ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL AND COMPUTATIONAL SCEINCES

SCHOOL OF EARTH SCIENCE

FOREST DEGRADATION MONITORING AND ASSESSMENT OF BIOMASS IN HARENNA BULUK WOREDA, BALE ZONE, ETHIOPIA, USING REMOTE SENSING AND GIS TECHNIQUES

A **Thesis submitted to the school of Graduate Studies in Partial Fulfillment of Requirements for the Degree of Masters of Science in Remote Sensing and Geo-informatics**

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This is to certify the thesis prepared by **Dinku Shiferaw Jote** entitled as *"Forest Degradation Monitoring and Assessment of Biomass in Harenna Buluk Woreda, Bale Zone, Ethiopia, using Remote Sensing and GIS Techniques*" is submitted in partial fulfillment of the requirements for the Degree of Master of Science in Remote Sensing and Geo-informatics compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Acknowledgements

First and foremost, I would like to thank the 'Almighty God' who made it possible, to begin and finish this research successfully.

I would like to express my deepest appreciation and sincere thanks to my advisor Dr. K. V. Suryabhagavan, Associate Professor, School of Earth Sciences, Addis Ababa University for his constant encouragement, helpful discussions and valuable suggestions.

I am also indebted to the Ethiopian Mapping Agency (EMA) for sponsoring me and giving all the necessary support in preparation of this thesis.

I specially thanks to National Metrological Agency, Oromia Forest and Wildlife Enterprise for providing me necessary data to carry out this research.

Many thanks go to my Remote Sensing and Geo-informatics classmates. They helped me a lot. I will remember them forever.

I would like to thank my family for their selfless love and invaluable encouragements and supports.

Finally, I want to thank all of those people who, once upon a time, were my teachers and who helped me begin this long journey. Their names are too numerous to mention, but many of them inspired me to continue learning and sharing with others.

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List of Acronyms

AGB	Above Ground Biomass
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CDM	Clean Development Mechanism
CSA	Central Statistics Agency
EFAP	Ethiopian Forestry Action Program
ESA	European Space Agency
EPA	Environmental Protection Authority
ESCAP	Economic and Social Commission for Asia and the Pacific
ETM+	Enhanced Thematic Mapper
FAO	Food and Agricultural Organization
GIS	Geographic Information System
GOFC-GOLD	Global Observation of Forest and Land Cover Dynamics
GPS	Global Positioning System
HSR	High Spatial Resolution
IPCC	Intergovernmental Panel on Climate Change
ITTO	International Timber Trade Organization
IUCCN	International Union for the Conservation of Nature
LIDAR	Light Imaging Detection And Ranging
LULCF	Land Use, Land Use Change and Forestry
MSI	Multi Spectral Scanner
MSS	Multi Spectral Scanner
NDVI	Normalized Differencing Vegetation Index
NMA	National Metrology Agency

OBIA	Object Based Image Analysis
OLI	Operational Land Imager
OSFESA	Oromia State Forest Enterprise Supervising Agency
RADAR	Radio Detection and Ranging
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RS	Remote Sensing
SNNPRS	Southern Nation Nationalities and People's Regional State
SPOT	System Pour I 'Observation de la Terre
TM	Thematic Mapper
TIFF	Tagged Image File Format
UN	United Nation
UNFCCC	United Nations Framework Convention on Climate Change
USD	United Sates Dollar
USGS	United States Geological Survey
UTM	Universal Transverse Mercator

Forest Degradation Monitoring and Assessment of Biomass in Harenna Buluk Woreda, Bale Zone, Ethiopia, Using Remote Sensing and GIS Techniques

Dinku Shiferaw, MSc. Thesis

Addis Ababa University June, 2017

Abstract

Forest is one of major natural resources, which play vital role in maintaining the ecological balance of nature. Detection of forest degradation with remote sensing remains a challenging field of study. Over utilization of forest resources has resulted in the depletion of forests resources. The present study was undertaken to monitor deforestation, forest degradation, and biomass estimation using remote sensing and GIS technology in Harenna Buluk Woreda in Ethiopia. Supervised classification technique was applied to Landsat images of 1995, 2005 and 2016. Satellite images were classified into different land-use/land-cover classes using maximum likelihood algorithm with the aid of field observations and Google Earth. Forest degradation was assessed using Object Based Image Analysis (OBIA) from Sentinel-2A satellite image. Results of this study has revealed that during, 1995–2016, forest and shrubland areas were decreased by 119.2 km^2 (6.19%) and 12.1 km^2 (0.62%), respectively. Farmland, bareland, grassland, settlement and water body were increased by 99.94 km^2 (5.19%), 43.11 km^2 (2.24%), 75.78 km^2 (3.94%), 20.54 km^2 (1.06%) and 6.93 km^2 (0.36%), respectively. As a result, the biomass dramatically decreased. The Normalized Difference Vegetation Index (NDVI) value between years 1995 and 2016 was significantly decreased indicating that vegetation cover in the study area was highly disturbed. Results derived from the Sentinel-2A satellite image showed that there was significant decrease of forest area. The estimated degradation from the result of Sentinel-2A image classification during the year 2016 was 145.91 km^2 (7.58%), while deforestation accounted for 171.39 km^2 (8.91%) of the total study area. Thus, advanced satellite images are more useful to monitor forest cover and degradation process of natural habitats in the context of human related impacts.

Key words: Forest, Biomass, OBIA, Remote Sensing, GIS, Sentinel-2A, Forest Degradation

CHAPTER ONE

1. INTRODUCTION

Forests provide economic, socio-cultural and ecological values. Livelihoods of hundreds of millions of people worldwide have been engaged on forest products either directly or indirectly (FAO, 2006). Forests have a vital safety role in time of needs. Forest degradation is a widespread global concern and an important contemporary issue for several United Nations (UN) organizations and conventions. Forest degradation is broadly defined as a reduction in the capacity of a forest to produce ecosystem services such as carbon storage and wood products as a result of anthropogenic and environmental changes (IPCC, 2003; Mosisa, 2015).

Degradation of forest resources is an important concern that is perceived in many different ways. Forest degradation can be a serious environmental, social and economic problem with the potential to adversely affect millions of people who depend on forest goods and services. Given the contribution of forests to sustainable development and their role in human well-being, the state of the forests is important to all of us (FAO, 2011).

Forest degradation is a serious problem environmentally, socially and economically particularly in developing countries. It is estimated that as much as 850 million hectares of forests and forest lands are degraded. Yet, it is difficult to quantify the scale of the problem as at national and regional levels forest degradation is perceived differently by the various stakeholders who have different objectives (Anteneh *et al*., 2013).

Estimation of the accumulated biomass in the forest ecosystem is important for assessing the productivity and sustainability of forests. Remotely sensed data have become the primary source for biomass estimation (Kilograms or tons per hectare), the organic matter that can be found in Ecosystem at any given time (Penner *et al.*, 1997). The use of remote sensing technology has become the most effective approach to biomass analysis and estimation.

Historical sources indicate that about 40% of Ethiopia's land area was originally covered with dense forest mostly coniferous and broad-leaved types. Another 26% consisted of the savanna woodlands. At the beginning of the 1950’s, dense forests were reduced to 16% of the country's entire land area (EFAP, 1994). In the 1980’s, the estimate for land areas covered by forests was 3.65% (IUCN, 1990). At present, this resource has declined to an estimated 2.6 per cent or less.

The major force behind the decline of the forest resources is lack of proper policy framework and population pressure, which direct to expansion of agricultural land, overgrazing, unsystematic felling of timber for fuel wood and construction purposes. On the other hand, the studies by EFAP (1994) and McKee (2007) demonstrate that an annual forest loss of the country was between 150,000 and 200,000, and 146,000 ha, respectively.

The forestry sector was restructured at country level several times over the last 30 years. In the 1980s, it was established as a forestry department with a total of 60 employees. In 1995, the department was expanded to the ministry level with a total staff of over 300, and in 2004 it was reduced to a small section with 10 employees. Recently, the forestry sector has got much attention at regional levels. The Oromia National Regional State, for instance, has the largest forest resource in the country and has pioneered in the establishment of a new management initiative system to control degradation of forests (Bekele *et al*., 1999). Accordingly, in 2007 the Oromia Forest Supervising Agency (OFSA) was established to coordinate the establishment of eight forest enterprises across the region. These enterprises are mainly aimed at capturing and merging the effort of community based forest management and government owned projects (FARM/SOS, 2008).

According to OSFESA (2007), in the year 1995, 32,000 ha of forest cover land was converted to agricultural land in the Oromia region. The years between 2000 and 2010, the loss of forest resource was estimated at 8.7%. It is further estimated that the years between 1990 and 2000, the Oromia Region could lose 27% of forest resources from agricultural and settlement expansion (OSFESA, 2007). As this agency's report, the situation indicated above for Oromia region holds true for Bale Zone Eco-region and also the Harenna Buluk Woreda, which is under investigation in this study.

Remotely sensed data sources can be used to detect forest degradation with the integration of GIS and relevant information obtained from locally. Hellden (1987), stated that whenever environmental data are needed for retrospective analysis, the historical remotely sensed data are often the only available solution. This is because useful satellite data (Landsat MSS) are available from 1972 onwards. Besides, it is possible to analyze the spatial distribution of forest cover changes using GIS. In this regard, Aronoff (1989) indicated that GIS has gained a considerable importance and application in the context of computer analysis of remotely sensed data for resource management. Thus, one can recap that remote sensing provides the primary source of spatial data, while GIS act upon a computational environment for analysis to extract the required information. Therefore, in the present study emphasis was given to detect forest degradation and the rate of its depletion as well as estimating biomass in Harenna Buluk Woreda and preparing degradation mapping using integrated techniques of Remote Sensing and GIS.

1.2. Statement of Problem

Ethiopia has faced a number of environmental problems such as severe soil erosion, land degradation, deforestation, expanding desertification, drought, flood and decline of bio diversity to name but few. In tropical regions, deforestation and forest degradation are progressive process that are advancing at alarming rates resulting in the conversion of forest land in to a mosaic of mature forest fragments, pasture, and degraded habitats (Laurance, 1999). Forest degradation is a more subtle process; it may involve opening of the canopy, modification of the vertical structure or change of other attributes.

Harenna Buluk Woreda contain Harenna forest, which is one of the 58 National Forest Priority areas of Ethiopia and one of the remnant montane forests with diverse of flora and fauna, however this resources are with a more serious anthropogenic factors and conservation problem this resources are depleting

The forest in the study area (Harenna Forest) despite its economical, hydrological and biological importance both nationally and globally, the Woreda are under serious threat due to unsustainable use of this natural resource. Like in many other parts of the country, the problem of forest degradation is a very serious environmental problem in the Harenna Buluk Woreda. A decade ago, the area was covered with rich natural and indigenous vegetation. But, ruthless pressure put on forests by anthropogenic activities are the existence of these forest cover lands. The depletion of forest resources was mainly due to use of forest products for household use purpose and income generation.

Major causes of forest degradation in Ethiopia are forest fire, illegal logging, overgrazing and charcoal production. Indigenous forest based livelihood activities and main socio-cultural attachments of the local communities with forest resources seem discarded (Tesfaye, 2007). Due to the speed of exploitation, illegal cutting and burning, forests are diminishing rapidly.

The people of the Woreda depend on forest for fodder, fuel wood, and timber and generate income from forest to maintain their daily needs. Besides, they use intentional fire as a tool for clearing forest to execute grazing. As a result, the natural environments as well as ecological balance of the area are under serious of threat.

The forest cover change detection was done by different researchers with different methods in Bale eco-region but the status of the forest degradation is not studied yet. Thousands of people in Bale Mountain Ecoregion especially, in the Harenna Buluk Woreda are dependent on forest resource for their livelihood activities (OSFESA, 2007).

Hence, this research focuses on assessing forest cover change, forest degradation and biomass estimation using Landsat and high resolution Sentinel-2A satellite image to fill the research gap of the current knowledge of the study area. Though forest degradation is considered a significant source of emissions in Ethiopia, there is no accurate, reliable and consistent data at the national and regional scales.

1.3. Objectives

1.3.1. Main Objective

The main objective of this study was to assess forest degradation and biomass estimation of the Harenna Buluk Woreda, of Ethiopia using Remote Sensing and GIS techniques.

1.3.2. Specific Objectives

- To produce land-use/land-cover and forest cover maps of Harenna Buluk Woreda.
- To assess forest degradation using high resolution (Sentinel-2A) satellite image.
- To estimate biomass productivity of the forest area using remotely sensed data and ground truth.

1.4. Significance of the Study

One of the challenges Ethiopia has been facing is the alarming rate of deforestation and degradation all over the country. The rates and extent of the problems are still debatable due to limitations of reliable data, and as the processes involved are not clearly understood. This study is considered to be an important step towards the bridge of the information gap at the study area.. The study contributes additional insights and perspectives for addressing forest management issues, causes of forest degradation and to understand the current situation of forest resources. Also expect to generate first hand information on the problem of forest degradation in the study area for those who are interested to conduct further research on the issue.

1.5. Scope of the Study

The present study mainly deals with the assessment of forest degradation and biomass estimation and analyses of the trends and changes in forest cover and forest degradation monitoring. Spatially, the study was confined only to the administrative boundary of Harenna Buluk Woreda in the Bale Zone of Oromia National Regional State of Ethiopia.

1.6. Limitation of the Study

The limitation of the study was lack of time series high resolution satellite data and lack of historical forest degradation data. Forest inventory data with also unavailable at local and national levels.

1.7. Organization of the Thesis

This thesis is organized into six chapters: Chapter one deals with the background of the study, statement of the problem, objectives, limitations and significance of the study. Chapter two of the thesis covered review of literature that explained the basic concepts on related issues of the research. In chapter three, background information about the study area in terms of location, topography, soil, climate and vegetation cover are discussed. This chapter also elaborates the sources of the data, software used and methodology applied in order to achieve the mentioned objectives.

Chapter four provides results. In this chapter LU/LC, forest cover change, NDVI, forest degradation and biomass accumulation was analyzed. Chapter five is discussion on and finally, Chapter six on conclusion and recommendations.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Definition and Concept of Forest

According to FAO (2006a), forest is defined as the presence of trees with land cover more than 0.5 ha. The tree must be able to reach a minimum of 5 m in situ and canopy cover at least 10%. Existing international definitions of forest vary from one another in a number of ways (Margono *et al*., 2012). For examples, FAO (2006b) defines forest based on a minimum threshold for height of tree 5 meter, a minimum crown cover 10% and minimum of forest area size (0.5ha). On the other hand according to the CDM of the Kyoto protocol, forest is defined as an area of 0.5–1.0 ha with a minimum of a tree crown cover of 10–30%,with tree defined as a plant with the capability of growing to be more than 2–5 m tall (UNFCC, 2002). Participant countries can choose from the specified ranges for the forest definition modified to their needs. Brazil defines forest as an area of land greater than 1 ha, with more than 30% canopy cover and a minimum tree height of 5 m. In 2007, Ethiopia defines forest as community of plants, either naturally grown-up or developed by planting and mainly consisting of trees and other plants have woody character.

In February 2015, Ethiopia adopt a new forest definition as follows, land cover at least 0.5 ha covered by trees with the potential to reach these thresholds in situ due to coarse. The reason for Ethiopia to change the national forest definition is to better capture dry and lowland-moist vegetation resources. In specific, the reason for lowering the tree height from 5 m to 2 m is to capture *Termilania-Combretum* dense woodlands found in Gambella and Benishangul Gumuz Regional States, which in its primary state consists of trees reaching a height of around 2–3 m and above (Ethiopian Forest Reference Level Submission, 2016).

A recent Forest Resources Assessment of FAO (2010) estimated the global forest cover at just over 4 billion hectares, which is 31 percent of the total land area of the world, this corresponds to an estimate of average of 0.6 ha. Forests are different things to different people in different places and are also defined in various ways in different international legal frameworks. Forests may be valued as ecological, political, economic and cultural entities. There exist over 1,500 documented definitions of forests across the world and these derive from the international community, national definitions, and state, provincial or local definitions. Customary forest dwellers and indigenous peoples may define and interpret their environment differently across regions, cultures and generations. Forests also have a customary and spiritual meaning as a source of livelihood, cultural significance and individual and collective identification.

2.2. Extent and Trends of Forest Cover Change Global Perspectives

Human society and the global economy are linked with forests. More than 1 billion people depend on forests ecosystem for their livelihoods (Secretariat of the convention on Biological Diversity, 2010). Forest ecosystems play a critical role in stabilizing the climate: providing water, food, wood products, and vital medicines, and supporting much of the worlds biodiversity (Chao, 2012).

According to the FAO (2015), the global forest area fell by 129 million hectares (3.1 percent) during the period 1990 –2015, to just under 4 billion hectares. As stated by Hosonuma *et al*. (2012), timber extraction and logging account for more than 70% of total degradation in Latin America and Asia. Fuel wood collection and charcoal production are the main degradation drivers for the African continent, and of small to moderate importance in Asia and Latin America. Uncontrolled fires are more prominent in Latin America. In terms of absolute net forest area change over the period 2000–2010, the largest driver remains commercial agriculture, with the largest deforested area located in Latin America. In Africa and Asia, subsistence and commercial agriculture contribute roughly equally to forest area change. Global forest coverage is given in Table 2.1.

Table 2.1: Global Forest resources

Country	Total Forest area (million ha)
Russia	809.0
Brazil	520.0
Canada	310.0
USA	3040.
Chaina	207.0
DRC	154.0
Australia	149.0
Indonesia	94.0
Sudan	70.0
India	68.0
Others	1,347.6
World	**4,033.6**

Source: (FAO, 2010)

2.3. Definition and Concept of Forest Degradation and Deforestation

2.3.1. Forest Degradation

Forest degradation is the long term reduction in the overall capacity of a forest to produce or provide benefits (goods and services) ITTO (2002) such as carbon storage, wood, biodiversity, and other products due to environmental and anthropogenic forces. It results the decrease of species in the forest and in tree cover and/ or the change of the forest structure (Foley *et al*., 2007; Morales-Barquero *et al*., 2014). It is worth noting that forest degradation is not as obviously defined, agreed upon, or understood as is deforestation (Chao, 2012).

According to Asner *et al*. (2005), forest degradation is a major source of greenhouse gas emissions. Forest degradation and deforestation are distinctly different processes. Degradation results when forests remain forests, but lose their ability to provide ecosystem services or suffer major changes in species composition due to overexploitation, exotic species invasion, pollution, fires, or other factors (Millennium Ecosystem Assessment 2005; Sasaki and Putz, 2009**)**.

Forests may be degraded in terms of loss of any of the goods and services that they supply wood, food supply, habitat, water and other protective socioeconomic and social values (Guariguata *et al.,* 2010). The combination of various forest characters or forest qualities can be expressed as the structure or function, which determines the capacity to supply forest products and services. In the context of REDD+, degradation has been grouped together deforestation, but in terms of monitoring it has more features in common within forest activities (sustainable forest management and enhancement of forest carbon stocks).

According to FAO (2008), forest degradation is generically defined as the reduced capacity of a forest to provide goods and services. However, in the context of climate change, the International Panel on Climate Change developed a definition of forest degradation that focuses on anthropogenic changes in the carbon cycle in the long run (IPCC, 2003). The succession curve of the level of forest degradation given in Figure. 2.1.

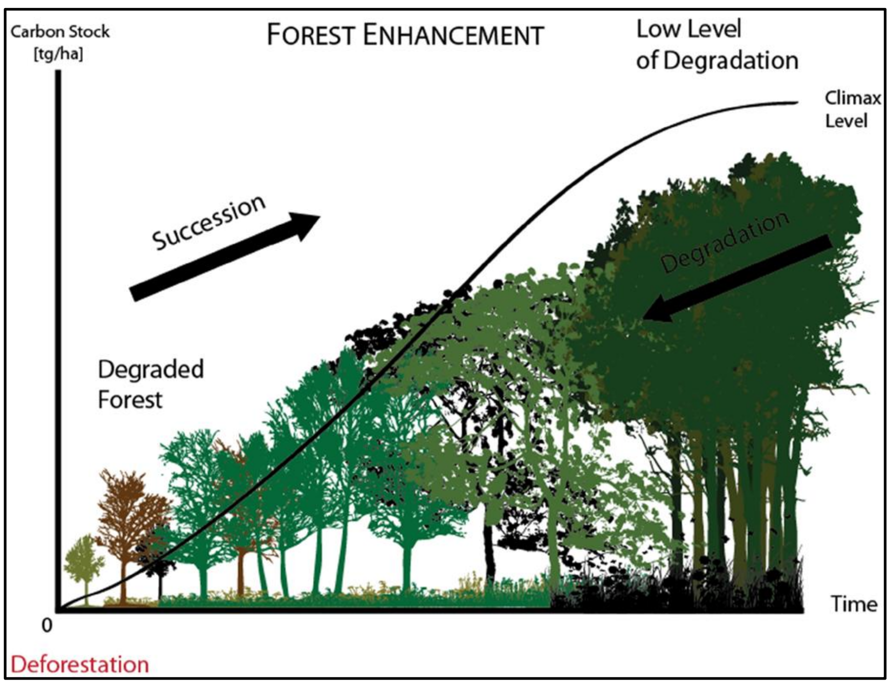

Figure 2.1: Forest Succession Curve (Source**:** Eckert *et al*., 2011 as cited in Morales-Barqueo *et al*., 2014).

2.3.2. Deforestation

Deforestation is expressed as the conversion of forests to other land cover types, if an area is defined as deforested only if it remains without trees for at least 20 years, then a great deal of what has been labeled deforestation should instead be categorized as degradation (Morales-Barquero, 2014).

Deforestation is defined as the removal of the stand where land is changed in to a non-forest land-use (Hannes *et al*., 2009). IPCC (2003) defines deforestation as the direct human induced conversion of forested land to non forest land or other land cover types. This alteration of forests for other land-use is broadly for shifting cultivation, agriculture, plantation, and pastures. If forest cover decreases due to logging, fire and the forest is expected to re-grow the crown cover to above the threshold, then this reduced forest area is not considered as deforestation (GOFC-GOLD, 2013).

2.4. Remote Sensing and GIS to Monitor Forest Degradation

2.4.1. Remote Sensing

Remote Sensing is defined as the art and science of obtaining information about an object through the analysis of data acquired by a device that is not in physical contact with an object under investigation (Jensen, 2000). It is a scientific technology that can be used to measure and monitor important biophysical characteristics and human activities on earth. Using Remote Sensing it is possible to directly obtain information; in the second dimension (Lagner, 2009). Within the frame work of this study, the focus of Remote Sensing is the measurement of emitted or reflected electromagnetic radiation, or spectral characteristics, from a target object by a multispectral satellite sensor. Remote Sensing satellite images are immensely used in natural resources monitoring and management, to study time to time changes due to its repetitive coverage especially in forest resources estimation and monitoring.

Remote Sensing data can be used to provide forest related information to governments and civil society in a timely and cost effective way. The use of satellite data to map forests has become an increasingly common way to pinpoint deforestation, active fires and logging in protected areas. (CIFOR, 2004). Remote Sensing technique for forest cover change detection and monitoring has been used to assess the dissimilarities in forest cover over two or more time periods caused by environmental conditions and human actions (Kreuter *et al*., 2001; Zhongmin *et al*., 2003). It brings together a multitude of tools to better analyze the scope and rate of forest degradation .Multi-temporal data provides for change detection analysis. Image of earlier years are compared to recent scenes, to tangibly measure the difference in the sizes and extents of forest cover change. Data from a variety of sources are used to provide consequent information. Satellite image data can be used to efficiently monitor the condition of existing clear cuts or emergence of new ones, and even assess regeneration condition. In countries where cutting is controlled and regulated remote sensing serve as a monitor tool to ensure companies are following cut guidelines and specification.

Another unique quality of RS data is that it provides a means of quickly identifying and delineating various forest types, a task that would be difficult and time consuming using traditional ground surveys. Data are available at various scales and resolutions to satisfy local or regional demands. Species identification can be performed with multispectral, hyperspectral, or air photo data interpretation. Both imagery and the extracted information can be incorporated into a GIS to further analyze as slopes, ownership boundaries, or roads (Franklin, 2001).

2.4.2. Geographic Information System

There are many different definitions for GIS (Clarke, 2001), but the basic concept common to all definitions is that GIS is a set of programs that store, manage, manipulate and represent data with some kind of spatial components (Richards and Jia, 2006; Chuvieco and Huete, 2010). According to ESCAP (1996), GIS is defined as definite information system applied to geographic data and is mostly referred to as a system of hardware, soft ware and procedures designed to support capture, management, manipulation, analysis, modeling and display of spatially-referenced data for solving complex planning and management problems.

2.5. Forest Degradation in Ethiopia

Ethiopia is characterized by a high rate of forest degradation (Alemtsehay, 2010). Tree cutting is a common occurrence which has been taking place for centuries EPA (1998), as cited in (Temesgen *et al*., 2015). As a result, the forest cover has been changed through time. At the beginning of the 20th century, forests covered 40% of the land in Ethiopia (Badege, 2001). Around the late 1950s, forests covered 16% of Ethiopia's land area (EPA, 2003). During 1973 to

1976, forests covered 6.08 %, while during 1986–1990, some 10 to 15 years later than 1973–1976, it was around 4.75% of the country. At present this Figure decline from time to time (Table 2.2).

In Ethiopia the major cause of Forest Degradation is use of forest resource for different purposes, Such as, cutting trees for charcoal production, fuel wood, and construction materials. The consequences of forest degradation are decline of productivity of land and decrease household in welfare (FARM/SOS, 2007). Njkl;This is true at least for two reasons. First, the removal of trees without sufficient reforestation has resulted in drought and this in turn results in reduction of agricultural production as agriculture in Ethiopia highly dependent on rainwater. Second, forest is influential to control soil erosion and land degradation.

According to Belay (2002), a group of interacting variables are responsible for the extreme decline of forest land despite the generally anticipated over grazing by live stock and subsequent bush encroachment. Forest degradation in Ethiopia is closely linked with the ongoing rapid population growth. The distribution of forest resource in Ethiopia is given in Table 2.2.

Table 2.2: Distribution of Forest Resources by Region

Region	**Total (ha)**	**Area (%)**
Oromia	2,547,632	62.5
SNNP	775,393	19
Gambella	535,948	13.2
Amhara	92,744	2.3
Tigray	9,332	0.2
Benishangul-Gumuz	68,495	1.7
Afar	39,197	1
Somali	4,257	0.1
Others (Harari, Dire Dawa)	216	0
Total	**4,073,214**	**100**

Source: (WBISPP, 2004).

2.6. Causes of Forest Degradation

Scholars recognized different causes of forest degradation for example according to FAO (2006) and Schoene *et al*., (2007) degradation is usually caused by disturbances, which vary in terms of the extent, quality, origin and occurrence of the changing process can be natural Thakur and Singh (2014) caused by fire, storm, drought, snow, pest, disease, atmospheric pollution, change in temperature. (or it can be human induced for example illegal logging, excessive fuel wood collection, shifting cultivation, and overgrazing). There are also other indirect underlying reasons for degradation such as inappropriate policies, lack of clearly established tenure rights, institutional weaknesses, and lack of financial resources, corruption, and various economic, technological, cultural and demographic factors (Simula, 2009).

2.6.1. Forest Fires

Forest fire for example commonly happen in tropical forests, and act as are a major cause of forest degradation. Forest fire may arise on account of natural, accidental, and human causes. Almost every year, forest fires are witnessed across different forest region on earth, which persistently affects the economy and biodiversity. Moreover, forest fire plays an important role in the decline of both quality and quantity of forest resources. Between 1990 and 2000, Africa lost about 52 million ha of forest, accounting for about 56% of the global reduction in forest cover. Southern Africa (Tanzania inclusive) accounted for about 31% of the forest loss on the continent (Saklani, 2008). According to Roy (1996), forest fire, which has intense impacts on the physical environment including; land-use/land-cover, biodiversity, and climate change and forest ecosystem? Different researchers have founded the part of biomass burning to global budgets of many chemically active gases such as carbon dioxide, carbon monoxide, methane, nitric oxide, methyl chloride and elemental carbon particulate (Genanaw, 2008).

The entire Bale eco-region massif, in particular, the high altitude belt but to lesser extent also Harenna Forest (which is found in the Harenna Buluk Woreda of Bale Eco-region) is affected by recurrent fires which often significantly threaten local biodiversity and key habitats. The fire that occurred in the year 2000 between February and April was the most severe of the past hundred years, and destroyed approximately 20,000 ha of moist evergreen forest in the area .The loss of biomass during the fire in the eco-region was estimated at 18 million tones, results in direct and indirect losses to the local and national economy of nearly USD20 million (Anteneh, *et al*., 2013).

2.6.2. Overgrazing

Ethiopia owns the largest livestock resources among the African Countries. There are about 35 million tropical livestock units (TLU) or about 80 million head(ca. 30 million cattle, over 42 million sheep and goats and 7 million equines) of livestock in Ethiopia (Reusing, 200). Forest grazing and browsing is the major source of feed for the vast population of livestock in Ethiopia. Some 17,5000km^2 or nearly 35 percent of Ethiopia rangelands are found under forest cover of bush and shrub, and fodder deriving from forest lands provides 10 percent and 60 percent of livestock feed in the wet and dry seasonal respectively. In pastoral areas, forest grazing and browsing constitute the sole land-use system.

2.6.3. Illegal Logging

Demand for timber and furniture are other causes of forest degradation. This demand leads people to illegal logging and cutting down of immature trees in the forest areas. Selective logging is described as a harvesting system practiced mainly in native forests and in hardwood plantations where a few desired and commercially valuable trees species are harvested following a predefined criteria as opposed to clear cutting where a whole forest compartment is completely clear-cut in the harvesting process. Selective harvesting is said to remove some portion of the standing trees leaving a viable forest for natural regeneration and growth. The natural spatial configuration, stand structural elements and growth stages of the native forest are maintained by retaining at least (Topa *et al*., 2009).

2.7. Normalized Different Vegetation Index-based Monitoring of Forest Degradation

The normalized Different Vegetation Index (NDVI) is the most important tool for the detection of degradation and deforestation (FAO, 2009). The Normalized Different Vegetation Index is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyze remote sensing measurements and evaluate whether the target being observed contains live green vegetation or not (Nath, 2014). This vegetation index is an indicator of vegetation health, because degradation of ecosystem plants, or a decrease in

NDVI value. According to Weng *et al*. (2004), the NDVI is an amount of the balance between energy received and energy emitted by objects on earth surface. When applied to plant communities, this index establishes a value for how green the area is, that is, the amount of vegetation present in a given area and its state of health or vigor of growth.

2.8. Land-use/land-cover Change

The term land cover originally referred to as the kind and state of vegetation, such as forest, farmland or grass cover, but it has broadened in subsequent usage to include other things such as human structures, soil types, biodiversity, surface and ground water (Meyer, 1995). Mankind has modified Land-use/land-cover change for thousands of years to obtain fuel, food, fiber and other materials, but current rates and intensities of land-use/land-cover are far greater than ever before (Mayux *et al.*, 2008).

Human activities directly or indirectly modified the natural environment. This is due to the production demands by human cannot fulfill without modification or conversion of land cover. Human activities impacts on the topography such as changes in land-use/land-cover are often observed with synchronous changes in vegetation, structure of the land-cover (Zhou *et al*., 2008). Land-use/land-cover changes play a significant role in the monitoring of forest condition as most environmental problems are related to the changes in land-use/land-cover patterns.

2.9. Remote Sensing-based Biomass Estimation

Biomass includes as the organic matter both above and below the ground, and both living and dead, trees, crops, grasses and root (Lu, 2006). Above ground biomass includes all living biomass above the soil, while below ground includes all biomass of live roots, exceeding fine roots (<2 mm diameter). Biomass concerns the dry weight of organic matter that can be found in the eco-system at any given time (Penner *et al*., 1997). Total biomass includes both above ground biomass and below ground biomass (example roots, dead fine and coarse litter) associated with the soil. Due to the difficulty of collecting field survey data of below ground biomass, the majority of previous biomass studies only focused on above ground biomass (Dengsheng *et al*., 2014). Therefore, in this study ‘biomass’ represents only aboveground forest biomass (AGB).

According to Makela and Pekkarinen (2004), different approaches have been used to estimate AGB based on RS data, like crown diameter using regression analysis to estimate DBH or using canopy reflectance models. Also others such as neural network, K nearest neighbor have been used (Zheng *et al*., 2004). Thereupon, sensors from medium to low spatial resolution have been used for AGB estimation.

Remote Sensing approach has been widely used in many studies on biomass assessment (Kale *et al*., 2009). The advantage of remote sensing techniques and high correlation between spectral data and vegetation make it useful for large scale above ground biomass mapping. The biomass measurement from sample plot can be integrated into the remote sensing techniques to get effective and large spatial information on above ground biomass distribution.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Location

Harenna Buluk Woreda is one of the Woredas in Bale Zone of the Oromia Regional state of Ethiopia. The administrative center of the Woreda is at Angetu, which is located south east of Addis Ababa, 132 km from Robe, capital of Bale Zone and 570 km from Addis Ababa. This Woreda is located geographically between latitude $06^{o}07'33''-06^{o}44'00''$N and longitude $39^{o}16'41''-39^{o}46'10''$E. Harenna Buluk Woreda share boundaries with Goba Woreda in the North, Meda Walabu Woreda in the South, Delo-Mena Woreda in the east and Nansebo Woreda in the West.

The Woreda has a total area of 1923 km^2 (Figure. 3.1) and characterized by highlands of the ranges from 1108−3310 m m.a.s.l and includes the upper catchments of several important rivers such as Genele and Welmel.

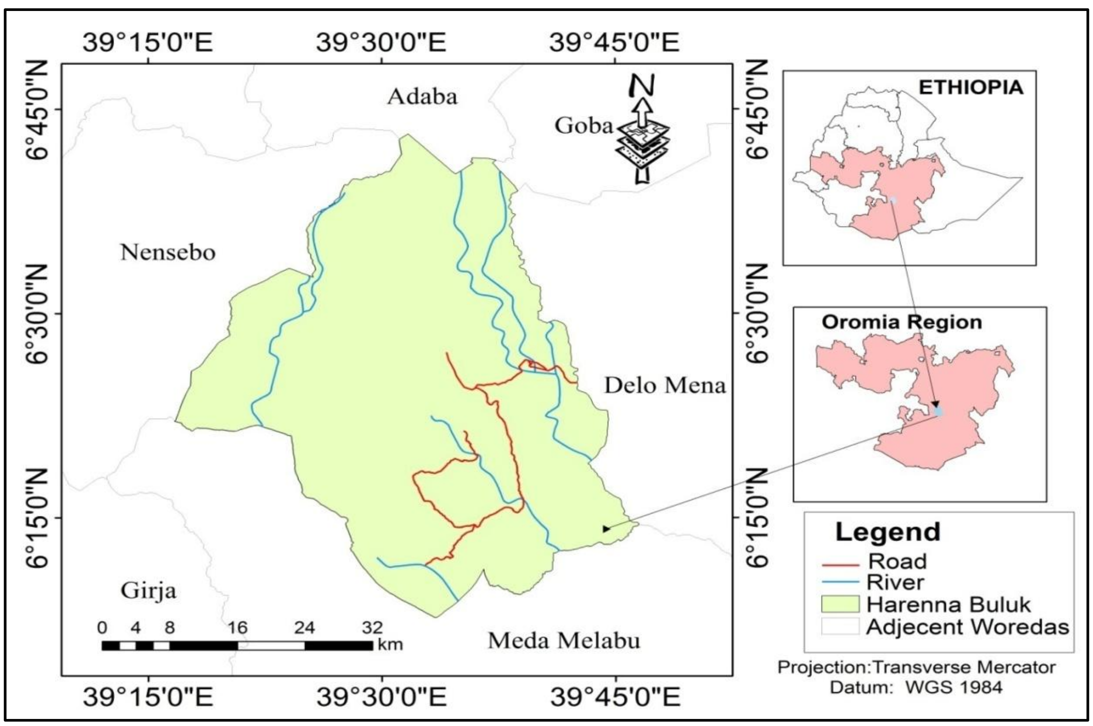

Figure 3.1: Location map of the study area.

3.1.2. Topography

The study area was characterized by rolling topography, flat lands; moderately gently sloping hills with valley bottoms and waterways. The altitudes in the study area ranges between 1108 m at lower valleys to 3310 m a.m,s.l.(Figure.3.2).

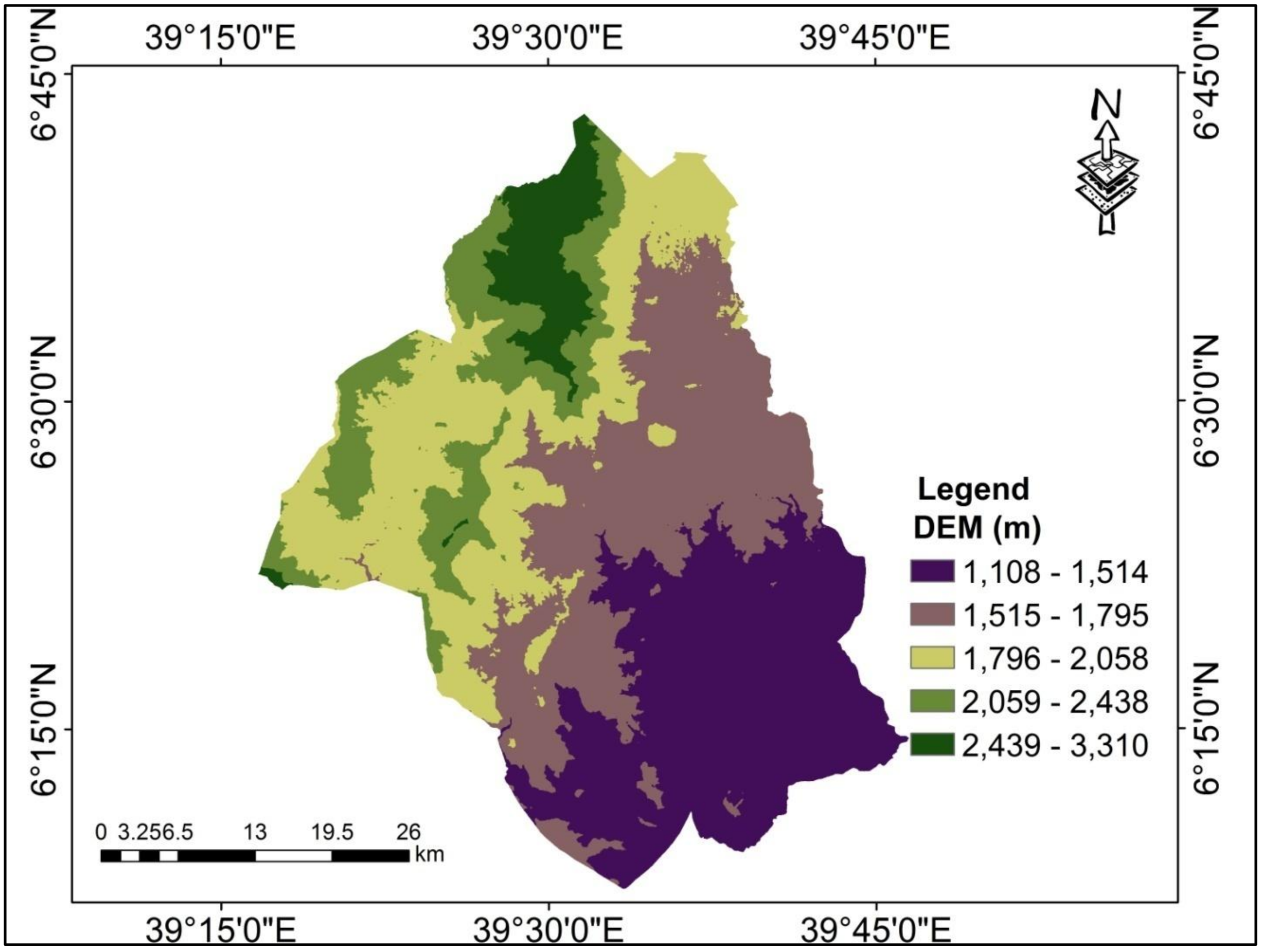

Figure 3.2: Digital elevation model map of the study area.

3.1.3. Vegetation

Harenna Buluk Woreda has a type of moist montane forest (Harenna forest) and forest groups are also found in southwestern part of Ethiopia. This Woreda consists of different species of plants, including *Erica arborea, Pouteria adolfi-friederici,* Baehni, *Podocarpus falcatus* and *Polyscias fulva* Harms, those are commercially important in the country.

3.1.4. Population

According to local sources, the total population of the study area is increasing rapidly. Immigration from other parts of the country and polygamous marriage system in the area contributed to high rate of population growth in the area. Harenna Buluk Woreda is relatively sparsely populated (total population of 94,051), the area has a population density of 49 people per km^2.

3.1.5. Local Livelihood Activities

The local population depends on the forest for their livelihood, especially for food, medicine, handicraft and energy. They harvest various seeds, fruits, leaves, and barks, which are used either as ingredients, thickeners, or as vegetables. Agricultural is the major sector that supports the livelihood of household and communities in and around the forest area. The agriculture in the area involves two major activities, these are: Farming activities and Livestock production. The common characteristics of the people living in the Harenna Buluk Woreda are do practice livestock husbandry through at different scale. The average number of each livestock type owned per household is relatively higher compared to many areas in the country. For the Bale people animals mean a source of income, transport, foods, and fame.

3. 1.6. Climate

According to the National Metrological Agency (NMA), the study area has a dry season from November to February with low rainfall, low temperature, and low humidity and eight months of wet season from March to October. The wet season is characterized by a high bimodal rainfall, high humidity and higher night and lower day temperatures. The maximum and minimum temperatures of the study area are, 26.83°C and 14.56°C, respectively. The rainfall distribution in the study area is shown in Figure.3.3 and Figure.3.4.

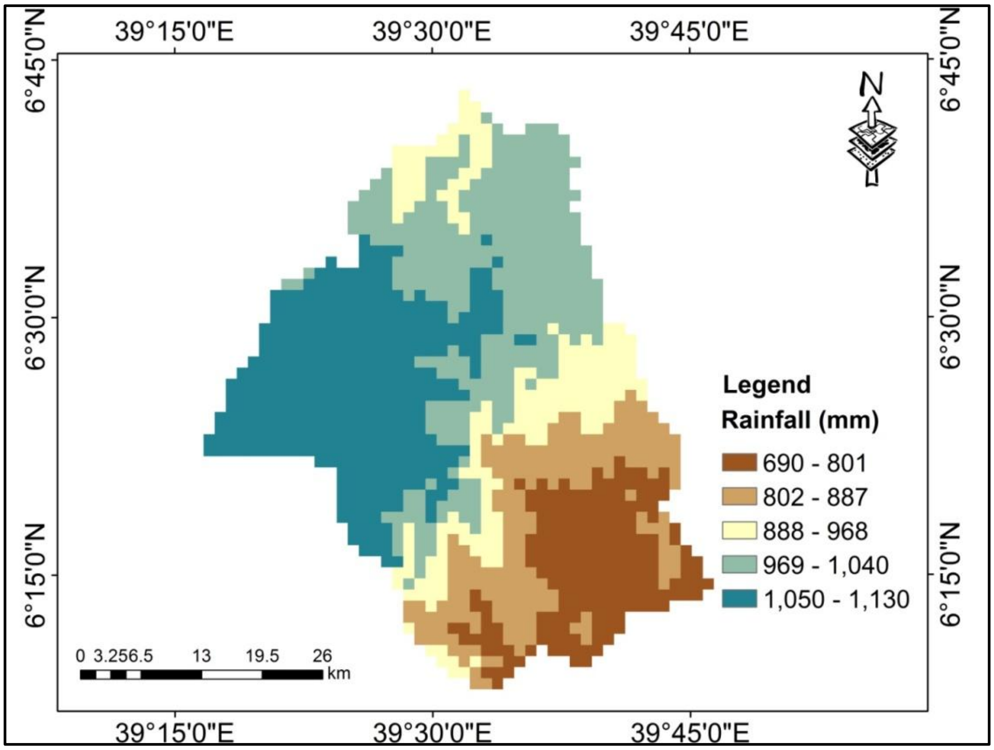

Figure 3.3: Annual rainfall map of the study area (source: www.worlidwideclim.org).

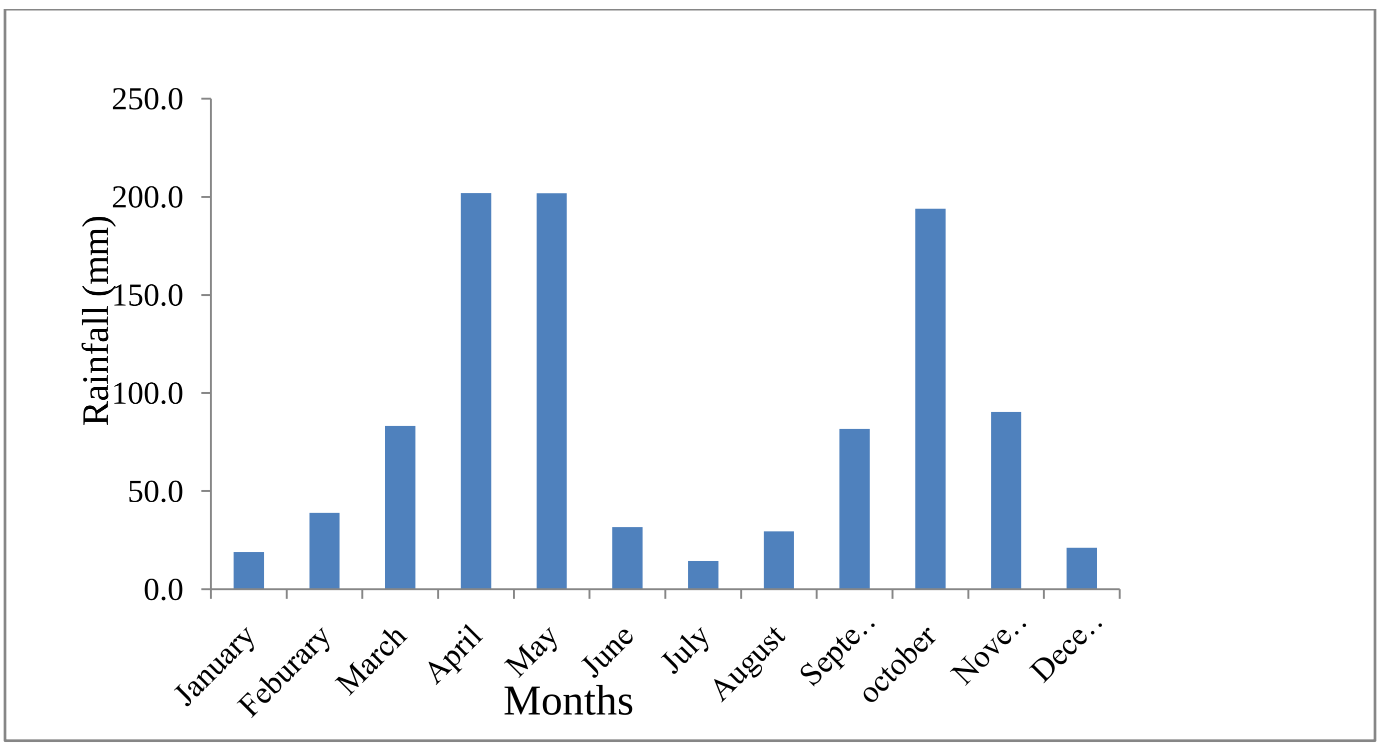

Figure 3.4: Monthly Average Rainfall Distributions (source: NMA).

3.2. Materials

3.2.1. Remote Sensing Data

The data used for the forest cover change, forest degradation and biomass estimation in Harenna Buluk Woreda was a time series of Landsat (TM, ETM+ and OLI) satellites downloaded in zipped files from USGS and Sentinel-2A image from European Space Agency (ESA). In total 6 Landsat scenes and 2 Sentinel-2A scenes were downloaded for analysis (Table 3.1).

Table 3.1: Remote sensing data used in the study.

Acquisition Date	Sensors	Spatial Resolution	Number of band	Format	Source
05/12/1995	TM	30m	7	TIFF	USGS
05/12/ 2005	ETM+	30m	8	TIFF	USGS
07/12/2016	OLI	30m	11	TIFF	USGS
13/12/2016	Sentinel-2A	10	13	TIFF	ESA

3.2.2. Field Data Collection

Ground truth points were established at random locations to validate observations obtained from remotely sensed data. During the field work, photographs were taken from different land-cover types, identifying the forest degradation condition and spatial locations of the features ,which were recorded using a Global Positioning system (GPS). Besides, information on aspects of forest cover in the study area was collected.

3.2.3. Software Packages

The software used in this study were ERDAS imagine 2014 for image processing and image classification, ArcGIS 10.3 for producing the outputs layout and displaying and analyzing the tabular data, eCognition Essential 9.1 Essential for OBIA method for forest degradation mapping, Sentinel Application Platform (SNAP) for Sentinel-2A image extraction and re-sampling.

3.2.4. Satellite Data and Description

Landsat Thematic Mapper (TM)

The Landsat TM sensor was conceded on board Landsat 4 and 5 from July 1982 to may 2012 with sixteen day repeat time. This sensor data files consist of seven spectral bands (Table3.1). The spatial resolution of the Landsat 4–5 are 30 m for multispectral bands or from band 1–7 and the thermal infrared of band 6 was collected at 120 m (Table 3.1). The full scene size of the image was 170 km north to south and 183 km east to west which was taken from an altitude of 705 km (Chander *et al*., 2009). The false color image product from this sensor had projection of UTM WGS 84, which was taken with repeating cycle of 16 days.

Table 3.1 lists the spectral bands, their range and resolution. Band 1 effectively penetrate water bodies and discriminate soil/vegetation and is useful when mapping different forest types. The band 1 and 2 (green and red) are suitable when detecting healthy vegetation and measuring the absorption of chlorophyll (Lilesand *et al*., 2008 and USGS, 2009a).

Table 3.2: Description of Landsat Thematic Mapper.

Bands	Wavelength(μm)	Resolution	Nominal Spectral Location
1	0.45–0.52	30	Blue
2	0.52–0.60	30	Green
3	0.63–0.69	30	Red
4	0.76–0.90	30	Near Infrared
5	1.55–1.75	30	Mid Infrared
6	10.40–12.50	30	Thermal Infrared
7	2.08–2.35	30	Mid Infrared

The near-infrared band (band 4) was used to determine different vegetation types and biomass. Band 5 and 7 (the two Mid-IR bands) was used for measuring moisture in the vegetation and in the soil (USGS, 2009a). Band 7 was used to distinguish different rocks and minerals. The band 6 (Thermal-IR band) was great use in thermal mapping applications, but and distinguish soil moisture and to analyses vegetation stress (Lilesand *et al*., 2008).

Landsat Enhanced Thematic Mapper plus (ETM+)

The Landsat ETM+ was built by SBRS (Santa Barbara Remote Sensing) and mount on Landsat 6 and 7. This sensor was derived from the Thematic Mapper (TM) engineered for Landsat 4 and 5. The primary importance related changes of the ETM+ was the addition of panchromatic band and two gain ranges (added for Landsat 6). The data from ETM+ sensor consists of eight bands; multi spectral bands, thermal bands and panchromatic bands with spatial resolution of 30 m, 60 m and 15 m respectively. The scene of this sensor is cover 185 km. The Lansat ETM+ data consists of eight spectral bands. Bands 1–5 and band 7 have the spatial resolution of 30 m and band 8 has 15m. The spectral bands have different wavelength range and nominal spectral location (USGS, 2010d).

Table 3.3: Description of Landsat Enhanced Thematic Mapper Plus.

Bands	Wavelength(μm)	Resolution (m)	Nominal Spectral Location
Band 1	0.45–0.52	30	Blue
Band 2	0.52–0.60	30	Green
Band 3	0.63–0.69	30	Red
Band 4	0.76–0.90	30	Near IR
Band 5	1.55–1.75	30	Mid IR
Band 6	10.40–12.50	60	Thermal IR
Band 7	2.08–2.35	30	Mid IR
Band 8	0.52–0.9	15	Panchromatic

Lansat Operational Land Imager (OLI)

Landsat 8 satellite sensors were part of the Landsat Data Continuity Mission, which was successfully launched on February 11, 2013. This satellite has two main sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) (Mishra *et al*., 2014). Operationl Land Imager was collect images using 9 spectral bands in different wavelengths of visible, near-infrared, and shortwave light to observe a 185 km swath width of the earth. This sensor gives an image data having spatial resolution 15–30 m covering wide areas of the earth's landscape (Table 3.3). Thermal Infrared Sensor was added to the satellite mission when it became clear that state water resource managers rely on the highly accurate measurements of Earth's thermal energy (Mishra *et al.*, 2014). The Lansat OLI data consists of 11 bands. Bands 1–7 have the spatial resolution of 30 m, band 8 has 15 m and band 10 and 11 have 100 m spatial resolution. The spectral bands have different wavelength range and nominal spectral location.

Table 3.4: Description of Landsat Operational Landsat Imager.

Bands	**Wavelength(μm)**	**Resolution (m)**	**Nominal Spectral Location**
Band 1	0.435–0.451	30	Coastal/Aerosols
Band 2	0.452–0.512	30	Blue
Band 3	0.533–0.590	30	Green
Band 4	0.636–0.673	30	Red
Band 5	0.851–0.879	30	NIR
Band 6	1.566–1.651	30	SWIR-1
Band 7	2.107–2.294	30	SWIR-2
Band 8	0.503–0.67	15	Panchromatic
Band 9	1.363–1.384	30	Cirrus
Band 10	10.60–11.19	100	TIR-1
Band 11	11.50–12.51	100	TIR-2

Sentinel-2A

The Sentinel-2A satellite image, which was launched on 23 June 2015 is becoming an important image data source for a wide spectrum of applications for monitoring agriculture, forestry, environment and urban planning. Sentinel-2A is a multi-spectral high resolution imaging mission. This satellite image is a key element of the Copernicus programme of the European Union and features a two satellite land monitoring constellation designed by the European Space Agency (ESA) and built by Airbus Defence and Space. This high resolution multispectral instrument image is high revisit frequency of five days at the equator, which are orbital swath width of 290 km.

The Sentinel-2A datasets was enable creation of automated composite images and conducting multi-temporal analysis with much higher temporal frequency compared to any earlier high spatial resolution dataset image. This may even open up possibilities to study new aspects of land area change processes, which until now have been impossible to monitor on regional level (e.g. up-to-date monitoring of the forest degradation).

Sentinel-2A's Multi-Spectral Instrument (MSI) features 13 spectral bands from the visible (V) and near-infrared (NIR) to the short-wave infrared (SWIR), featuring four at 10 m, six at 20 m and three at 60 m resolution (Table 3.4). Wide coverage (swath width of 290 km) and minimum five-day global revisit time the satellite's orbit is Sun-synchronous, at 786 km altitude, 98.5° inclination. The temporal resolution is 10 days with one satellite and 5 days with 2 satellites. In this study, the Sentinel-2A satellite data dated 2016, was used is to monitor forest degradation.
The Sentinel-2A mission will provide systematic coverage over the following areas:

- All continental land surfaces (including inland waters) between latitudes 56° south and 83° north
- All coastal waters up to 20 km from the shore
- All islands greater than 100 km^2
- All EU islands
- All Mediterranean Sea
- All closed seas

Table 3.5: Description of Sentinel-2A image.

Band name	Resolution (m)	Central wave length (nm)	Bandwidth (nm)	Part of spectrum	Description
B01	60	443	20	Visible	Coastal Aerosol
B02	10	490	65	Visible/VNIR	Blue
B03	10	560	35	Visible/VNIR	Green
B04	10	665	30	Visible/VNIR	Red
B05	20	705	15	VNIR	Vegetation(red edge)
B06	20	740	15	VNIR	Vegetation(red edge)
B07	20	783	20	VNIR	Vegetation(red edge)
B08	10	842	115	VNIR	NIR
B08A	20	865	20	VNIR	Vegetation(red edge)
B09	60	945	20	VNIR/SWIR	Water vapour
B10	60	1375	30	SWIR	Cirrus
B11	20	1610	90	SWIR	SWIR
B12	20	2190	180	SWIR	SWIR

(Source: Ruben, 2016)

3.3. Data Processing and Analysis

3.3.1. Image Pre-processing

Preprocessing is the preliminary step which transforms the data into a format that will be more easily and effectively processed. The raw images collected from the websites are not suitable for direct processing due to the various noises present in these images. Preprocessing includes importing, layer stacking, and subsetting of the image based on the boundary of Harena Buluk Woreda, geometric correction, radiometric correction, and removal of stripes, pan sharpening and other image enhancement techniques. These all mentioned activities were done in order to improve visible interpretability of an image by increasing apparent distinction between the features in the scene. The acquired data from the different sources have been adjusted to Ethiopian projection system. For the study area the projection is Universal Traverse Mercator Zone 37.

3.3.2. Image enhancement

The principal objective of image enhancement is to process a given image so that the result is more suitable than the original image for a specific application. It accurate or sharpes image features such as edges, boundaries, or contrast to make a graphic display more helpful for display and analysis.

Landsat imageries of three bands (4, 3, and 2) for Landsat TM and Landsat ETM+ whereas bands (5, 4, and 3) to Landsat-8 were used in image enhancement to identify changes in land-use/land-cover features. The other Sentinel-2A image band for identification of forest area was band 2, 3, 4 and 8 .These all satellite images had original format in TIFF.

3.3.3. Image Classification

Image classification uses the spectral represented by the digital numbers in one or more spectral bands, and attempts to classify each individual pixel based on the spectral in formations. A common method of monitoring forest disturbances and patterns is categorize the pixels in an image to different land cover classes and compare the size of the classes (Wulder and Franklin, 2007). Image classification is necessary to convert image data to the thematic data. Lillesand and Kiefer (2000), states that the objectives of image classification procedures are automatically categorize all pixels in an image into land-use/land-cover classes.

In this study, supervised classification was used in order to identify land-use/land-cover classes in the study area.

Supervised Classification

Supervised classification needs the analyst to select training areas where he/she knows what is on the ground and then digitize a polygon within that area. Supervised classification is the essential tool used for extraction of quantitative information from remotely sensed image data. Using this method, the analyst has available sufficient known pixels to generate representative parameters for each class of interest. This process is called training. Once trained, the classifier is then used to attack labels to all the image pixels according to the trained parameters. The most commonly used supervised classification is Maximum Likelihood Classification (MLC) algorithm, which assumes that each spectral class can be described by a multivariate normal distribution. Supervised classification needs a prior knowledge of the scene area to provide the software with unique training classes. It is up to the user to define the original pixels that contain similar spectral classes representing certain feature classes. Based on the field observation the study area, seven land-use/land-cover classes such as grassland, forest, shrubland, bareland settlements, water body and farmland were considered as training areas in image based on samples collected. By using ERDAS Imagine software, signature editor was created for defining the classes. The boundaries and number of pixels for each class were added into signature editor using Area of Interest (AIO) tools. Finally, land-use/land-cover maps of the year 1995, 2005 and 2016 were classified.

The description of each of the land-cover categories of the study area are presented in Table 3.5.

Table 3.6: Description of land-use/land-cover.

S. No	Land-cover type	Description
1	Bareland	Areas with no dominant vegetation cover on at least 90 % of the areas covered by lichens/ moss
2	Farmland	Areas of land ploughed or prepared for growing crops
3	Grassland	Areas where the vegetation is dominated by grasses
4	Forestland	An area of more than 0.5 ha, with tree canopy cover of more than 10%, which are not primary under agriculture or urban land-use.
5	Settlement	Small rural communities
6	Shrub land	These types of lands includes areas covered with different species of shrubs and bushes with widely varying density from one area to other, and often found in hilly areas
7	Water body	Rivers are included in this class

3.3.4. Change Detection Analysis

To examine the forest cover change detection and the rate of its changes, post classification comparison change detection method was used. This type of change detection method identifies and provides where and how much change has occurred. In the mean time, four aspects of forest cover change detection characteristics such as, detecting the changes that have occurred using satellite images, measuring the area of the change, and assessing the spatial pattern of the change was investigated. From land-use/land-cover map of the years 1995, 2005 and 2016, the statistical analyses of forest cover changes were identified. Lastly the raster data converted into vector layer by using ArcGIS 10.3 software, then after land-use classification, land-use/land-cover maps were prepared, and forest cover changes of Harenna Buluk Woreda were analyzed.

3.3.5. Mapping Forest Degradation

Forest degradation and its associated impacts have drawn the attention of scientific, environmental and policy making bodies. Spatial distribution of forest was large and hence some places are inaccessible and difficult to assess. Uncertainty exist in current estimates of forest degradation, due to confusing definition of forest degradation with that of deforestation and general lack of quantitative, spatially explicit and statistically representative data. For this reason, the importance of satellite images to identify forest degradation, at local, national and international level is increasing. The role of remote sensing as tool for degradation monitoring is essential in natural resource management and still in a testing phase. Medium and high spatial resolution sensors such as Landsat, ASTER, Sentinel-2A and SPOT have been mostly used so far to address forest degradation. In the present study, Sentinel-2A was used using OBIA to assess forest degradation in the study area. Methods for mapping forest degradation range from simple image interpretation to highly sophisticated algorithms (GOFC-GOLD, 2009).

3.3.6. Object Based Image Analysis method to Map Forest Degradation

The Object based Image Analysis (OBIA) techniques are tied with high spatial resolution image situation. Recent studies have utilized OBIA methods for high spatial resolution of Sentinel-2A image. The Object based Image Analysis is used in remote sensing image change into meaningful objects, and assessing their characteristics, through spatial, spectral and temporal characteristics.

Object based image analysis is divided into three steps: Multi-resolution Segmentation, create general classes, and classification rules. In the first step, image segments are defined and calculated. The parameters are defined by the user for the scale, spectral and shape properties (Figure.3.6). These image segments to be calculated on several hierarchical levels in a “trial and error” process to result in final image segments to represent single objects of interest (Moeller *et al.*, 2004).

The organization of the work flow step is as follows: 1)Input images, 2) Multi-resolution segmentation, 3) Image object hierarchy, 4) Creation of class hierarchy, 5) Classification using training samples and nearest neighbor, 6) classification base segmentation and, 7) final merge classification (Laliberte *et al*., 2004).

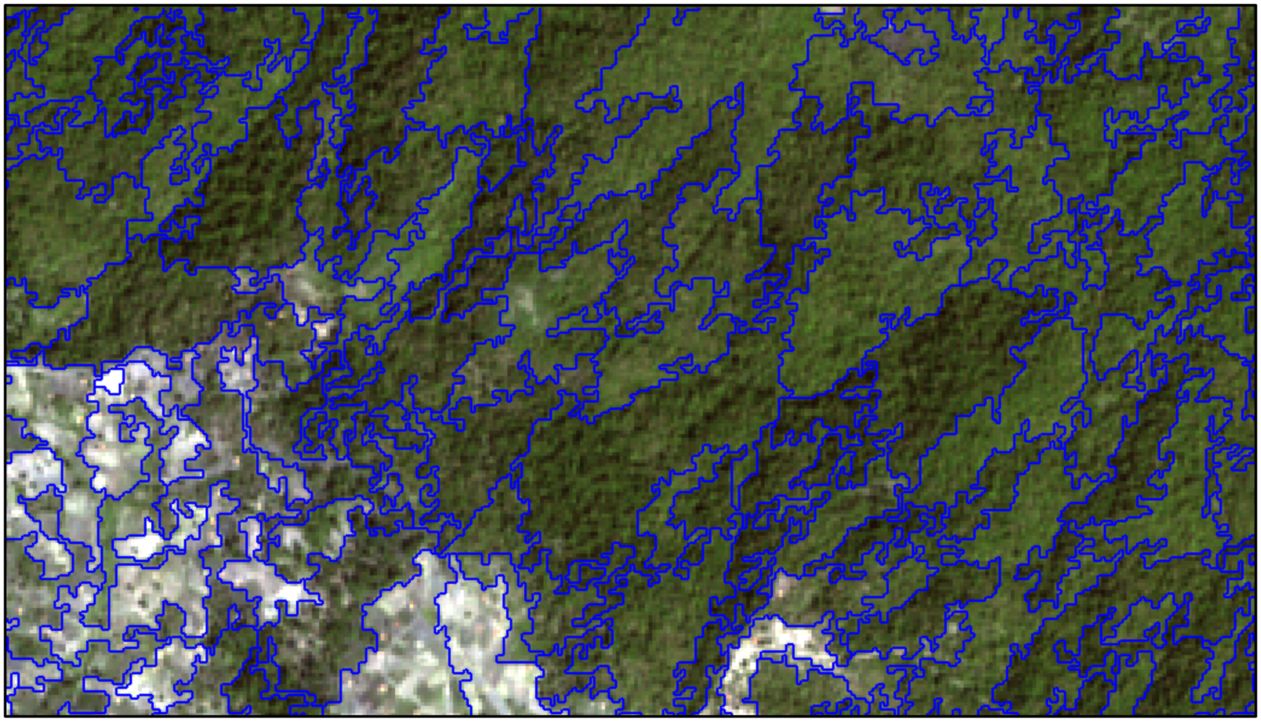

Figure 3.6: Image Segmentation.

Table 3.7: Multi-resolution segmentation parameters.

Segmentation setting	
Image Layer Weights	1,1,1,1,1,1,1,1,,1,
Scale parameters	70
Composition of homogeneity criterion	
Shape	0.7
Compactness	0.9

The scale parameter is a value to determine the maximum possible change of heterogeneity. Shape includes compactness and smoothness, which are two geometric features that can be used as evidence. Compactness describes the closeness of pixels clustered in an object by comparing it to a circle (Table 3.6).

After defining parameters, the next step is creating class hierarchy by creating and defining classes. Four classes were created in order to assess forest degradation; as follows deforestation, degradation, forest and non forest areas.

Object Based Image Analysis works on homogeneous objects produced by image segmentation and more elements can be used in the classification. As an object is group of pixels, object characteristics such as standard deviation, mean value, ratio, can be calculated. The object based image analysis has advantage over the pixel based image classification, and in accuracy rating, the advantage was better represented by higher spatial resolution satellite images.

3.3.7. Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index is an index commonly used when observing vegetation (Lillesand *et al*., 2008). It measures the density of the green vegetation it is often used to monitor photosynthetic at every scale. As vegetation reflects red and near-infrared light it is possible to calculate the NDVI by using following formula:

For Landsat TM and ETM+ the formula expressed as:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \qquad \text{Eq. (3.1)}$$

NIR = Band 4

RED = Band 3

For Landsat 8(OLI) the formula can change into the following equation:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \qquad \text{Eq. (3.2)}$$

Where, NIR = Band 5

RED = Band 4

3.3.8. Biomass Estimation

Many methods have been used to estimate biomass of an area. The main approaches biomass estimation in forested areas is direct measurement and remote sensing based measurements. The most accurate method to measure forest biomass is based by field measurements, harvest tree oven dry them to weigh the dry matter. But this direct method is normally prohibitively expensive, time consuming and labor intensive, and it is impossible to census large geographic areas. The remote sensing techniques has become an effective way to estimate forest biomass

(Rosenqvist *et al*., 2003), especially taking to account the recent availability of data with increased spectral, temporal and spatial resolution. Therefore, this study focuses on remote sensing based biomass estimation in forest area. IPCC(2003), states that remote sensing methods are suitable for verifying the national LULUCF (Land Use, Land Use Change, and Forestry) carbon pool estimates especially the above ground biomass.

To map and estimate woody biomass, the land-use/land-cover map of the study area were used. The land-use/land-cover map was prepared from optical sensor such as Landsat images. During land-use/land-cover classification field data (ground truth) data Google earth satellite data was used as reference to classify the features. An interpretation of satellite image was done by false color composition of bands to stratify forest types. The ground truth sites, which could be identified on satellite imagery, were used as training sets for classification. In this study, the forest biomass available from tress can be estimated by applying the following formula used (Sharma, 2013):

Growing stock (tons/ha/yr) = Area under plantation or canopy (per ha)*Productivity (m^3/ha/yr) Eq. (3.3)

Biomass productivity estimates made by indicative of hardwood volume for the project "forest plantation yields in the tropical and subtropical zone" for indicative plantation yields by species and country for hardwood species grown in the tropical and sub tropical area. There was different species types are found in the study area, but among the species *Podocarpus facults* and *Erica arborea* which are dominants. The productivity of these two species ranged 12–19 m^3/ha/year (Leech, 1998). By using FAO source, an average 15.5 m^3/ha/year is used to compute sustainable yield estimation. For the extraction of the size of woody biomass stands the time series Landsat images were used.

3.3.9. Accuracy Assessment

Accuracy assessment is a general term for comparing the classification to geographical data to that are assumed to be true, in order to determine the accuracy of the classification process. Accuracy assessments in remote sensing image classification are important for evaluating the obtained result. This will allow a degree of confidence to be attached to those results and will serve to indicate whether the analysis of objectives has been achieved. A reference point represents geographic point on the classified image for which actual data are known. The reference data are also derived from field survey, high resolution satellite imageries or Google Earth. This set of reference points are usually used in accuracy assessment.

Forest degradation can be difficult to detect and characterize using imagery only, especially when single trees are cleared from forest with a high biomass or high vegetation density. To overcome the limitations of Remote Sensing based reference datasets, the validation of method was based on field data. Field data were collected during April, 2017. To ensure the visibility of degradation process the validation was centered on changes in 2016. For efficient data collection, mobile devices with integrated GPS and camera functionality were used.

The schematic representation and analysis method is shown in Figure. 3.7.

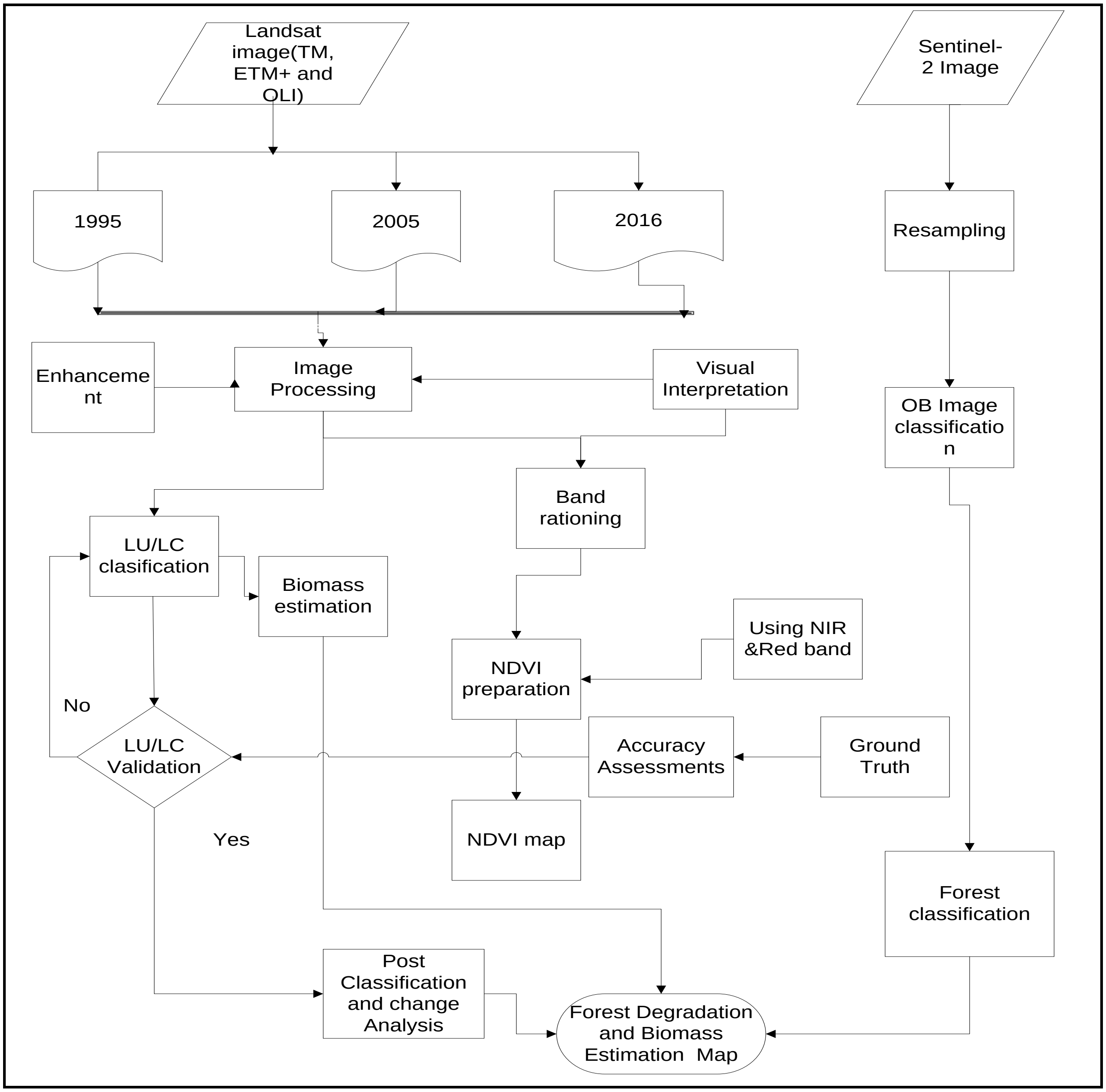

Figure 3.7: Flow Chart of the Methodology

CHAPTER FOUR

4. RESULTS

4.1. Land-use/Land-cover Change Detection

Multi spectral images from Landsat TM, ETM+ and OLI images of 1995, 2005 and 2016 were used to evaluate forest cover changes in the study area. Training sample were collected and used to create classification of the satellite image using ERDAS imagine software. Land-use/land-cover maps produced are presented in the (Figure. 4.1) for the year 1995, 2005 and 2016 respectively. Initially, images were classified in to seven land cover classes these are, bareland, farmland, forest, grassland, shrubland, settlement and water body. In addition, the statistics of land-use/land-cover change in general and forest cover change in particular were computed. The areal extent of each land-use/land-cover types with the respective percentage is presented in (Table 4.1).

Table 4.1: Land-use/land-cover areas during 1995, 2005 and 2016.

Land-cover classes	**Years**					
	1995		**2005**		**2016**	
	Area (km^2)	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Bareland	57.20	2.97	187.37	9.74	100.31	5.21
Farmland	343.84	18.14	407.76	21.20	448.78	23.33
Forest	1187.43	61.72	1090.26	56.69	1068.23	55.55
Grassland	69.55	3.61	120.05	6.24	135.33	7.55
Settlement	8.83	0.45	21.20	1.10	29.37	1.52
Shrubland	247.47	12.86	84.35	4.38	120.37	6.24
Water body	3.68	0.19	12.01	0.62	10.61	0.55
Total	**1923**	**100**	**1923**	**100**	**1923**	**100**

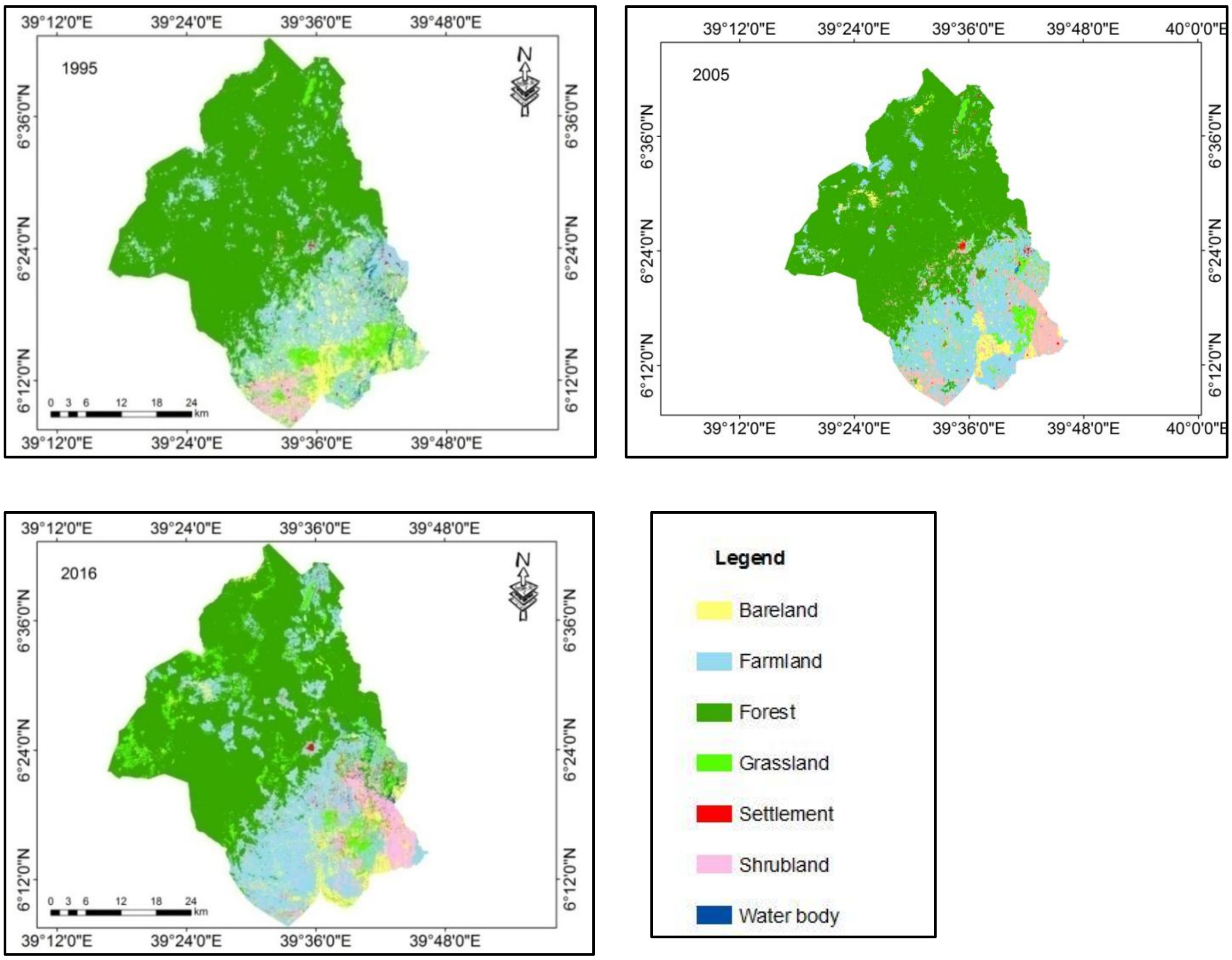

Figure 4.1: Land-use/land-cover maps of 1995, 2005 and 2016**.**

During 1995, the highest extent of the study area was covered with dense forest 1187.43 km^2 (61.72%), while bareland, farmland, grassland, settlement, shrubland and water body, represented only 57.20 km^2 (2.97%), 343.84 km^2 (18.14%), 69.55 km^2 (3.61%), 8.83 km^2 (0.45%), 247.47 km^2 (12.86%) and 3.68 km^2 (0.19%), respectively. By the year 2005, the areal coverage of bareland, farmland, grassland, settlement, and water body have incresed to 187.37 km^2 (9.74%), 407.76 km^2 (21.20%), 120.05 km^2 (6.24%), 21.20 km^2 (1.10%) and 12.01 km^2 (0.62), respectively. As per the image, areal coverage of forest, and shrubland were decreased to 1090.26 km^2 (56.69%) and 84.35 km^2 (4.38%), respecyively. By the year 2016, the coverage of bareland decreased by 100.31 km^2 (5.21%), followed by forest 1068.23 km^2 55.55% and water body 0.55%, while the coverage of farmland, grassland, settlement and shrubland increased to, 10.61 km^2 (23.33%), 135.33 km^2 (7.55%), 29.37 km^2 (1.52%) and120.37 km^2 (6.24%), respectiveliy (Figure. 4.2).

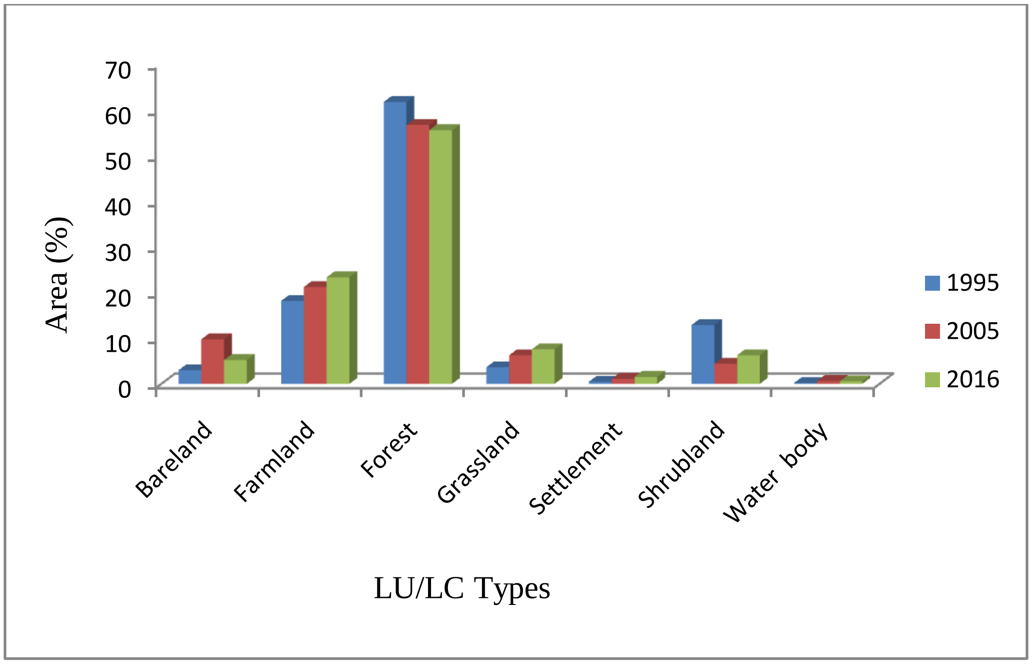

Figure 4.2: Patterns of land-use/land-cover changes of Harenna Buluk woreda durig the years of 1995, 2005 and 2016.

4.2. Trends of Land-use/land-cover Changes

Multi-date Landsat images of 1995, 2005 and 2016 were classified and the area was calculated for each land cover classes. The percentage change of land-use changing during 1995–2016 is accompanied in (Table 4.2).

During the period 1995–20015, shrubland and forest area have highly decreased. Forest areas have decreased by 97.17 km^2 (5.05%) during the last 10 years of this study. Areas under shrubland have decreased by 163.12 km^2 (8.48%). Farmland, bareland, grassland, settlement and water body areas have increased by 58.92 km^2 (3.03%), 135.17 km^2 (7.02%), 50.5 km^2 (2.62), 12.37 km^2 (0.64%), and 8.3 km^2 (0.43), respectively.

During the periods of 2005–2016, the extents of bareland, forest and water body have decreased by 4.52%, 1.14% and 0.07%, respectively, while farmland, grassland, settlement and shrubland have increased by 2.13%, 1.31%, 1.87% and 0.42%, respectively. During these 11 years, the extent of farm land has dramatically increased.

Detection of land-use/land-cover during the years, 1995–2016 showed bareland, farmland, grassland, settlement and shrubland have increased by 43.11 km^2 (2.24%), 99.94 km^2 (5.19), 75.78 km^2 (3.94), 20.54 km^2 (1.06%) and 6.93 km^2 (0.36), respectively, while forest were decreased by 119 km^2 (6.19%) and shrubland decreased by 12.1 km^2 (0.62%). The summary of land-use/land-cover areas during periods of 1995–2005, 2005–2016, and 1995–2016 is shown in Table 4.2 and Figure. 4.3.

Table 4.2: Trends of Land-use/land-cover rate changes in the study area during 1995, 2005, and 2016

	1995–2005		2005–2016		1995–2016	
Land-cover class	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Bareland	135.17	7.02	-87.06	-4.52	43.11	2.24
Farmland	58.92	3.03	41.02	2.13	99.94	5.19
Forest	-97.17	-5.05	-22.03	-1.14	-119.2	-6.19
Grassland	50.5	2.62	25.28	1.31	75.78	3.94
Settlement	12.37	0.64	8.17	0.42	20.54	1.06
Shrubland	-12	-8.48	36.02	1.87	-12.1	-0.62
Water body	8.33	0.43	1.4	-0.07	6.93	0.36

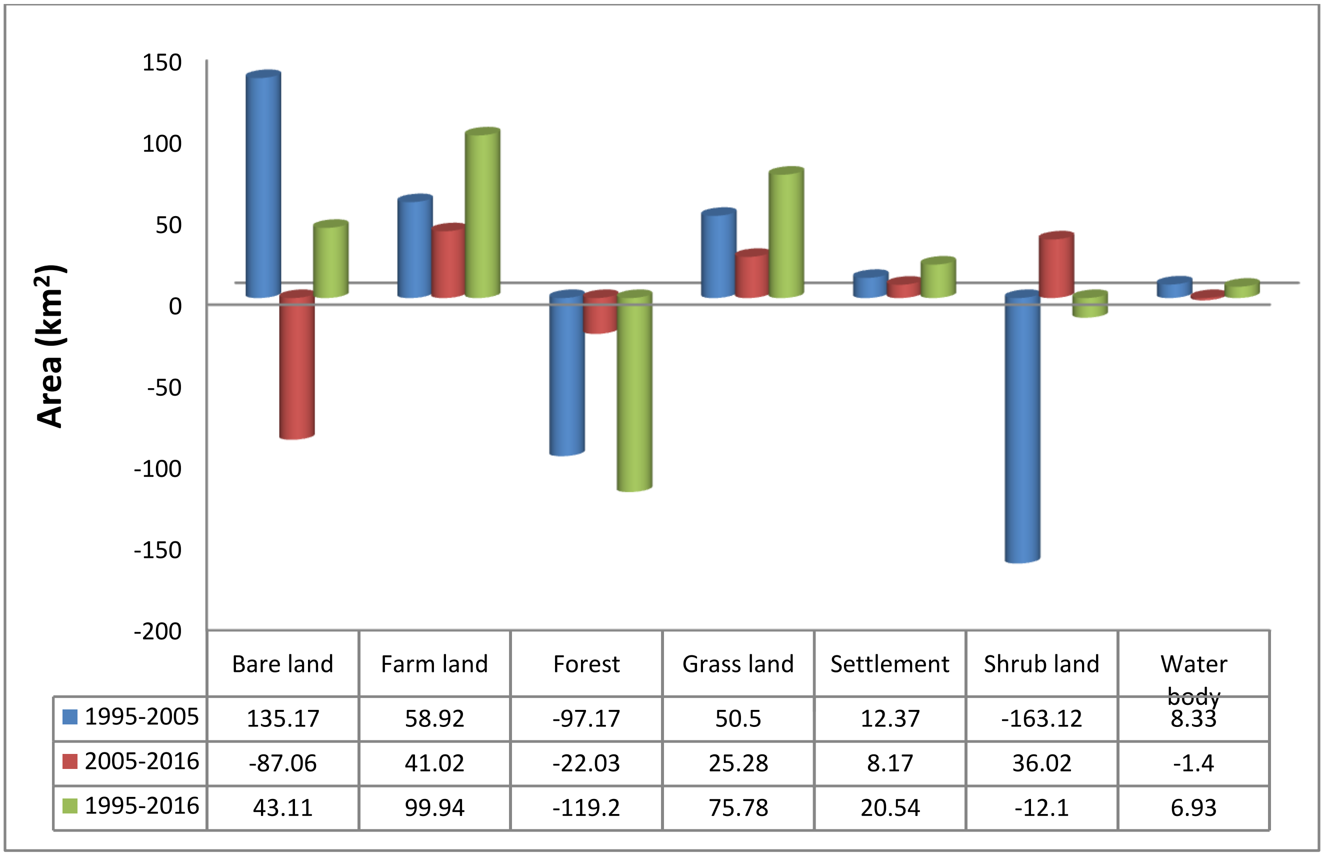

Figure 4.3: Land-use/land-cover changes during 1995–2005, 2005–2016, and 1995–2016.

Table 4.3: Matrix of Land-use/land-cover Changes between1995 and 2016 of Harenna Buluk Woreda

		Land -use / land -coverof 2016							
		Water body	Bareland	Forest	Farmland	Settlement	Grassland	Shrubland	**Class Total**
Land -use / land -coverof 1995	Water body	**7.89**	0.02	0.02	0	0	0.01	0	7.94
	Bareland	0.09	**39.48**	2.01	6.23	0.04	13.15	13.23	75.05
	Forest	0.02	26.58	**1001.84**	56.86	0.02	12.38	26.83	1124.53
	Farmland	0.04	33.12	3.21	**105.26**	4.25	55.03	28.26	229.17
	Settlement	0	3.23	0.02	0.08	**13.85**	0.02	0.01	17.21
	Grassland	0	1.23	0.28	88.23	2.51	**189.23**	11.04	292.52
	Shrubland	0.04	9.45	5.28	46.35	2.1	28.38	**78.26**	176.86
	Class Total	8.89	120.12	1012.24	303.01	22.77	298.2	157.63	**1923**

During 1995–2016, results showed that forest and shrubland was highly decreased while bareland, grassland, farmland, water body and settlement were increased (Table 4.3). This table showed that an areal distribution of land-use/land-cover units and provides information about what proportion of each land-cover types into other land-cover.

4.3. Areal Extent and Rate of Forest Cover Change

Analysis of forest cover change was done using remote sensing and GIS techniques with the integration of field survey. During the analysis stage, digital image interpretation of forest cover area for each year was performed and total area of the forest cover in terms of km^2 and its percentage from each date of satellite interpretations were computed and summarized Figure 4.4 and Table 4.4

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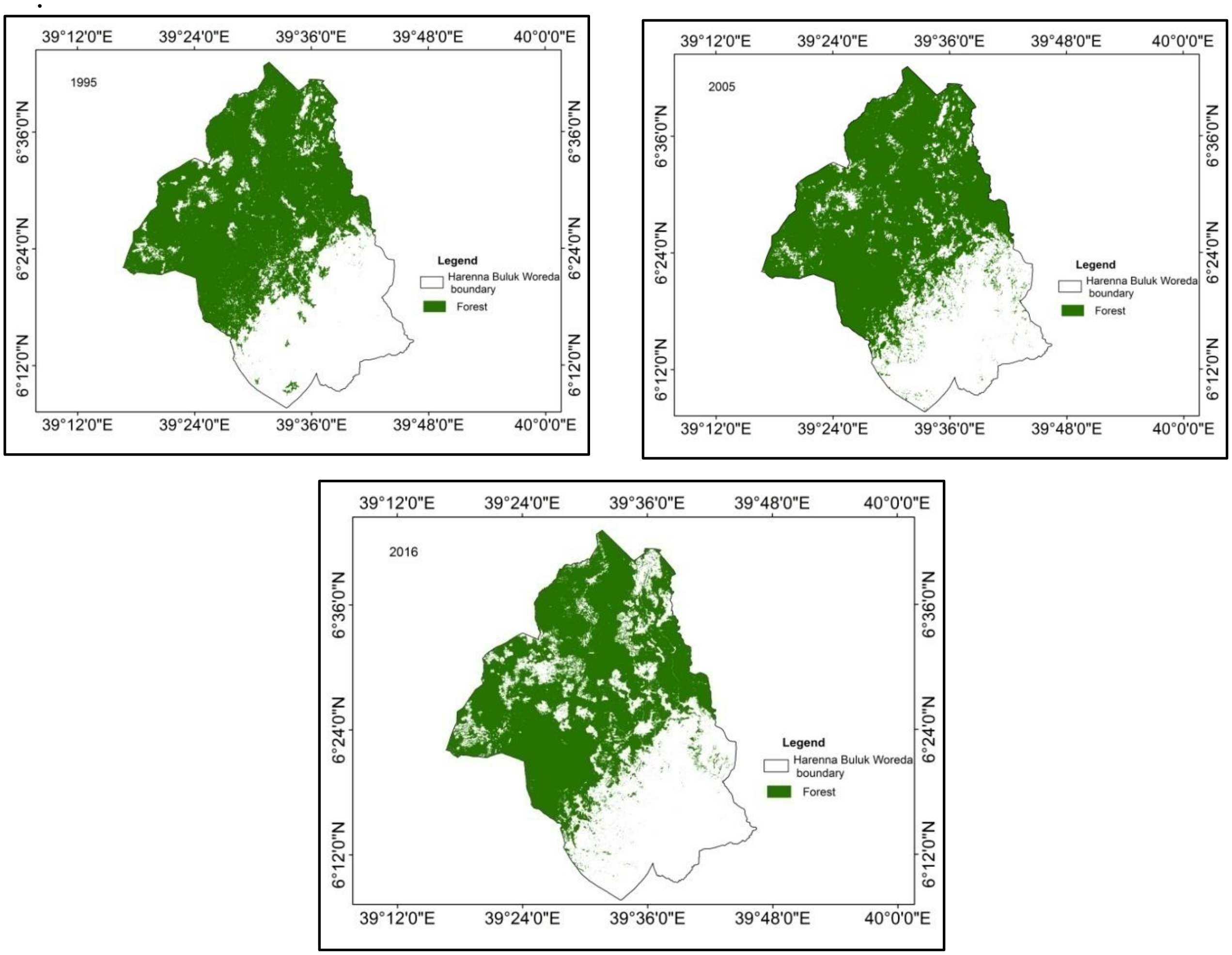

Figure 4.4: Forest Cover Map of Harenna Buluk Woreda, during, 1995, 2005 and 2016

Table 4.4: Forest Cover Land Area of Harenna Buluk Woreda; 1995, 2005 and 2016

Year	Forest cover form the total area (km^2)	Forest cover (%)
1995	1187.43	61.72
2005	1090.26	56.69
2016	1068.23	55.55

4.4. Assessment of Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index values of the different land cover types in deferent land-cover class were presented. These NDVI values were extracted from Landsat (TM, ETM+ and OLI) images of the years 1995, 2005 and 2016 in the study area (Fig. 4.5.). Forest areas have a higher NDVI values than agriculture, grassland, shrubland settlement water body and bareland. However, these values of NDVI were dramatically decreased between the years of 1995–2016. It is important to note that NDVI images were used to measure the balance between energy received and energy emitted by objects on earth surface.

The NDVI value of the year 1995 ranges from -0.76 low to high 0.97. From a low of -0.22 to high 0.70 for the year 2005 and low -0.99 to high 0.56 for the year 2016, respectively. Values close to -1 indicates non-vegetation surfaces and values close 1 represent maximamum vegetation coverage. Normalized Difference Vegetation Index (NDVI) map in Figure 4.5 indicates that the vegetaion decreased the year 1995–2016.

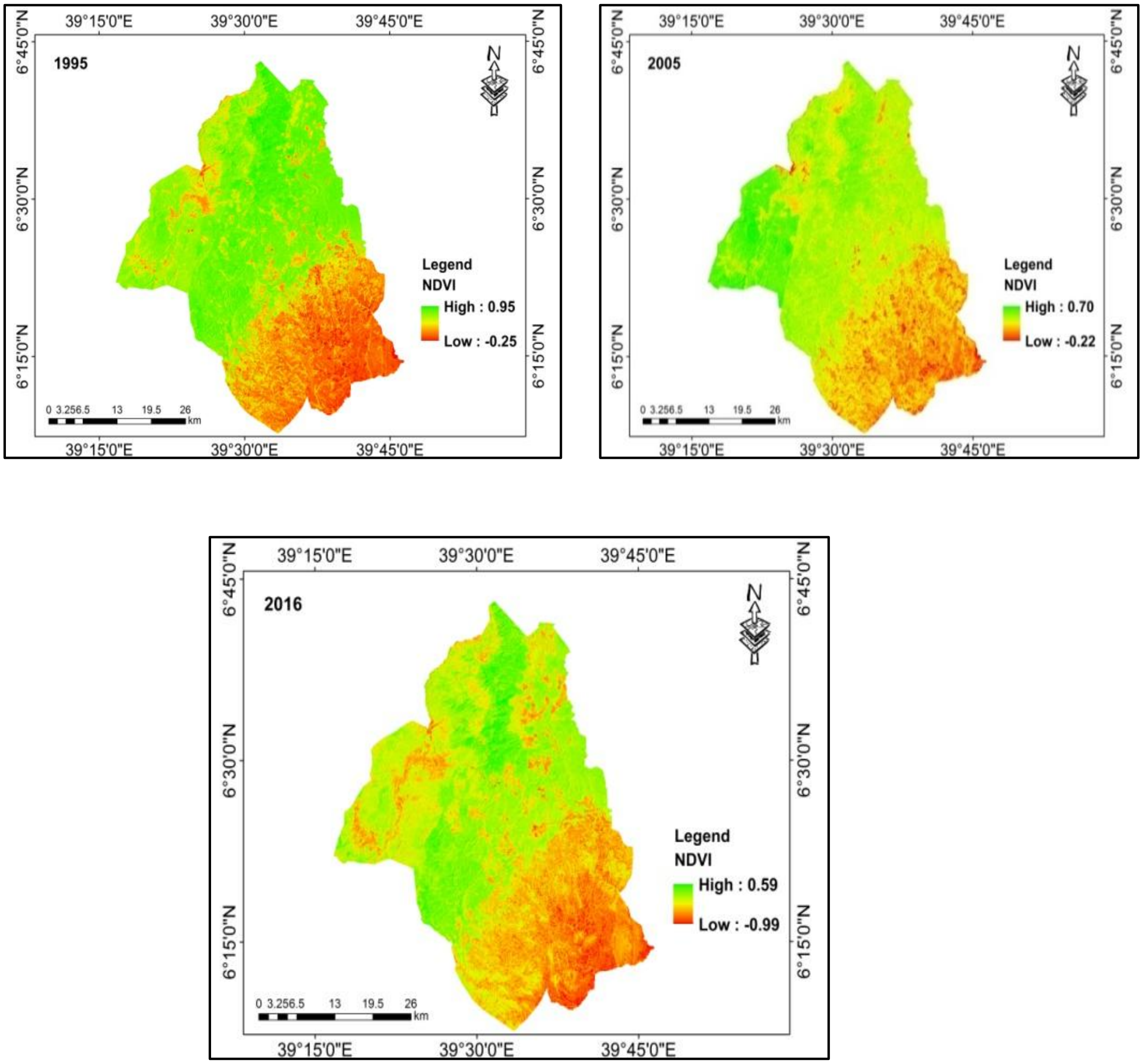

Figure 4.5: Normalize Different Vegetation Index maps of the study area

4.5. Forest Degradation

Form the forest extent of 1187 km^2 on the Landsat image of 1995 about 145.91 km^2 were degraded and 171.39 km^2 was deforested by the year of 2016 (Table 4.5 and Figure 4.6).

Table 4.5: Forest degradation and other land-classes.

Class Name	Area (km^2)	Area (%)
Deforestation	171.39	8.91
Degradation	145.91	7.58
Forest	869.57	45.18
Non Forest	736.13	38.28
Total	**1923**	**100**

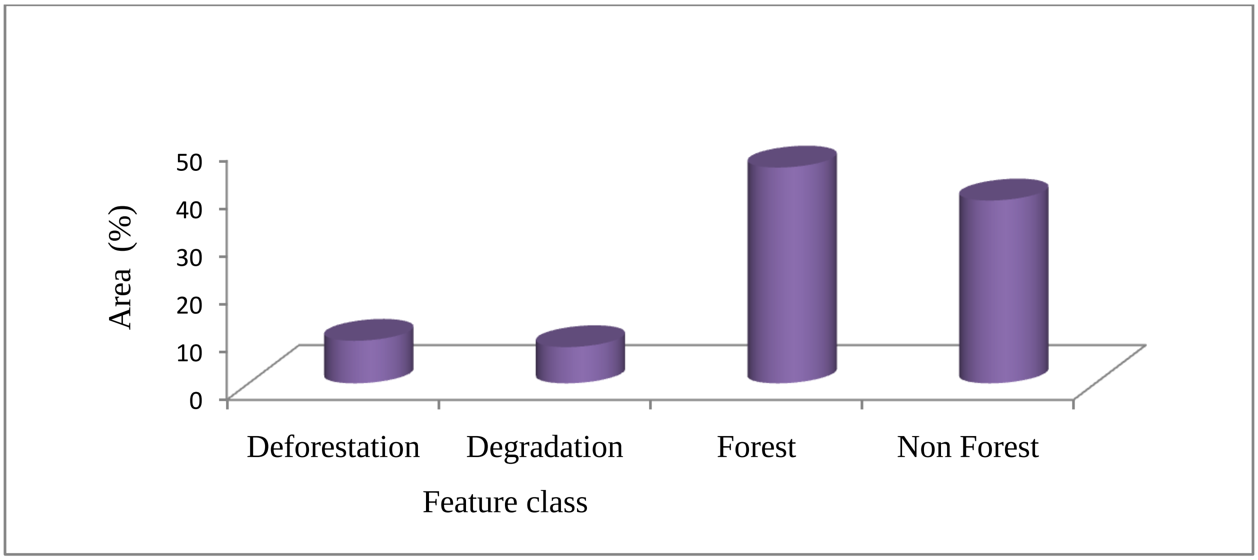

Figure 4.6: Area coverage of forest degradation of the year 2016 using Sentinel-2A satellite image.

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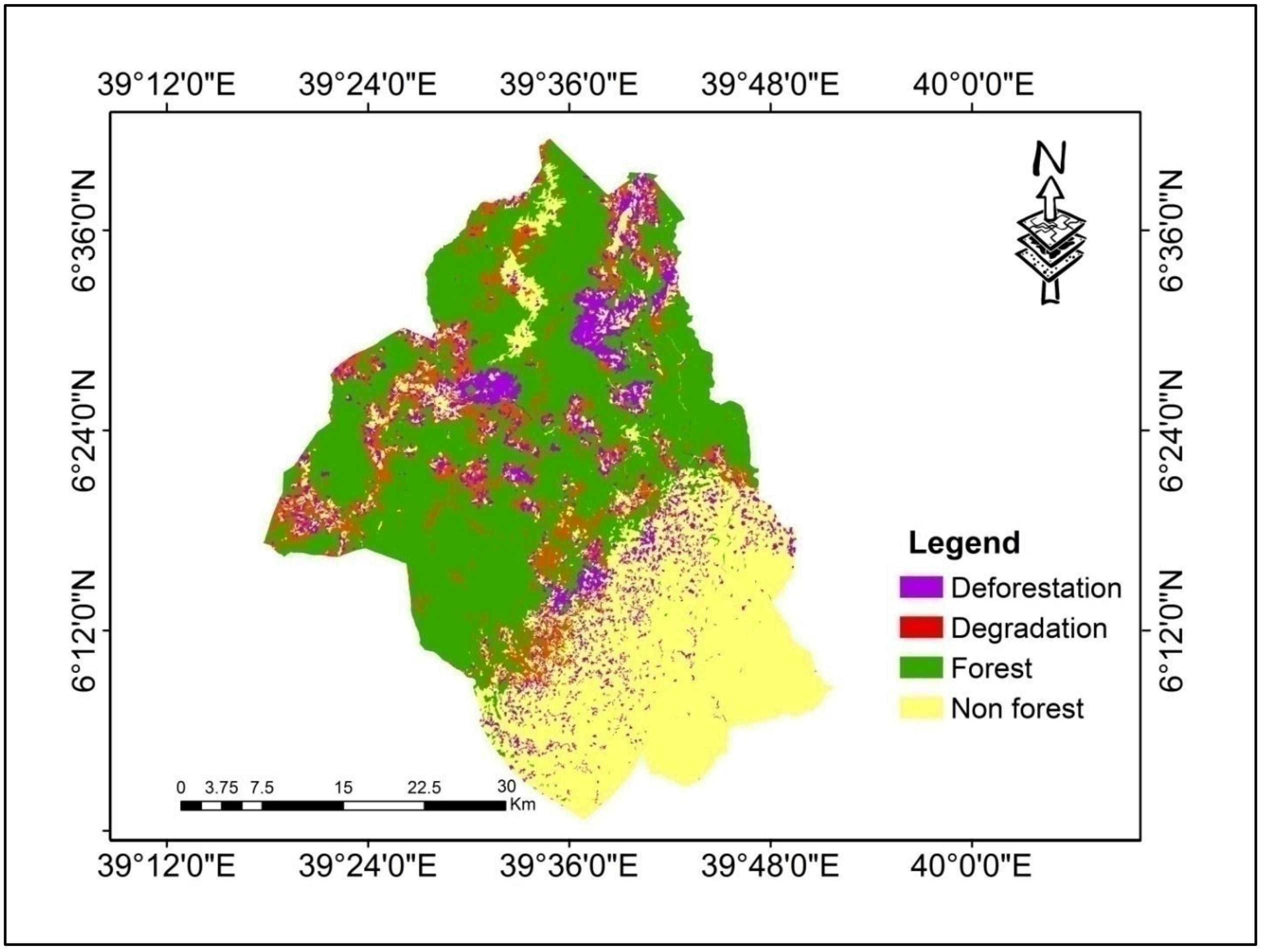

Figure 4.7: Forest degradation map of the study area by the year 2016 using Sentinel-2A image

As shown in Figure. 4.7 above, forest area was highly degraded by the year 2016. By using high resolution Sentine-2A image with the help of field observation in the month of April 2017, the anthropogenic factors were identified as causes of forest degradation.

4.6. Accuracy Assessment

The accuracy assessment for the year 1995, 2005 and 2016 from Landsat image show that for the year 1995 the Kappa statistics was 0.82 and the overall accuracy was 85%. For the year 2005, Kappa statistics was 0.76 and overall accuracy was 80%. For the year 2016 Kappa statics was 0.85 and overall accuracy 87.5%. While the accuracy assessment result for the deforestation and degradation classification when using Sentinel-2A data which was 10 m spatial resolution; the Kappa statistics 0.86 and overall accuracy 88.28%.

Table 1 **Table 4.6**: Statistical information of accuracy assessment for the year 1995, 2005 and 2016.

Land-cover class name	1995		2005		2016	
	Producers Accuracy (%)	Users Accuracy (%)	Producers Accuracy (%)	Users Accuracy (%)	Producers Accuracy (%)	Users accuracy (%)
Shrubland	100.00	80.00	66.67	80.00	100.00	80.00
Bareland	71.43	100.00	66.67	80.00	66.67	100.00
Settlement	75.00	75.00	66.67	80.00	71.43	100.00
Farm land	87.50	100.00	100.00	100	100.00	85.71
Forest	87.50	87.50	87.50	87.5	100.00	88.89
Waterbody	75.00	60.00	75.00	60.00	10.00	80.00
Grassland	100.00	83.00	83.33	83.33	80.00	80.00
Overall classification accuracy	85.00%		80.00%		87.50%	
Overall Kappa statistics	0.8234		0.76		0.8532	

4.7. Estimation of Spatial Distribution Woody Biomass Production

Data on spatial distribution of the estimated forest biomass production showed that the estimated aboveground woody biomass production was 8685056, 6091855 and 4951005 tons/ha/yr during the years of 1995, 2005 and 2016, respectively (Figure.4.8).

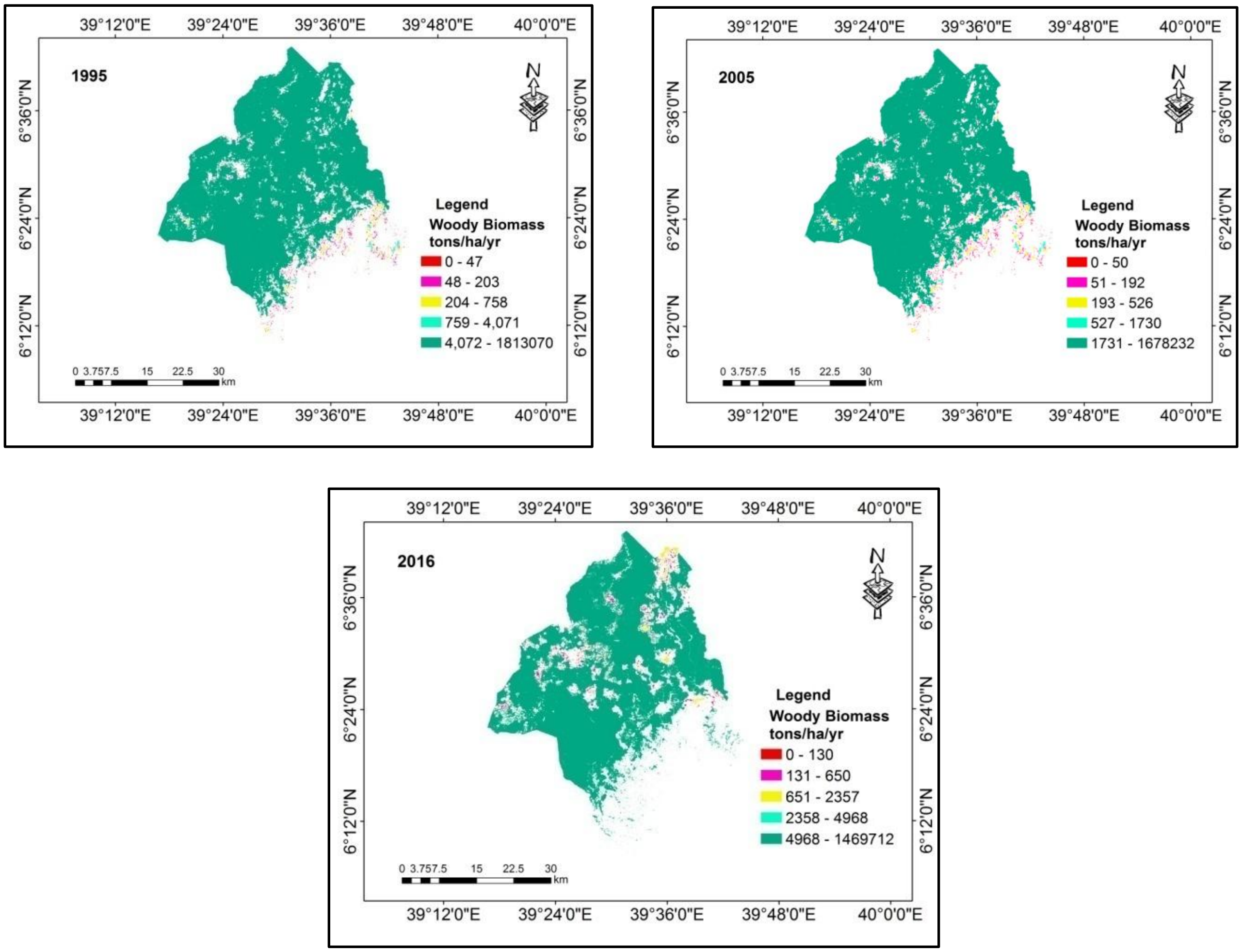

Figure 4.8: Spatial distribution of the estimated aboveground woody biomass during years 1995, 2005 and 2016.

The estimated woody biomass dramatically decreased during the year 1995–2016. These are due to natural succession wildfire, and climate change and human activities such as harvesting and degradation.

CHAPTER FIVE

5. DISCUSSION

The classification of the multi-date Landsat images for the years 1995, 2005 and 2016 revealed that Harenna Buluk Woreda has been experiencing rapid land-cover dynamics. The change detection analysis maps showed the variation that occurred in land-cover types such as farmland, grassland bareland, water body and settlement were increased while there was a reduction in forest cover and shrubland. The level of forest cover change and degradation reported in this study was analyzed in terms of anthropogenic factors as studied in several studies such as (Qamer *et al*, 2016; Hashim *et al*, 2011). The forest area was depleted in the study area due to high anthropogenic activities. It was ascertain that through time series analysis there has been a significant land-use/land-cover change especially the conversion

Growth of farmland and settlement at the expense of other LULC classes in the Harenna Buluk Woreda was identified. Giving priority to agriculture was among the major factors that have contributed to the observed undesirable loss in the study area coverage of the different land classes particularly, forests.

It is important to note that NDVI images were used to measure the balance between energy received and energy emitted by objects on earth's surface.

Many studies such as Rahm (2013) and Nath (2014) indicated that remote sensing techniques supported with field observation are robust methods for monitoring forest degradation. Reliable maps of forest cover disturbance can be achieved through the combined use of medium and high spatial resolution satellite images such as Landsat and Sentinel-2A. The extent of forest loss varies from one year to another depending on different factors. Usually government policies tend to help food security programs that intensify the rate of deforestation. As indicated in Dereje *et al*. (2015), local administrators in Harenna Buluk Woreda encourages immigration and settlements in the forest and other natural vegetation areas was the cause of forest depletion in the study area.

The Object Based Image Analysis (OBIA) method used in this study was an efficient and accurate approach to detect, map and quantify deforestation and forest degradation in Harenna buluk Woreda. The object-based method combines the advantage of the contextual analysis of visual interpretation with the quantitative spectral information is an important asset when classifying the very complex mix of different land cover in decreased forest area (Blaschke, 2010). This method can proceed through the classification process and adjust the multi-resolution segmentation set for assigning a class in order to enhance the classification accuracy (Binyam *et al*., 2014). The result revealed here demonstrated the potential of monitoring frame work to improve the understanding of the spatial and temporal dynamics of both deforestation and forest degradation process. As showed in the results of this study, data from high resolution sensor Sentinel-2A have high potential for detecting forest degradation. Rahm *et al.* (2013) argues that OBIA method was effective to monitor forest degradation using high resolution optical remote sensing. The study by Ibid, (2013), has detected, map and quantify deforestation and forest degradation from optical high resolution satellite image (<20 m) in Democratic Republic of Congo.

Biomass estimation using Remote Sensing data was an emerging technology and has been increasing to be used for the inventory of forest biomass. As showed in the results of the years 1995, 2005 and 2016 the woody biomass was significantly decreased. The rapid reduction of biomass productivity of the study area was due to population pressure, expansion of rural towns, overgrazing and fire. Sheikh *et al*. (2011) estimated forest biomass in India for the years of 2003, 2005 and 2007 by using secondary data of growing stock and satellite data. Similar study by Lemlem *et al*. (2017) estimated the woody biomass using satellite images of 2001, 2010 and 2015. The study showed that there was a continuous decrease of woody biomass. Lu D (2005) estimated above ground biomass, in the Brazilian Amazon using Landsat satellite images.

Forest degradation is triggered by various factors that undermine the forest cover potential and its productivity, which lead to irreversible deterioration. Harenna Buluk Woreda is attracting people because of its favorable climatic conditions and the population growth is the major factor which affects forest resources in the Harenna Buluk Woreda. According to Dereje *et al*. (2015) the major immigrant populations in Harenna Buluk Woreda are from Sidama Zone of the Southern Nation Nationalities and People's Regional State (SNNPRS) and from West Hararge Zone of Oromia Regional State. Based on field observations increase of the demands of forest products both natural and plantation forests has grown the Woreda have been depleting.

In Ethiopia the energy supply comes from biomass. One third of the energy comes from wood and charcoal. In rural areas fire wood, which is collected from the nearby forest is the most important sources of energy. According to information from Woreda Agricultural office, fire wood is commercially important and its demand have increased especially in areas devoid of trees and in the urban areas like Angetu, which is capital town of Harenna Buluk Woreda. Hence, the increased demand for forest resources, in the form of fire wood and charcoal within and outside of the Woreda has been the causes of forest degradation in Herena Buluk Woreda.

Demand for forest resources for construction of houses, household furniture and fence have been aggravated the destruction of the forest in Harenna Bulluk Woreda. According to information from local people and foresters of the Woreda, cutting trees to fulfill the demands of construction materials are the main cause of forest degradation. During field observations, the researcher identified the woody biomass was the single most important house construction material in the Harenna Buluk Woreda.

CHAPTER SIX

6. CONCLUSION AND RECOMENDATIONS

The purpose of this chapter is to give a conclusion of what has been investigated from different data sources and to give possible recommendations based on result of the study.

6.1. Conclusion

Results of present study have revealed that the study area is composed of seven major land-use/land-cover types; bareland, farmland, forest, grassland, settlement, shrubland and water body. Quantitative evidence of land class dynamics was presented and delivered by time series satellite images coupled by GIS. From the analyzed results, the extent of land-use/land-cover in general and forest cover change in particular were observed between the years of 1995 and 2016 in the study area. It was observed that forest has changed remarkably in these periods. Especially, the expansion of farmland, settlement and decline of forest land were observed. In addition of this, the overall condition of the forest resource covers of the study area is strongly disturbed. As showed in the result part of this study, the total area of the forest land was about 1187.43 km^2 in year 1995. However, this Figure declined to 1068.23 km^2 in the year 2016. This study revealed that NDVI values are an indicator of forest resource disturbances. The values of the NDVI were decreased dramatically in the periods of 1995–2016.

Quantifying forest degradation is more challenging than quantifying deforestation. However, OBIA method can be one of the alternatives to monitor the forest degradation. Satellite-based technologies to monitor forest resource cover and biomass density have advanced tremendously in recent years. In the study area, most of degraded forest is located near the human settlements and along the road. The computed quantitative data revealed that from the total area of Harenna Buluk Woreda of the year 2016, about 145.91 km^2 was categorized under forest degradation. On the other hand, 171.39 km^2 forest areas were deforested from total area (1923 km^2) of the study area. The derivers of forest degradation within the study area were mainly related to logging activities, fire, and population growth, fuel wood.

Generally, the forest resource has been degraded due to population growth with other variables such as demand forest products for construction, illegal logging, fire wood and charcoal production. These circumstances lead to further depletion of forest resources in the study area.

As a result, the problem of deforestation and forest degradation with other related factors has been aggravated biodiversity depletion in the study area. Hence, this type of study was useful for the concerned bodies in and protecting the remaining forest resources from destruction.

6.2. Recommendations

To protect forest resources from further depletion the following important suggestions are forwarded based on the result drawn.

- Further analysis is needed on different causes or drivers (natural and anthropogenic) of forest cover change and forest degradation in time to time for the congruent data.
- Minimizing direct depend on forest resources for firewood, fodder and charcoal production
- Creation of conservation awareness on biodiversity conservation, livelihood improvements and creation campaigns especially for the farmers who are living in and nearby forest area.
- There is a need of national level land-use/land-cover data to be updated and this data can be done through increase use of Remote Sensing and GIS for monitoring forest resources for better results.
- There is a need of appropriate design policies and strategies to keep forest resources from depletion, illegal logging, in the name of landless, flood victims.

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Appendices

Apendex 1: Accuracy Assessement of LU/LC of 1995

CLASSIFICATION ACCURACY ASSESSMENT REPORT

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Shrubland	4	5	4	100.00%	80.00%
Bareland	7	5	5	71.43%	100.00%
Settlement	4	4	3	75.00%	75.00%
Farmland	8	7	7	87.50%	100.00%
Forest	8	8	7	87.50%	87.50%
Water body	4	5	3	75.00%	60.00%
Grassland	5	6	5	100.00%	83.33%
Totals	40	40	34		

Overall Classification Accuracy = 85.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8234

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Shrubland	0.7778
Bareland	1.0000
Settlement	0.7222
Farmland	0.9900
Forest	0.8438
Water body	0.5556
Grassland	0.8095

----- End of Kappa Statistics -----

Apendex 2: Accuracy Assessement of LU/LC of 2005

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Shrubland	6	5	4	66.67%	80.00%
Bareland	6	5	4	66.67%	80.00%
Settlement	3	4	2	66.67%	50.00%
Farmland	7	7	7	100.00%	100.00%
Forest	8	8	7	87.50%	87.50%
Water body	4	5	3	75.00%	60.00%
Grassland	6	6	5	83.33%	83.33%
Totals	40	40	32		

Overall Classification Accuracy = 80.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.7645

Conditional Kappa for each Category.

Class Name	Kappa
Shrubland	0.7647
Bareland	0.7647
Settlement	0.4595
Farmland	1.0000
Forest	0.8438
Water body	0.5556
Grassland	0.8039

----- End of Kappa Statistics -----

Apendex 3: Accuracy Assessement of LU/LC of 2016

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Bareland	4	5	4	100.00%	80.00%
Shrubland	6	4	4	66.67%	100.00%
Settlement	7	5	5	71.43%	100.00%
Farmland	6	7	6	100.00%	85.71%
Forest	8	9	8	100.00%	88.89%
Water body	4	5	4	100.00%	80.00%
Grassland	5	5	4	80.00%	80.00%
Totals	40	40	35		

Overall Classification Accuracy = 87.50%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

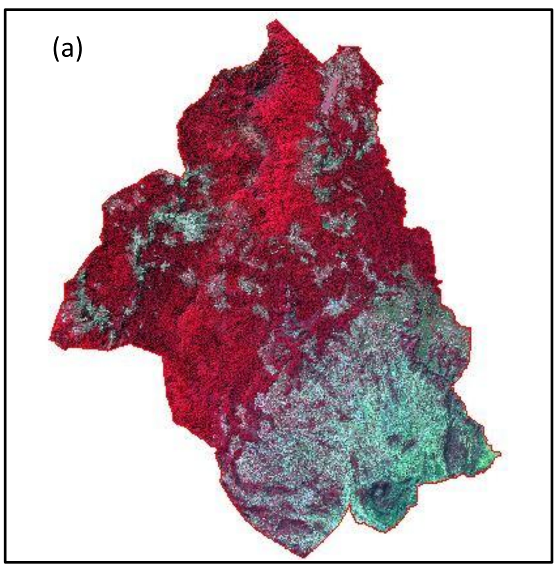
Overall Kappa Statistics = 0.8532

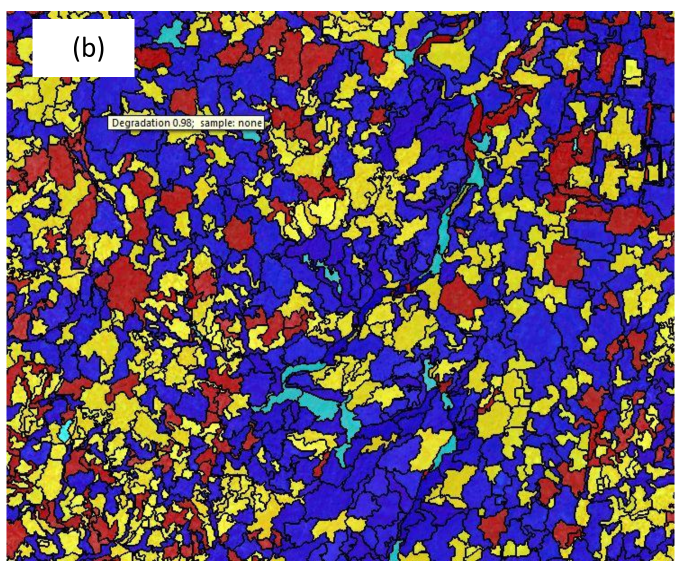
Conditional Kappa for each Category.

Class Name	Kappa
Bareland	0.7778
	0.0000
Shrubland	1.0000
Settlement	1.0000
Farmland	0.8319
Forest	0.8611
Water body	0.7778
Grassland	0.7714

----- End of Kappa Statistics -----

False Color Composite(band 2, band 3, band 4, band 8) of Sentinel-2A sattelite image (a)and classified image (b) using OBIA method.





Appendix 4: Plate-1. Data collection using GPS in Harenna Buluk Woreda

Appendex 5: GPS point from field survey

Northing	Easting	Feature type
565410	708157	Settlement
567663	707605	Forest
568469	705790	Settlement
567301	706372	Water body
568850	706237	Forest
567501	705742	Farmland
567676	705792	Water body
570025	708355	Degradation
569705	708512	Deforestation
573210	711712	Grassland
577675	707944	Settlement
578965	709610	Degradation
578715	710228	Forest
578716	710325	Forest
573745	710858	Grassland
564246	709412	Forest
563792	710539	Degradation
562846	713371	Degradation
562673	714274	Settlement
562476	715691	Grassland
562855	713126	Settlement
563051	711815	Degradation
566398	708454	Farmland
571615	716195	Forest
570700	717806	Forest
566398	708454	Forest
564498	736393	Deforestation
570019	708413	Degradation
547016	712716	Deforestation
583855	687833	Farm land
554438	688280	Farmland
575259	706599	Water body
579293	702825	Shrubland
567218	732343	Grassland
543672	709782	Forest
567218	732341	Deforestation
560966	695036	Bareland
573169	698310	Shrubland
548528	710771	Degradation
573124	698316	Shrubland

Declaration

I, the undersigned, declare that this thesis entitled "*FOREST DEGRADATION MONITORING AND ASSESSEMENT OF BIOMASS USING REMOTE SENSING AND GIS TECHNIQUES, IN HARENNA BULUK WOREDA, BALE ZONE, ETHIOPIA*" has been carried out by me under the supervision of Dr. K.V. Suryabhagavan, Associate professor, School of Earth Sciences college of Natural and Computational Sciences, Addis Ababa University, Addis Ababa during the year 2016–2017 as a part of Master of Science program in Remote Sensing and Geo-informatics. This thesis is my original work and has not been presented for a degree in any university and that all sources of materials used for this thesis have been interestingly acknowledged.

Dinku Shiferaw Jote

Signature____________________

Date________________________

Certificate

This is certified that the thesis entitled "Forest degradation Monitoring and Assesseent of Biomass Using Remote Sensing and GIS Techniques in Harenna Buluk Woreda, Bale Zone, Ethiopia" is original work done by Dinku Shiferaw Jote for the partial fulfillment of the Degree of Masters of Science in Remote Sensing and Geo-informatics from Addis Ababa University under my supervision.

Dr. K. V. Suryabhagavan

Associate Professor

Signature: ____________________

School of Earth Science

Addis Ababa University