**80**	**83.33**	**97.22**	**66.66**	**100**	**90**	

Confusion matrix for LULC map of 2018.

Map data	Reference data						User accuracy
	Bare-land	Built-up	cropland	Forest	Water	Grand Total	
Bare-land	**5**	0	0	0	0	**5**	**100**
Built-up	1	**4**	0	0	0	**5**	**80**
Cropland	1	0	**39**	2	0	**42**	**92.85**
Forest	0	1	1	**7**	0	**9**	**77.77**
Water	0	0	0		**5**	**5**	**100**
Grand Total	**7**	**5**	**40**	**9**	**5**	**66**	
producer accuracy	**71.42**	**80**	**97.5**	**77.77**	**100**	**90.9**	

Appendix 2: Ankasha GuwagusaWoreda population density in the year 2018.

No.	Kebele Name	Area in ha.	Population No
1	Gimija Bet(01&02)	822	18899
2	Zewula Degeha	1343	2465
3	Bakona	2633	6585
4	Sositu Gimija Bet	2738	3988
5	Gewena	1385	4078
6	Dimama	1598	4500
7	Aeyisana Harisha	2942	4947
8	Manija Tenikosha	1382	4593
9	Hateta Zuriya	2746	5512
10	Tulita	3095	5886
11	Dingusha	2269	6032
12	Buya Sehanitu	2022	5197
13	Mesele	4947	10993
14	Bayina Gunisi	2892	6586
15	Sositu Tirba	2215	5074
16	Den Zuriya	2633	6953
17	Bekafita	3265	8876
	Total	**47038**	**111164**

Appendix 3. GPS points (Source: field survey, 2018).

No.	Location name	Easting	Northing	Degree of susceptibility model
1	Mesele	246030	1208627	High
2	Mesele	246463	1208559	High
3	Mesele	246748	1208605	High
4	Mesele	246691	1209031	High
5	Mesele	245251	1213136	High
6	Mesele	246600	1211252	High
7	Mesele	245827	1211331	High
8	Mesele	247122	1211073	High
9	Mesele	248209	1209611	Moderate
10	Mesele	255297	1210298	Low
11	Bakona	249970	1202296	High
12	Bakona	248025	1200840	High
13	Aeyisana Harisha	256197	1203372	Low
14	Mesele	253400	1207953	High
15	Mesele	254352	1208112	Moderate
16	Aeyisana Harisha	257185	1207183	Moderate
17	Sositu Tirba	265293	1197981	Moderate
18	Gimija Bet	268402	1199670	Extreme
19	Bekafita	266273	1206307	High
20	Mesele	254067	1211555	Moderate
21	Bakona	251003	1200081	High
22	Bakona	246805	1203657	High
23	Mesele	250275	1206764	High
24	Mesele	250389	1209263	High