



COLLAGE OF DEVELOPMENT STUDIES

CENTER OF ENVIRONMENT AND SUSTAINABLE DEVELOPMENT

COURSE TITLE: MA THESIS (DSESD - 731)

Implication of Land use Land Cover Dynamics of Wufe-Washa Forest and Neighboring Areas in Amhara Region's of Ethiopia

BY

AKLILU ASSEFA HAKE

JULY, 2023

ADDIS ABABA, ETHIOPIA

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This is to certify that the thesis work contained by Aklilu Assefa Hake, entitled “Implication of Land use land cover Dynamics of Wufe-Washa Forest and Neighboring Areas in Amhara’s Region of Ethiopia ” submitted to the college of development studies of Addis Ababa University in partial fulfillment of the requirements for the Degree of Master of Arts in Environment and Development Studies complies with the regulation of the University and meets the accepted standards with respect to originality and quality.

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ACRONYMS

CHIRPS	Rainfall Estimates from Rain Gauge and Satellite Observations
ETM +	Enhanced Thematic Mapper plus
GDAL	Geospatial Data Abstraction Library
GIS	Geographic Information System
KII	Key Informant Interview
LU	Land Use
LC	Land cover
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Change
MLAs	Machine Learning Algorithms
MSS	Multi Spectral Scanner
NDVI	Normalized Differentiate Vegetable Index
OGRL	Open GIS Simple Features Reference Implementation library
OLI	Operational Landsat Imagery
RF	Random Forest
RS	Remote Sensing
SPL	Spatial Package Library
SPSS	Statistical procedures in Statistical Package for Social Science
TM	Thematic Mapper
UNDP	United Nation Development Program
FGD	Focus Group Discussion
FAO	Food and Agriculture Organization of the United Nations

Abstract

LULCC pertain to the changes in the quantity of land use and land cover, which may alter a specific type of land. In Ethiopia, LULCC has been identified as a significant contributor to environmental change, making it necessary to systematically analyze it to understand the extent of the changes and take appropriate management decisions and actions. Therefore, this study aimed to comprehend the dynamics of LULC in the Wufe-Washa forest and its surrounding areas. It analyzed the LULCC that occurred over the past 45 years, evaluated the impacts of LULCC on the forest environment and socioeconomic factors, and identified the drivers of LULCC in the study areas. To achieve these objectives, sequential Landsat satellite images from 1973, 1985, 2000, and 2022 were utilized, using RS data, GIS technique mainly via machine learning (ML) algorithms, along with field verifications. Additionally, a socio-economic survey was conducted to interpret the drivers of LULCC and their negative impacts on the biophysical and local communities. During the first and second comparison periods, due to large-scale government-initiated tree plantation, the LULCC analysis showed that forest cover increased by 39.03%, 45.37%, and decreased by 4.58% during the three comparison periods, i.e., 1973-1985, 1985-2000, and 2000-2022, respectively. Grassland increased by 68.5% during the first initial period but lost by 42.54% (1985-2000) and 82.96% (2000-2022) in the two consecutive analysis periods. Shrub and bare lands continuously decreased during the three periods. The shrub land decreased by 21.50%, 68.95%, and 33.7% respectively over the analysis period, while bare land declined by 58.7%, 9.37%, and 41.22%, respectively. On the other hand, cropland showed continuous increments of 22.65%, 17.77%, and 19.46%, and settlements increased by 20.22%, 22.41%, and 41.22% during the three periods in the respective order of the analysis period. Post-classification accuracy assessment was conducted for the years 1973, 1985, 2000, and 2022, with an overall accuracy of 88.70%, 89.65%, 87.73%, and 95%, respectively. The kappa coefficient values for the years 1973, 1985, 2000, and 2022 were 85%, 87%, 84%, and 93%, respectively and the RF algorithm showed good performance in the categorization of the geographic features especially for vegetation land cover types. The prominent causes of LULCC in the study area are deforestation of natural forests, farmland expansion, population growth, and the lack of government institution policy implementation. These lead to the destruction of natural resources, such as the reduction in flora and fauna availability, soil degradation, climate change, and a decline in water resources. Therefore, it is essential to have an appropriate land use plan and policy to ensure a well-taught LULCC.

Keywords: LU/LC Dynamics, Change Detection, GIS, RS, MLs, and RF

CHAPTER ONE

1. INTRODUCTION

1.1. Background

Throughout history, human activities have brought about a significant shift that has profoundly impacted the Earth's natural systems. Causes such as the construction of massive walls, urban planning, industrialization, settlements, and agricultural practices have resulted in substantial alterations to the Earth's surface over time, comparable to the establishment of national boundaries (Sreenivasulu and Bhaskar, 2010; FAO, 2016; Talooet et al., 2020). These activities, coupled with land utilization and land covering, have become key drivers of far-reaching environmental change, leading to the destruction of ecosystems worldwide and fundamentally transforming the physical landscape in unprecedented ways (Winkler et al., 2021; Negassa, 2020).

Among the most significant factors influencing natural landscape, changes in land use and land cover (LULC) have local, regional, national, and global implications, as highlighted by Lin et al. (2009). Lambin et al. (2003) further emphasize that LULC changes are major contributors to global environmental change, posing a significant obstacle to achieving sustainable development. Since the 1970s, the dynamic nature of LULC has garnered increasing attention in global ecological studies. These changes are complex processes influenced by a range of interrelated phenomena, encompassing natural forces and socioeconomic dynamics, which greatly impact the structure, purpose, and dynamics of landscapes worldwide (Lambin et al., 2006).

Land cover refers to the physical characteristics of different land types, such as urban areas, forests, water bodies, and grasslands, as explained by Lambin & Ehrlich (1997). On the other hand, land use encompasses the diverse activities and purposes for which land is utilized, including agricultural production, urban and suburban development, transportation infrastructure, and natural resource extraction (Foley et al., 2005).

The Food and Agriculture Organization (FAO) of the United Nations, in 2006, emphasized the link between the loss of natural capital, particularly the decline of natural ecosystems, and land

use changes that significantly impact land cover. Peter Holmgren (2006) identifies the expansion of urban areas and infrastructure encroaching upon farmland, along with the expansion of agricultural land negatively affecting grasslands and forests, as the primary contributors to global alterations in land utilization. Additionally, according to FAO's 2020 report, approximately 4.06 billion hectares of the world's lands are covered by forests, with human activities dominating tropical forests. Like many developing nations, Ethiopia has heavily relied on its forests and other plant resources for thousands of years. However, these resources have been rapidly depleting, jeopardizing their size, quality, species composition, and overall structure (Forum for Environment, 2010; Berihun et al., 2019). FAO (2015) reports that Ethiopia's forest cover accounts for only 11–15.5 percent of the total land area. The country lost 28,180 km² (equal to 18.6 percent of its forest area) between 1990 and 2015 due to various factors, including the conversion of land for agriculture and grazing, urbanization, and the rising demand for fuelwood.

The Wufe-Washa Forest, located in the North Shewa Zone of the Amhara Regional State in Ethiopia, is one of the country's oldest state-owned forests situated in the central highlands. Unfortunately, due to a long history of settlement and intense human pressure, deforestation has occurred in this forest. The recent increase in demand for agricultural land, building materials, and firewood has made the Wufe-Washa Forest one of the most vulnerable forest ecosystems, resulting in the eradication of a significant portion of vegetation in regions currently unsuitable for farming (Fisaha et al., 2013; Teshome, 2018; Ayalew, 2018).

Recent changes in LULC dynamics, particularly the expansion of habitats in protected areas, necessitate the utilization of machine learning algorithms in Geographic Information Systems (GIS) and Remote Sensing (RS) to enhance the accuracy of LULC classification and develop forest LULC maps. The application of machine learning techniques in digital image processing has become a significant advancement in the industry, thanks to its computational and technical capabilities, which greatly impact the accuracy and precision of Leverage Detection Information Enhanced (LULC) classification (Mao et al., 2020; Talukdar et al., 2020).

Accurate information about LULCs in our environment is crucial for various purposes, including natural resource monitoring and management, development planning, and global change

research (Baamonde et al., 2019). Traditional methods of LULC mapping using satellite data distribution have been widely employed, utilizing sophisticated approaches capable of handling and analyzing big data to generate precise maps of large areas at the appropriate time (Leeuwen et al., 2021).

Machine learning (ML), a field of artificial intelligence, plays a vital role in training computers to recognize patterns based on available data. Recent advancements in computer technology, including increased data storage and processing capabilities, have made machine learning an effective method for uncovering relationships in various fields. By training models with existing data, machine learning allows us to expand our understanding of these relationships and make predictions about future events or situations (Awad & Khanna, 2015; Paoletti et al., 2019).

Therefore, in this study, a combination of machine learning algorithms, RS, and GIS techniques was employed as a common approach to extract spatial information, specifically the dynamics of LULC, and classify the Wufe-Washa Forest using Landsat time series multispectral satellite imageries. More specifically, the random forest (RF) package in R Studio software was utilized to generate accurate and effective LULC maps. Furthermore, the relationship between spatial data and socio-economic data was examined to identify the driving factors and implications of LULC dynamics on the forest and its surrounding areas.

1.2. Statement of the problem

The dynamic nature of land use and land cover (LULC) change encompasses a range of transformations, including the conversion of grazing and forest land into agricultural areas, vegetation removal, and the shift towards non-agricultural uses. These changes have profound implications for the physical and biological attributes of land, affecting ecosystems and natural resources (Shiferaw et al., 2011). While LULC change is a global phenomenon, its magnitude and characteristics vary across different regions. Developing countries, particularly in sub-Saharan Africa, have witnessed a rapid expansion of cultivated land driven by population growth, resulting in the depletion of vegetation covers and wetland resources (Berihun et al., 2019; Degife et al., 2019). Despite various interventions, the deterioration of LULC remains a prevalent issue in many sub-Saharan African countries (MEA, 2005).

In East Africa, LULC transformation is an inevitable occurrence that poses significant environmental challenges, especially in regions where agriculture plays a crucial role in the economy (Berihun et al., 2019). Consequently, rural communities are highly vulnerable to the adverse effects of these LULC changes. Research findings suggest that the rising population and the pursuit of economic development in East African nations have intensified the pressure on various types of land use and land cover (Gebremicael et al., 2018). Notably, the conversion of vegetation cover into cultivated land has emerged as a prominent feature of LULC changes in this specific region (Degife et al., 2019). Additionally, inadequate land management practices and the growth of livestock populations further contribute to LULC alterations in the area (Gebremicael et al., 2018). In the highlands of Ethiopia, the excessive utilization of forest resources for fuelwood, construction, and agriculture has significantly diminished forest coverage (Eshetu Yirdaw, 2001). As one of the oldest settled regions in the country, the Ethiopian highlands face the combined impacts of human-induced and natural factors affecting forest resources (Friis et al., 2012).

The increasing demands of a growing human population have further intensified the pressure on these natural resources (FAO, 2010). Deforestation in Ethiopia has resulted in various socio-economic and environmental challenges, severely impacting the ability of forests to provide ecosystem services and other benefits (Teketay, 2001). The rapid rate of deforestation poses a threat to biodiversity loss, land degradation, and ultimately, the erosion of flora and fauna in the highlands

of Ethiopia (Battles and Fahey, 2000). The depletion of forest resources carries significant implications for the environment, climate change, biological diversity, and the socio-economic conditions of the communities residing in and around the forests (Sisay Nune et al., 2016).

Similarly, the Wufe-Washa forest, located in the central highland of Ethiopia, has experienced substantial expansion, proliferation, and various developmental activities such as residential construction, deforestation, and extensive farming over the past decades, mirroring the trends observed in other exploited areas of the country. The rapid population growth and increasing socio-economic needs have exerted immense pressure on the forest and its surrounding environment. However, due to a lack of proper planning and interventions, the Wufe-Washa forest has undergone significant changes in land use and land cover over time.

In recent decades, the study of changes in land use and land cover has gained significant attention in environmental research and discussions in Ethiopia (Zeleeke and Hurni, 2001; Kindu et al., 2016; Temesgen et al., 2017; Yesuph et al., 2019; Etefa et al., 2018; Mathewos et al., 2019). Accurate and up-to-date information on the dynamics of land use and land cover, the driving forces behind these changes, and their environmental impacts is crucial for planning sustainable land use and resource management practices in neglected areas.

Despite some existing studies focusing on specific aspects of the Wufe-Washa forest, such as forest biodiversity degradation, tourism challenges, willingness to pay for ecosystem services, and floristic composition and structural analysis, there is a noticeable research gap in investigating the overall patterns, drivers, and consequences of land use and land cover changes in this particular forest (Bekele, 1993; Teketay et al., 1995; Birhan, 2018; Ayalew, 2018; Tadesse and Teketal, 2017). Therefore, this study is to comprehensively examine the alterations in land use and land cover that have occurred in the Wufe-Washa forest over the past five decades (1973-2022), identify the factors driving these changes, and assess their environmental consequences.

1.3. Objectives

1.3.1. General Objective

The primary aim of this study is to conduct a comprehensive analysis of the dynamics of land use and land cover (LULC), examine the factors driving these changes, and assess their implications for the Wufe-Washa forest and its surrounding areas.

1.3.2. Specific Objectives

In order to accomplish the overall goal, this research aimed to focus on the following specific objects:

- I. Analyze the spatiotemporal LULC dynamics of the last 49 years (1973 to 2022)
- II. Examining the dynamics of forest land cover and identifying the factors that propel these dynamics
- III. Examine the causes of LULC, and its implication on the forest and the forest neighboring areas

1.4. Research Question

- i. What is the study area's historical and contemporary land use and cover dynamics status?
- ii. What are the major driving causes and factors for land use and land cover changes?
- iii. What are the implications of land use and land cover changes on the environment?

1.5. Significance of the study

Numerous studies on Land Use and Land Cover (LULC) have been carried out in Ethiopia and other locations, are area specific and focus on the drivers of LULC changes and their effects on certain aspects of resource deterioration. However, LULC dynamics in the Wufe-Washa forest in the central highlands of Ethiopia have not been recently and comprehensively investigated so far, as a result, the extent of such change, its driving forces, and its effects are not understood. In addition, to effectively guide policymakers and encourage sustainable land use and management in order to address land degradation and enhance environmental resource management, it is essential to gain a profound comprehension of the factors behind the changes in LULC as well as their environmental and socio-economic consequences.

The outcome of the research is expected to hold significant significance for the forestry sector, environmental planning, and management of natural resources. It also serves as the basis for future related research work using the customized R- programming language it could help the re-searchers and students to produce LULC maps, LULC classification, and detection of alterations analysis efficiently and effectively within a short time of period. Consequently, up-to-date LULC maps and the data produced in this study has the potential to be utilized by both natural resource managers and scholars, studied landscapes for the purpose of stock-taking resources and facilitating design appropriate interventions for improved use and sustainable management of natural resources. Thus, this study is of utmost importance to bring the issues into focus. to policymakers and development practitioners, used by government bodies and non-governmental organizations at the district and regional levels to devise targeted strategies and action plans for rural land use planning and the implementation of measures aimed at achieving specific land use advancements

1.6. Scope of the Study

Spatially speaking, this study concentrated on evaluating the land use land cover changing aspects and its implications and impacts on the Wufe-Washa forest, and its neighboring areas. Due to the rough topographic nature of the forest location and the vast area covered, the socioeconomic status data of the society is only focused to the adjacent parts of the forest. The study will integrate the techniques of GIS, RS, and MLAs for LULC classification from 1973 to 2022 for analyzing the physical dynamics on land use land cover usage, and socio-economic data, to weigh the driving factors that cause land cover change/dynamics and implications on the forest and as well as on the neighboring area.

1.7. Limitation of the study

The research is limited to the Wufe Washa forest in the North Shewa Zone of Ethiopia's Amhara Regional State. The forest is divided into three administration provinces of zones, namely Ankober, Tarmaber, and BasoWorena Woredas, and socio-economic data were collected in three districts based on their proximity to the forest. Mescha in Ankober, Wufe Washa Genete in Tarmaber province, and Keyt in Baso Worena province were the districts or kebeles in question. The socio-economic survey was done using a cross-sectional research approach, with data acquired by a primary contact via field observation, interviewing influential sources (KII), focus groups discussions (FGD), and secondary sources used to quantify the geographic features dynamics of the

learning area and to investigate the drivers and implications of land use and land cover change. Although LULC dynamics has numerous implications, the learning only focuses on the drivers and effects of LULC change on the Wufe Washa forest. Despite this, the study could not be free from limitations, specifically arising from data collection problems like the steep topographic nature of the forest location to collect GCP. Another challenge is the obtainability, excellence, and precision of satellite imageries. LULC change analysis was conducted by Landsat images of medium (30m) spatial resolution.

1.8. Organization of the thesis

This study contains of 5 parts. The first part is an overview to the study that discusses the background, the statement of the problem, the research purpose or ideal, the research questions, the scope of the study, and the significance and limitations of the study. The second chapter covered a review of affiliated literature, while the third part bandied about the research method and materials. The fourth chapter will largely concentrate on the discussion of the findings of the field check result as well as integrate the result using different geospatial ways to analyze different time-series satellite image analyses of the Wufe-Washa forest in the years between 1973, 1984, 2000, and 2022 independently. The final chapter, conclusion and recommendation of the study.

CHAPTER TWO

2. LITRATURE REVIEW

2.1. Theoretical literature

2.1.1. Land use land, land cover concepts and definitions

In order to gain a comprehensive understanding of land use and land cover (LULC), it is crucial to delve deeper into the concept of land itself. Land encompasses a range of valuable resources, including soil, water, flora, fauna, and the entire ecosystem, making it the most prevalent and essential resource on our planet (Lutzenberger et al., 2014). While distinct from capital, land is recognized as a significant component of production in economic theory, providing essential elements for sustenance, such as food, water, energy, and housing, as well as space for human settlements, infrastructure, and recreational areas (Willy, 2009).

Economists draw a distinction between land and capital, viewing land as a natural endowment and capital goods as the result of human effort in the exploration and utilization of (natural) resources (FAO, 2004). Moreover, contemporary environmental studies often adopt the definition of land provided by the FAO (2004), which defines land as "a region of the outer layer of the earth that encompasses all reasonably constant or predictably recurring components of the biosphere extending vertically above and below, including the elements of the atmosphere, soil, underlying geology, hydrology, plant and animal populations, and their interactions."

The terms land use and land cover, commonly employed in the context of land use and land cover change (LULC), are often used interchangeably, although their intended meanings capture distinct facets of the landscape (Lambin et al., 2003; Ellis, 2013). However, ongoing discussions and divergent interpretations persist regarding the precise definitions of these terms.

Land cover specifically refers to the observable representation of physical and biophysical elements that span the Earth's surface, encompassing a rich assortment of features such as vegetation, exposed soil, solid substrates, water bodies, and human-made structures, collectively forming a diverse mosaic (Ellis et al., 2011; Bai et al., 2017). Scholars from social sciences and land management, as emphasized by Di Gregorio and Jansen (2000), adopt a broader perspective of land cover, encompassing the social and economic dimensions associated with land. Conversely, natural scientists place emphasis on the concept of land use to underscore the manifold beneficial

activities undertaken by human societies upon the land, including agriculture, agroforestry, and anthropogenic constructions.

These meaning distinctions between land use and land cover are of paramount importance in comprehending the intricate dynamics of LULC and its implications for the environment and society. By disentangling the meanings of these terms, researchers and stakeholders can gain deeper insights into the multifaceted changes occurring in the landscape. Precise classification of land cover elements provides a foundation for accurate mapping and monitoring, enabling a comprehensive understanding of spatial patterns and trends in LULC (Lambin et al., 2003). Additionally, recognizing the social and economic dimensions of land cover broadens the analysis, accounting for the multifunctional roles that land plays in supporting human activities, livelihoods, and societal development (Di Gregorio and Jansen, 2000). Meanwhile, emphasizing land use highlights the transformative actions and practices carried out by humans, shaping the physical and functional attributes of the land (Ellis, 2013). Understanding these distinct perspectives fosters a holistic comprehension of the complex interactions between human societies and the natural environment.

By exploring the nuances between land use and land cover, researchers can effectively capture the multidimensional nature of LULC changes, unravel the driving forces behind these transformations, and evaluate their consequences. This nuanced understanding informs decision-making processes, guiding the formulation of sustainable land management strategies and policies that balance environmental conservation, socio-economic development, and the well-being of communities. Consequently, incorporating these distinctions in LULC studies enhances the accuracy, precision, and relevance of research outcomes, fostering a comprehensive understanding of the ever-evolving landscapes and facilitating informed decision-making for a sustainable future.

2.1.2. Demands for land use

The utilization and transformation of land is influenced by a multitude of issues besides population increments, urbanization, economic progress, and shifts in consumption habits. These elements can result in alterations to land use configurations, such as the deforestation of wooded areas for agricultural purposes or the proliferation of urban sprawl. With the growing demand for food, fiber, and negative emissions solutions, a substantial segment of the Earth's surface land surface is being managed by humans. As such, it is crucial to comprehend the climatic ramifications of global

land use modifications, encompassing land management practices and associated changes in land cover (LULCC) (Goswami et al., 2016, Winkler et al., 2021). The expansion of the human population, according to Wolman (1985), been “linked to changes in land usage during the previous 6,000 years. For a long time, the extension of area under cultivation was a key factor in the rise of agricultural production, which also correlated with population growth”. Historical records, shows that varied population densities and varying population growth rates result in various patterns of land use that change over time. A recent investigation discovered that nearly one-third (32%) of the global land area has been impacted by land use changes within a span of six decades (1960-2019), an extent approximately four times greater than prior estimations derived from long-term land change evaluations (Winkler et al., 2021).

2.1.3. Important technical terminologies

Remote Sensing

Remote sensing refers to the discipline of acquiring comprehensive data about the Earth's terrain and environmental conditions from a distance. It involves the utilization of advanced sensors, such as cameras and satellites, to collect and analyze data on the Earth's terrestrial surface and atmospheric characteristics. Remote sensing technology plays a crucial role in various sectors, including studies related to land use and land cover (LULC). By employing remote sensing techniques, we are able to observe, measure, and capture satellite imagery of events and phenomena that are beyond our direct senses and capabilities (Lin et.al. 2013; Farfán et.al., 2022).

The advent of civilian remote sensing satellites in the late 1970s marked a significant milestone in the development of remote sensing applications for various fields, including natural resource management (Lillesand et al., 2008). Understanding the intricate interactions between human activities and the environment necessitates a deep comprehension of the spatial and temporal dynamics of LULC in a given area (Etefa et al., 2018). Remote sensing data plays a critical role in obtaining information about LULC changes, facilitating a better understanding of the relationships and interdependencies between human societies and the natural world.

Remotely sensed data has emerged as one of the primary sources of information for investigating spatial and temporal variations in LULC. When processed and analyzed effectively, multi-temporal remote sensing datasets enable the mapping and identification of landscape changes, leading to more informed and sustainable landscape design and management practices (Dewan et al.,

2009). Moreover, the impacts of changing LULC on forest ecosystems have heightened the demand for remote sensing data in mapping land use and land cover changes (LULCC). By utilizing high-resolution images with superior spatial, temporal, radiometric, and spectral capabilities, it is possible to rapidly map large areas and develop automated methods and algorithms that yield accurate results for real-world applications (Liu et al., 2010; Teluguntla et al., 2018). These advancements in remote sensing play a pivotal role in the field of environmental change, providing critical insights into LULC dynamics (Lambin et al., 2001; Turner et al., 2003).

Random Forest Algorithm

Employing a subset of training samples and variables selected at random, the random forest (RF) classifier is an ensemble classifier that engenders multiple decision trees. Renowned for its exceptional accuracy in classification tasks, this classifier has garnered significant acclaim within the realm of remote sensing (Breiman, 2001). The Random Forest (RF) method, which exhibits great superiority and classification accuracy, is one of the most extensively used group MLAs in digital image classification (Goel and Abhilasha, 2017). Utilizing enormous datasets efficiently, RF offers a resilient algorithm that is strong and reliable to produce the best outcomes (Mao et al., 2020), by leveraging remotely sensed data, a notable level of classification accuracy is attained, as demonstrated by research conducted by (Talukdar et al. 2020).

Additionally, the RF has various advantages, including the ability to apply pre-generated trees fast and intelligently as opposed to applying multiple MLAs for the LULC classification utilizing remote sensing data (Talukdar et al., 2020). With identically distributed independent random vectors, the RF algorithm uses a nonparametric method to build numerous tree-structured classifiers. Therefore, each tree gave the most well-liked class at input x unit votes (Talukdar et al., 2020; Yulianto et al., 2021).

R Environment

R, a free and publicly available language and software, is an open-source solution of programming languages designed specifically for applications and functions, a language designed for documentation programming (Chambers, 2008). Despite its origins in software analysis and data analysis, R is rapidly used for dynamic simulations in many fields (Petzoldt and Rinke, 2007). In addition, it has grown into widespread use in the spatial analysis community over the past decade, largely

thanks to the Spatial (SP) and Tera libraries (Bivand et al., 2013). The library package named RGDAL (Bivand et al., 2014), allows R to read and write texts supported by the Open GIS Simple Reference Framework (OGRI) and the Geospatial Data Abstraction Library (GDAL). Most raster data processing, previously only available in GIS applications, is now provided by the raster package in R (Hijmans, 2014). Based on these features, several R packages have been developed for LULC research and efficient, site-specific ecological modeling (Fiske and Chandler, 2011).

2.1.4. Land Cover Classification and Change Detection

Image Pre_ Processing

Pre-processing an image is a phase in the process of enhancing the characteristics or attributes of image data that pertain to its overall quality prior to more processing or analysis. The four different forms of image pre-processing operations are topographic correction, geometric correction, atmospheric adjustment, and radiometric correction. The image data is radiometrically corrected to remove any unwelcome noise or distortions brought on by the limitations of the optical sensors employed within the realm of satellite imagery, alterations in scene lighting, atmospheric circumstances, and observation angles have been acknowledged as contributing factors, as observed (Lu et al. in 2004).

Similarly, atmospheric adjustment eliminates environmental phenomena of scattering and absorption, influencing the behavior of electromagnetic radiation, to determine surface reflectance (surface properties). Various acquisition dates' atmospheric conditions have an impact on the spectral fingerprints of invariant objects. The method determines the optical properties of the atmosphere and then uses them to correct the impacts of the atmosphere on satellite images (Lantzanakis et al., 2017). Additionally, topographic correction is a crucial step in the preprocessing of any satellite's satellite imagery in order to remove topographic effects such as different illumination caused by the irregular shape of mountain regions, which results in inaccurate classification into different land cover classes due to different topographic positions (Singhe et al., 2012).

Change Detection

Change detection involves identifying disparities in the state of an object or phenomenon over time. Analyzing LULC changes helps understand the magnitude of change and categorize them for informed decision-making. Timely and accurate detection of Earth's surface features enables a deeper understanding of the connections between human activities and natural events, facilitating improved resource management (Tafesse, 2017; Berihun et al., 2019).

$$\text{Mathematically: } \textit{Percentage Change} (\%) = \frac{(A2 - A1) \times 100}{A1} \quad (1)$$

Where: A1 represents the area in year 1 and A2 represents the area in year 2 of that class (Thonfeld, Steinbach, 2020).

The Normalized Difference Vegetation Index (NDVI)

NDVI mathematical computed as:

$$\text{NDVI} = \frac{\text{Near Infra Red} - \text{RED}}{\text{Near Infra Red} + \text{RED}} \quad (2)$$

As a result, this equation returns a worth between -1 and +1. If the RED bands have little reflectance (low values) and the NIR channel has high reflectance, the NDVI value drive be high, and vice versa. Overall, NDVI is a consistent technique of measuring the health of vegetation. When the NDVI number is high, we get healthier plants. When the NDVI is low, there is minimal or no vegetation (Ramachandra and Kumar, 2004). Furthermore, in general, it is a method that is frequently used to identify changes in LULC, particularly in the amount and pattern of vegetation (Sahebjalal and Dashtekian, 2013).

2.1.5. Causes of land cover Changes

Changes in land use and land cover are influenced by a multitude of factors that are interconnected and complex in nature. These processes cannot be attributed to simplistic explanations but require a comprehensive understanding of the interplay between various factors. Examining how individuals make decisions regarding land use and considering the diverse contextual factors involved is crucial for identifying the underlying causes of land-use change. While natural processes may have

some influence, it is primarily human activities that act as the driving force behind these changes. Researchers classify the causes of land use and land cover changes into two main categories: proximate direct factors and underlying indirect or root factors (Geist and Lambin, 2002).

2.1.5.1. Proximate causes land use land cover changes

The immediate or proximate causes of land-use and land cover change (LUCC) can be attributed to direct human impacts on local ecological processes and land cover. These causes have localized effects primarily on individual farmsteads, families, or societies, and their specific nature varies across regions and contexts (Geist and Lambin, 2002). These proximate factors directly contribute to changes in land cover, while underlying factors influence these immediate causes.

Historically, the expansion of agricultural land, wood extraction, and infrastructure development have been the primary immediate causes of land cover change. With population growth, technological advancements, and subsequent demands, human activities on land have significantly increased over the past two centuries. These changes have led to transformative shifts in entire landscapes, negatively impacting biological diversity, food and water cycles, and weather patterns. Currently, approximately one-third of the Earth's terrestrial area is utilized for pastures or cropland (Houghton, 1994).

In the context of Ethiopia, agricultural expansion, including the spread of sedentary agriculture and shifting cultivation, has been a major driver of land cover change, particularly in areas with natural vegetation. The increasing demand for construction materials, wood fuel, and charcoal also contributes to these changes. Charcoal use is widespread in the country's dry, semi-dry, and sub-tropical humid regions. Additionally, the prevalent practice of using fire for bee fumigation and hunting purposes leads to forest fires and the destruction of natural forest ecosystems (Yohannes, 2021).

These examples highlight how immediate causes such as agricultural expansion, wood extraction, and demand for construction materials directly contribute to land cover change, resulting in significant environmental consequences. It is crucial to understand and address these proximate causes in order to mitigate the negative impacts of LUCC and promote sustainable land management practices

2.1.5.2. Underline causes for land use land cover change

The causes of land use and land cover change (LUCC) encompass a range of factors that directly impact local and global processes. These factors extend beyond the local community and include social, legal, organizational, economic, demographic, technical, cultural, and biophysical elements (Geist and Lambin, 2002). While economic factors, such as fluctuating commodity prices, can influence land use decisions, political, legal, and cultural factors also play a significant role in shaping individual choices (Lambin and Geist, 2003; Lambin and Geist, 2007). Institutional factors contributing to LUCC operate at both the macro and micro levels, as governmental policies and people's access to land and resources are influenced by both local and large-scale structures (Lambin et al., 2003).

Government agencies have a substantial impact on land use and change through their policies and procedures, including land cover regulations, land reform initiatives, provision of government services, establishment of property rights, implementation of environmental measures, decision-making processes, negotiation practices, and legislative actions (Geist & Lambin, 2002; Lambin & Geist, 2007). Technological processes, such as advancements in agricultural practices or improper use of forest resources, can also contribute to LUCC, particularly deforestation in forested areas (Geist and Lambin, 2002). Demographic changes, such as shifts in birth and death rates, changes in family structures, employment patterns, migration, and urbanization, are significant phenomena observed in many regions, further influencing land use dynamics (Geist and Lambin, 2002). Additionally, culture, including historical legacies, values, beliefs, and societal understandings, shapes land use practices and decisions (Lambin et al., 2007; Geist and Lambin, 2002).

2.1.6. Impacts of LULC changes on Natural Resources

Soil erosion

Soil erosion is described as land decline induced by water or wind erosion (Seifu and Elias 2018). River erosion accounts for 56 percent of global land decline, whereas wind erosion accounts for the remaining 28%. Ethiopia's most serious environmental concern is land degradation caused by running water erosion (Sahle et al., 2015). The removal of the primary land covers without mitigation consequences in the physical, biological, and natural loss of soil. In addition, soil erosion is

caused by a lack of natural resource managing, the steepness of the slope, or bad agrarian practices (Wubie et al., 2020). Moreover, as Warra et al. (2013) pointed out, the exclusion of land cover accelerates runoff and soil erosion along steep slopes, the construction of gullies in many cultivated grasslands around hills, and water logging in plain areas. Due to the buildup of sediments transferred from higher terrain, the gullies develop narrower and less in-depth on top of the lower portions of gentle slopes (Wubie et al., 2020).

In general, the two most important climatic factors affecting soil erosion are rain and wind. Erosion is caused by the force provided by rain, wind, or a combination of these forces (Tibebe and Bewket, 2011). The ability of precipitation to form erosion is directly proportional to its amount, use and distribution. Wind erosion can increase when the soil is dry, loose (less) and bare. Therefore, the highest annual erosion is observed in the northern, central and eastern highlands of Ethiopia (Asfaw and Neka, 2017).

Forest degradation

Forest is one of the plant biomes dominated by various trees living in different biomes (Mekonnen et al., 2018). A forest is defined as an area of more than 0.5 hectares, over 5 m and over 10 percent of trees (FAO 2010). Forests in Ethiopia are defined as areas of timad or more with natural mosaics, dense agroforestry, acacia forests and shrublands, government and private plantations (timad, initial land area size = 0.25 ha) (Mekonnen et al., 2018).

Forests are essential for the control of soil erosion, land desertification and desertification as well as being beneficial for precipitation and climate in the short and long term. However, the interaction between humans and forests has changed over time across the globe due to economic and social changes (FAO, 2012). Deforestation is the destruction of forests in order to use the land for other purposes or to render it bare (FAO, 2012).

Poverty and fast population growth are recognized as the main drivers of deforestation and deforestation in Ethiopia (Sisay and Gitima, 2020). Fast population growth has led not only to the opening up of farmland, but also to overgrazing in important mixed rice-livestock production. In addition, he argues that the number of existing forests increases as the demand for feed, firewood and construction materials increases (Odiyo et al., 2014). Nationally, biomass energy accounts for more than 99% of all domestic energy consumption (92% for households and the rest for small businesses and food). About 78% of this comes from wood biomass, while 12% and 9% comes

from livestock and agricultural residues, respectively (Wassie, 2020). Forest resources are also used to generate income from the sale of logging, fuel and electricity. In the last 50 years, annual electricity production has increased from 1 million tons to over 3 million tons. During this period, gas consumption increased from 4 to 100 million cubic meters per year (Asfaw and Arya, 2012).

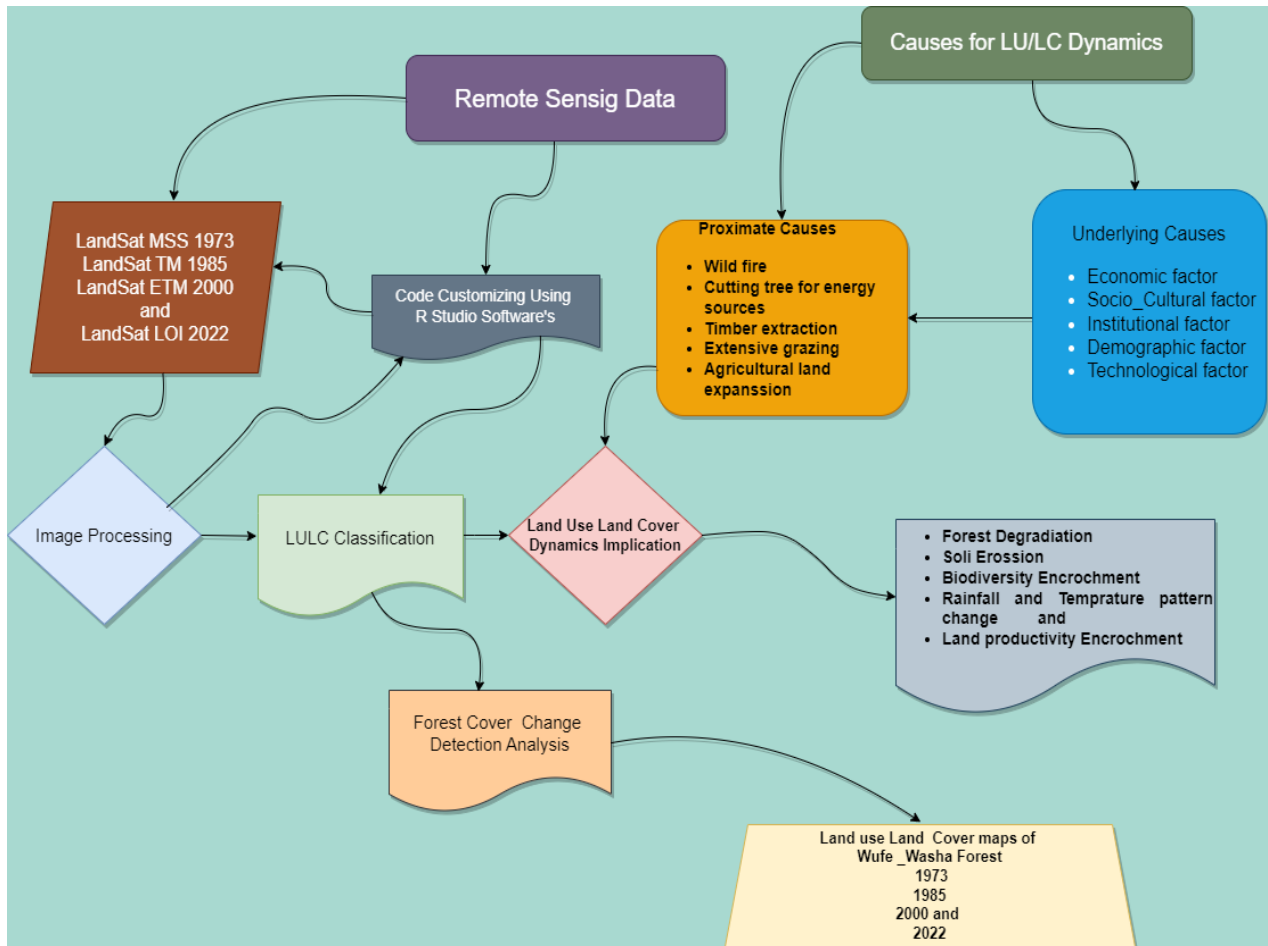
2.2. Empirical literature

Land is the most significant natural resource for human activities such as infrastructure, social, and economic growth (Lambin et al., 2001). Smallholder farmers who raise food for their families use the majority of the country's land. Even though smallholders need more land to grow crops and support them in the absence of agricultural intensification, deforestation and land conversion from other types of land cover to agriculture nevertheless take place. As a result, in the second part of the 20th century, Ethiopia's LULC drastically changed (Dibaba et al., 2019, Legese and Balew, 2021; Kuma et al., 2022). The rate of LULC changes in Ethiopia, estimated that these LULC changes in Ethiopia would cost \$4.3 billion annually, which is greater than Kenya's estimated yearly loss of \$3 billion in ecosystem value (Gebreselassie et al., 2016). From 40% at the beginning of the 20th century to 2.36 percent in 2000, Ethiopia's forest cover has decreased. Evidence from later indicated that the forest cover has restored to 12% (Ewnetu et al., 2021).

Forest sustainability is the main focus of land-use analysis in numerous works of literature. When there are trees covering more than half an acre of ground, it is called a forest. According to a recently available report by FAO and UNEP (2020), the world's forests cover only 4.06 billion hectares and make up 31% of the world's total area., or roughly half a hectare per person. Dinku (2017) used remote sensing and estimated biomass of forest and forest change in the *Halenabrook* area in Bale, Ethiopia. The analysis uses a period of Landsat images spanning 20 years at 10-year intervals. Thus, enhanced satellite image aided in the monitoring of forest cover and ecosystem deterioration in contrary an interesting study, done in the Guder-Abiy sub-basin between the years of 2012 (Berihun et al., 2017) used a supervised classification method to categorize land use. According to the study's findings, farmers have been choosing to practice tree planting over crop production because of changes in economic activity that affects their well-being.

2.3. Conceptual Framework

The conceptual framework of this thesis shows the important connections among research objective. It illustrates implication of the spatial temporal of land use land cover dynamics implication on Wufe-Washa forest, classification of the neighboring areas and mapping of the forest using machine learning classifier and as well as identification the major driving forces for the forest cover change and its implication.



Source: Adopted from Yenenish Hailu (2014)

Figure 1: Analytical framework developed by the researcher

CHAPTER THREE

3. RESEARCH METHDOLOGY

3.1. Description of the Study Area

3.1.1. Location

The districts of Tarmaber, Ankober, and Bassona Werenas encompass the expansive Wufe-Washa forest, which spans across 14 kebeles, Ethiopia's lower administrative divisions below the woreda or district. Specifically, within the Basonawerena woreda, the forest covers Baso Den-gora, Gudo Beret, Aba Mote, Keyt, Goshu Hager, and Debele kebeles. In Ankober woreda, it extends over Lay Gorebella, Mahel Wenz, Zego, Eme-Mehret, Mescha, and Zembo kebeles. Lastly, within Tarmaber woreda, the forest encompasses Wufe-Washa Genete and Debre Meaza kebeles (Ayalew, 2018). Geographically, the forest is located approximately 160 kilometers from Addis Ababa, the capital city of Ethiopia. It stretches between latitudes 9°36'00" and 9°52'00" N and longitudes 39°36'00" and 39°48'00" E (Figure 2).

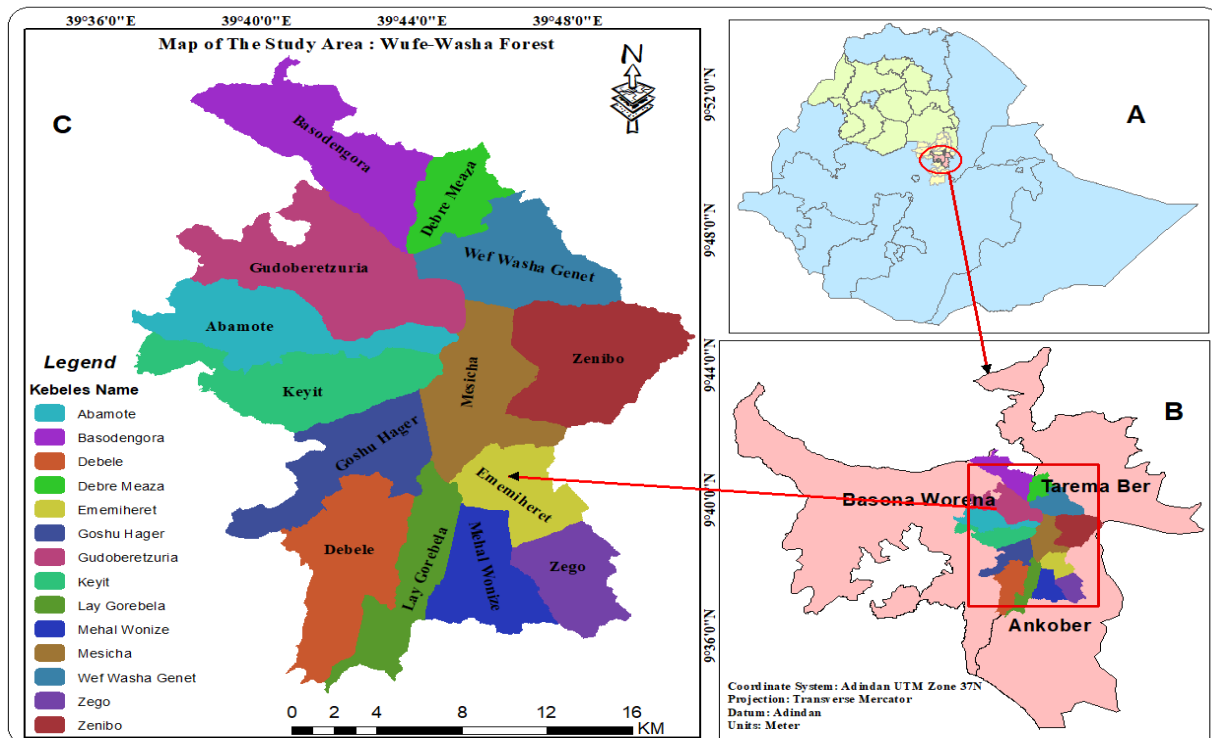
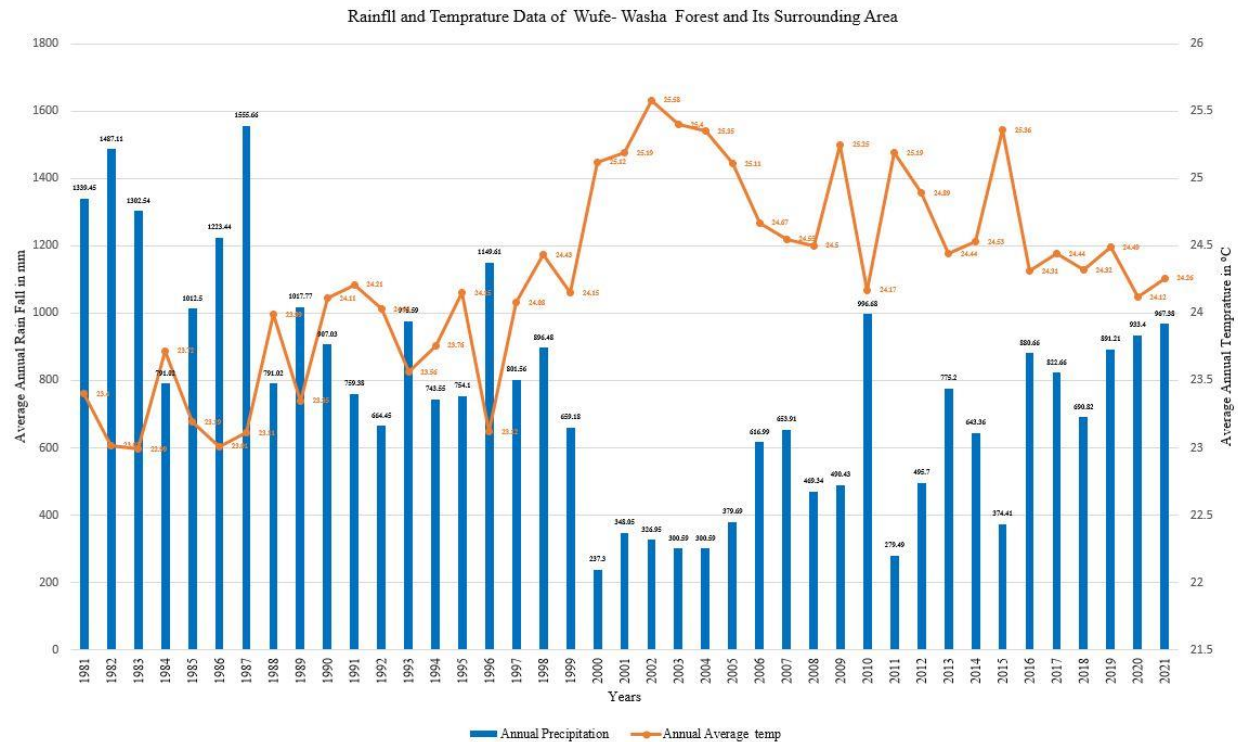


Figure 2: Location Map of the study areas: (A) Amhara region of Ethiopia, (B) Woredas of the study area (C) Study sample kebeles)

Location Map of the study areas: (A) Amhara region of Ethiopia, (B) Woredas of the study area (C) Study sample kebeles

3.1.2. Climate

July to September is the long rainy season and March to May is the short rainy season. Average annual precipitation is 1400 mm. (20°C) and 10°C (Bekele, 1995) are the annual average maximum and minimum temperature.



Sources: CHRIPS precipitations data

Figure 3: Rainfall and Temperature (1981 – 2021) of Wufe-Washa area

3.1.3. Vegetation

According to Friis et al. (2011), Wufe-Washa forest is an afro-montane forest that is dry and ever-green in the northwest central highlands, with a clear Ericaceous belt at higher elevations. At higher elevations, the most distinguishing species include *Ilex mitis*, *Maesa lanceolata*, *Juniperus procera* or *Hagenia abyssinica*. Orta rakımlarda yaşan bitkiler *Podocarpus*, *Allophylus abyssinicus*, *Halleria lucida*, *Euphorbia ab-yssinica*, *Polyscias fulva*, *Prunus africana* ve *Olinia rochetiana*, with a few solitary *Hagenia abyssinica* and *Pittosporum viridiflorum* trees on the inaccessible cliffy and steep slopes. The three species that are most common at elevations above

3,000 m are *Erica arborea*, *Hypericum revolutum*, and *Lobelia rhynchopetalum*. Additionally, there are huge clusters of the endemic *Kniphofia foliosa*, *Helichrysum*, and *Festuca* grass species, which are changed to the extremely cold temperatures, in the open spaces, on rocks, and on cliffs (A. Tilahun 2018).

3.1.4. Fauna

The Wufe-Washa forest served as a habitat for a variety of wild creatures, Demeke (2003) lists the following species of wild animals that can be found in the area: Menelik's Bushbuck (*Teragelaphus scriptus meneliki*), Geladababoon (*Theropithecus gelada*), Klip-springer (*Oreotragus oreotragus*), Rock Hyrax (*Procavia capensis*), and Common Jackal (*Canis aureus*) The Menelik's Bushbuck, East African Red Duiker, and Klipspringer are three species that are particularly affected by illegal hunting, which is a common activity in the forest (Teketay and Bekele, 1995). Illegal hunting also contributes to the continuous inherent destruction and subsequent local extinction of certain other class.

3.1.5. Topography

The Showa's upland, also known as the central highlands, makes up at least 11 percent of the country's total area, and bordered by the Omo valey in the south and west, the rift valley in the east and south-east, the Abay valley in the North and north-west, and the rift valley in the East and south-east (Mekonnen, et al., 2018). Wufe Washa forest, which is likewise located in the central highlands, built on a cliff with steep slopes and located at an altitude of between 1900 and 3700 meters. Multitudes of rivers and valleys that cut through the forest and give the escarpment an almost trapezoid shape give it has an esthetic view on (Ayalew, 2018).

3.1.6. Population

The Wufe Washa Forest area is situated in three administrative regions of Ethiopia, namely Baso Worena, Tarmaber, and Ankober. The population statistics obtained from both Amhara Regional State Environment, Forest, and Wildlife Protection and Development Authority 2021 and National the Central Statistical Agency of Ethiopia 2021 (<https://statsethiopia.gov.et>) reveal the demographic composition of these woredas. Baso Worena woreda has a total population of 145,293 individuals, consisting of 73,944 males and 71,394 females. Tarmaber woreda, on the other hand, has a population of 110,467 people, with 55,715 males and 54,749 females. Among the three

woredas, Ankober woreda has the smallest population, with a total of 95,368 individuals, comprising 48,057 males and 47,311 females. On the last 28 years in three woredas namely Taramaber, Baso Worena and Ankber the population of these woredas increased an alarming rate. In 1995, the population was 143,526. In 2007, it increased to 281,921, and in 2021, it was 351,128.

3.2. Materials and Methods

This study intends to observe the dynamics of LULCC of the in the last 49 years, as well as the likely causes and significant implications of the alteration of the study area the forest environment of the Wufe_Washa forest. The research applied quantitative and qualitative methodologies which better comprehend, explain, and analyses the changes in land use and land cover, as stated in Crestwell (2009). The research approach for this study separated into two portions as a result, i.e., study of LULC (spatial part), drivers of the change and its implication. Therefore, satellite image processing and interpretation were done to explore the change in LULC at the study area. In addition, socioeconomic survey carried out to determine the causes, motivating factors, and effects of LULCC at the study area. This survey helped to gather qualitative and quantitative data and semi-structured questionnaire through FGD, KII, and field observation were understood derives and implication of the change.

3.2.1. Sampling Procedure for socio-economic survey data collection

Selection for the socio-economic examination of the study area was arranged in two steps. The primary step elaborates the selection of the sample Kebeles, while the second stage selecting the individual households for the survey, elders, community representatives, farmers, experts, and development workers from the local governmental offices, and developmental agencies operate in the selected Kebeles for FGDs and (KIIs).

The three Keeble's were purposely designated from the 14 kebele's neighboring the forest at rate of one for each woreda that makes a total of three kebeles, the sampled kebeles were Mescha, Wof-Washa Genete and Keyit from Ankober, Tarmaber, and Baso Worena woredas respectively. Since most Kebele residents are economically homogeneous and their livelihood depends on agriculture, optimal sample numbers can represent socioeconomic situations of the study community. Finally, in order to identify the participants involved and guarantee adequate representation from all individuals involved selected kebeles, simple random sampling methods employed after the total number of households was proportionally allocated to select sample respondents.

3.2.2. Survey sample size determination of the target population

The combined population of the selected sample kebeles (Mescha, Wufe-Washa Genete, and Keyit) amounts to 2230 households. Specifically, Mescha kebele has 782 households, Wufe-Washa Genete kebele has 552 households, and Keyit kebele has the largest population with 898 households (Darwin Initiative Final Report, 2016; Tree Aid, 2019).

According to Barlett et al. (2001), the Cochran's Formula is a method used to calculate the sample size required for quantitative data collection. This formula is used to ensure that the sample chosen is representative of the population being studied. By determining an appropriate sample size, researchers can obtain reliable and accurate results from their study. The specific formula used to calculate the sample size may vary depending on the research design and objectives. It takes into consideration factors such as the desired level of confidence, the acceptable margin of error, and the variability within the population. By plugging in the relevant values into the formula, researchers can determine the appropriate sample size needed to achieve statistically valid results. In the context of the investigation mentioned, the sample size was determined using the Cochran's Formula. The specific formula used in this case is not provided, but it would have been selected based on the research objectives and requirements of the study

I) If the entire people size of the study area knows we can use this formula to get the de-

$$\text{sired sample } n_0 = N \times \frac{Z^2 \times P \times (1-P)}{e^2} \quad (3)$$

$$\left[N - 1 + \frac{Z^2 \times P \times (1-P)}{e^2} \right]$$

$$n_0 = 2230 \times \frac{1.645^2 \times .5 \times (1 - .5)}{.05^2} = 243$$

$$\left[2230 - 1 + \frac{1.645^2 \times .5 \times (1 - .5)}{.05^2} \right]$$

Where:

N = population size,

N0 = optimum sample; after the population size is known, size the population.

When the population is small, n = minimal sample size.

(1.645) Z = Critical worth of normal spreading at required confidence level

p = Sample fraction,

e = Error margin

II) For small sample size population number, when the population is low:

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} \quad (4)$$
$$n = \frac{243}{1 + \frac{(243 - 1)}{2230}} = 219$$

As a result, 219 households make up the sample size determined at a 5 percent precision and 95 percent confidence level. According to the table below, these 219 households proportionately assigned to each chosen Keeble (Table 1).

Table 1: Keeble's and sample proportion

No	Kebeles	Households	Percentage	Sample Selected
1	Wufe_Washa Genete	550	24%	52
2	Keyit	898	41%	90
3	Mescha	782	35%	77
Total		2230	100%	219

On the other hand, gaining ground reality data for LULC is not possible for most of the periods and is an expensive task. In its place, different sample procedures are used to gather training and test data for different LU/LC classifications where stratified random sampling, which is widely used for soil and forestry detection. In addition, my training samples considered spatial feature representation, coverage, and identification in order to produce a good output of the classified image. Furthermore, due to the rough topographic nature of the study area, in addition to field verification, I used Google Earth image and SPOT 2016 satellite images to identify and verify each selected feature class on Landsat imageries.

3.2.3. Data Types and Sources

The data of this research were obtained from primary and secondary sources. Much of the primary data was gathered through semi-structured surveys, key interviews, and focus group interviews with agronomists such as household leaders and land managers, agronomists, construction specialists, and Forest Service specialists.

Secondary data is collected from the Woreda Agriculture Office and various offices in Woreda. In addition, secondary data such as Landsat satellite images, unpublished data and reports from various offices, books, scientific journals and meetings will be used for analysis and interpretation of findings.

A) Primary data sources

To assess the current state of the research region, field observation, household surveys, key informant interviews, focus groups, and digital cameras for capturing different features would have gathered main data.

Household survey: Semi-structured surveys were distributed to selected families in Kekeble's research. The questionnaires contain both closed-ended and open-ended questions. The questionnaires address the following major issues: the demographic makeup of households, their primary economic activities, the pattern of land size and livestock numbers, the types LULC in the research location, significant changes in land use that took place, the reasons behind these changes, and the resulting biophysical and socioeconomic effects in the study area. The questionnaire was initially prepared in English and subsequently translated into the local language, Amharic.

KII: Key informants, individuals with extensive knowledge of the historical and current land use patterns in the study area and their impact on soil degradation, were purposefully selected for interviews. The interviews aimed to gather valuable insights regarding the changes and trends in land use within the Wufe-Washa Forest. Objective questions were employed to explore into the patterns and shifts in land use, aiming to gain a comprehensive understanding of the topic.

Focus Group Discussion: This type of data collecting is intended to enhance and cross-check the data gathered from home surveys. Three focus groups were held in each of the three Kebeles sampled. Discussions would be held in all three kebeles with a group of farmers representing various

social groups. The elders provided valuable information by sharing their observations and experiences regarding the shift in land use and land cover, the key drivers driving the change, and the associated impact noticed on both the biophysical and communal aspects of the area.

Observations: in order to supplement realized and ensure the responses gained from the respondents using questionnaires and interview, the researcher would have conducted the field observation. In this study, the LULC of the study area were carefully observed field survey. Ground truth of important LULC types in the study area collected by the using of Global Positioning System (GPS) alongside landscape feature.

B) Secondary Data Sources

The study utilized a combination of primary and secondary data sources. Secondary sources included the Woreda Office, Urban Land Management and Environmental Protection, and satellite image data. To assess the land use and land change in the study area over the past 49 years, four different Landsat images series from 1973, 1985, 2000, and 2022 were utilized (Table 2). Landsat images were specifically chosen due to their extensive historical coverage dating back to 1972, providing valuable insights into long-term trends. These images were obtained freely from Earth Explorer (<https://earthexplorer.usgs>), a platform that offers access to satellite imagery. The Landsat images were carefully selected to capture and measure changes in the study area. The data obtained from Earth Explorer was designed for the WGS 1984 coordinate system and georeferenced to the Universal Transverse Mercator (UTM) North 37 after downloading the images.

Table 2: Source and Satellite Images data collection processing

No	Satellite	Sensor	Path /Row	Acquisition Year	Spatial Resolution (ms)	Cloud cover %	Number of bands	List of bands
1	Landsat4	MSS	168 / 53	1973	57*57	0.01	4	1,2,3 and 4
2	Landsat5	TM	168/53	1985	30 *30	0.01	5	1,2,3,4 and 5
3	Landsat7	ETM+	168/53	2000	30 *30	0.01	6	1, 2, 3, 4, 5, and 7
4	Landsat8	OLI	168/53	2022	30 * 30	0.01	6	1, 2, 3, 4, 5, and 7

Note: MSS-Multispectral Scanner, TM-Thematic Mapper, ETM+ - Enhanced Thematic Mapper Plus, and OLI- Operational Landsat Imageries

3.2.4. Data preparation and analysis

A) Image Processing

Earth Explorer used to obtain the Landsat image of 1973, 1985, 2000, and 2022 were downloaded, preprocessed and processed using R studio 02.2-4 version, the processing activities performed include layer stacking, radiometric correction, geometric correction, atmospheric correction using different tools and software (Table 3). Radiometric corrections include transforming the data so they appropriately represent the reflected or emitted radiation detected by the sensor, correcting the data for inconsistencies in the sensor and unwelcome sensor or atmospheric noise, and correcting the data for irregularities in the sensor.

All satellite imagery was georeferenced and rectified using the World Geodetic System (WGS) 84 zone 37N datum and the Universal Transverse Mercator (UTM) projection. The individual bands of each image from the indicated path and row combined after geographic projection using R studio 02.2-4 to stack all the images into a multilayer image. Additionally, each image was subset (clipped) according to regions of relevance for the Wufe-Washa forest detection to read and distinguish the surface details clearly, false color layer stack images in the Red, Green, and Blue (RGB) band combination created for all images using the R studio 02.2-4 software. This is because vegetation reflects infrared light more so than it does visible light (Deneke, 2007).

Table 3: Software's applications used to conduct the study

Software	Purpose
ArcMap 10.8	For training different feature class and making LULC map layouts.
R Studio 02.2.4	For Image processing, layer stacking, clipping the satellite imageries by the boundary of the study area, and image categorizations, filtering, visualization and study the spatial data
QGIS 3.24	For pixel counting, area analysis and calculation
SPSS version 25	For descriptive statistical analysis

B) Image Classification

Using R Studio (version 02.2.4) software tools, image categorization of a satellite image is carried out under supervision. Each image is classified using the random forest (RF) classifier. A land

cover class or themes are automatically assigned to all pixels with the same spectral value under the supervision of a human observer. The field and the Google Earth map used to produce training samples at the study site correspond to each categorization item for the signature editor. For this study, a total sample size of 320, 370, 460, and 515 points was generated from Landsat images for 1973, 1985, 2000, and 2022, respectively. In addition, employing stratified random sampling of the sampled training points, 70% were used for categorization and the remaining 30% were used for accuracy testing (Shetty, 2019).

Generally, classification is carried out with the benefit of the target geographic features in mind, and the classification arrangement must include classes that may be used for the study (the research's purpose) and can be identified from the available data. For the classification of land use and land cover, Anderson et al.'s (1976) image categorization arrangements was used. Six land use classes were taken into account for image classification based on ground survey knowledge of the study area, additional information from previous research, physical site observation, and KII of the study area, which includes forest, cropland, bare land or open area, shrub land, grassland, and settlement, as described in Table 4 below.

Table 4: Description of the LULC class of the study area

LULC Class	Description
Forest	This class encompasses dense and sparse forests, both natural and plantation forests. It includes various types of tree species and vegetation cover.
Shrub/bush land	This class includes areas dominated by shrubs and bushes, with sparse tree cover.
Grassland	This class includes open areas dominated by grasses and may be used for grazing livestock
Bare land/Open area	This class represents areas with little to no vegetation cover, such as barren land or rocky surfaces.
Settlement	An area where people live and participate in various activities. They are often involved in infrastructure development, including housing, roads and public spaces, to support the needs of residents.
Cropland	This class involves areas used for cultivation of crops, such as fields for growing crops like maize, teff, barley, and other agricultural products.

3.2.5. Change Detection Analysis

The process of identifying changes in LULC involves classifying each land cover unit and then taking consecutive images. By analyzing two sets of image data, summary statistics were generated to determine the extent of each land cover type and how the classes differed. The analysis provides information on the area and percentage of each LULC category in each time period. QGIS 3.28 software was used to facilitate the analysis. The analysis focuses on forest change, looking specifically at the increase, loss and change in forest cover for the 1973-1985, 1985-2000 and 2000-2022 periods. The results of this analysis are analyzed and presented accordingly.

3.2.6. Accuracy Assessment and Kappa coefficient

The inaccuracy of the field has long been a concern for many researchers in various contexts (Kusumo et al., 2019). As suggested by (Lillesand et al. 2008; Becket al., 2015). Accurate measurement should generate points using separate images and compare the locations of points determined from ground truth data with coordinates on the original map. For accuracy assessment, a confusion matrix was used with sufficient soil test areas for each land use (Shalaby and Tateishi, 2007). Therefore, all accuracy and Kappa statistics are determined along with producer and consumer exposure. The confusion matrix and Kappa coefficient are used to evaluate the accuracy of image classification. The kappa coefficient indicates the level of agreement between taxonomic and reference data (Arumugam et al., 2019).

Accuracy calculated by the following equations:

$$k = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} x_{+i})} \quad (5)$$

Where: r denotes the number of rows and columns in the error matrix,

N denotes the total number of observations (pixels)

x_{ii} = row i and column

i observations,

x_{i+} = row i marginal total, and

x_{+i} = column i marginal total.

Landis and Koch (1977) divided kappa values between -1 and 1 into three categories:

- (i) greater than 0.80 indicates high agreement;
- (ii) 0.40 to 0.80 indicates moderate agreement; and
- (iii) less than 0.40 indicates poor agreement between classification and reference data.

Hence, the Kapa coefficient is calculated mathematically producer accuracy, user accuracy, and overall Accuracy are calculated from the following equations:

$$\text{Producer Accuracy} = \frac{\text{Total number of pixels in a classification}}{\text{Total number of pixels obtained from reference data (i.e.row total)}} \quad (6)$$

User accuracy pertains to the level of accuracy perceived by a map user. It signifies how often the class depicted on the map corresponds to its actual presence on the ground.

$$\text{User Accuracy} = \frac{\text{Total number of pixels in a category}}{\text{Total amount of pixels taken from the reference data for that clasification (i.e.column total)}} \quad (7)$$

Overall accuracy is a measure of the accuracy or precision of calculating the image as a whole, including all classes or groups contained in the isolated image. The overall map accuracy for each class is shown in Table 5, which estimates the percentage of pixels identified.

$$\text{Overall accuracy} = \frac{\text{Sum of the diagonal elements .}}{\text{Total number of accuracy sites pixels (column total)}} \quad (8)$$

Table 5: Summary of Kappa coefficient value

No	Kappa statistics	Strength of agreement
	Almost perfect	Poor
1	0.00 - 0.20	Slight
2	0.21 - 0.40	Fair
3	0.41 - 0.60	Moderate
4	0.61 - 0.80	Substantial
5	0.81 - 1.00	Excellent work

3.2.7. Data analytical framework

The analytical framework presents based on data availability, quality, and strength, satellite images processing, interpretation and analysis of LULC dynamics of the Wufe_Washa forest and the surrounding areas helped by using an appropriate software as well as a nonparametric machine learning classifier algorithm (ML). In this study, the ML supervised classifier i.e., random forest algorithm (RF) classifier used for categorizing and classifying different Landsat time series imageries accurately and efficiently. In addition, that, a socio-economic data alongside with spatial information to comprehend the direct and indirect causes and consequences of the study site's LULC dynamic, which will aid in the gathering of qualitative and quantitative data through selected household surveys, key informant interviews, and direct observation. The quantitative data was analyzed by SPSS software.

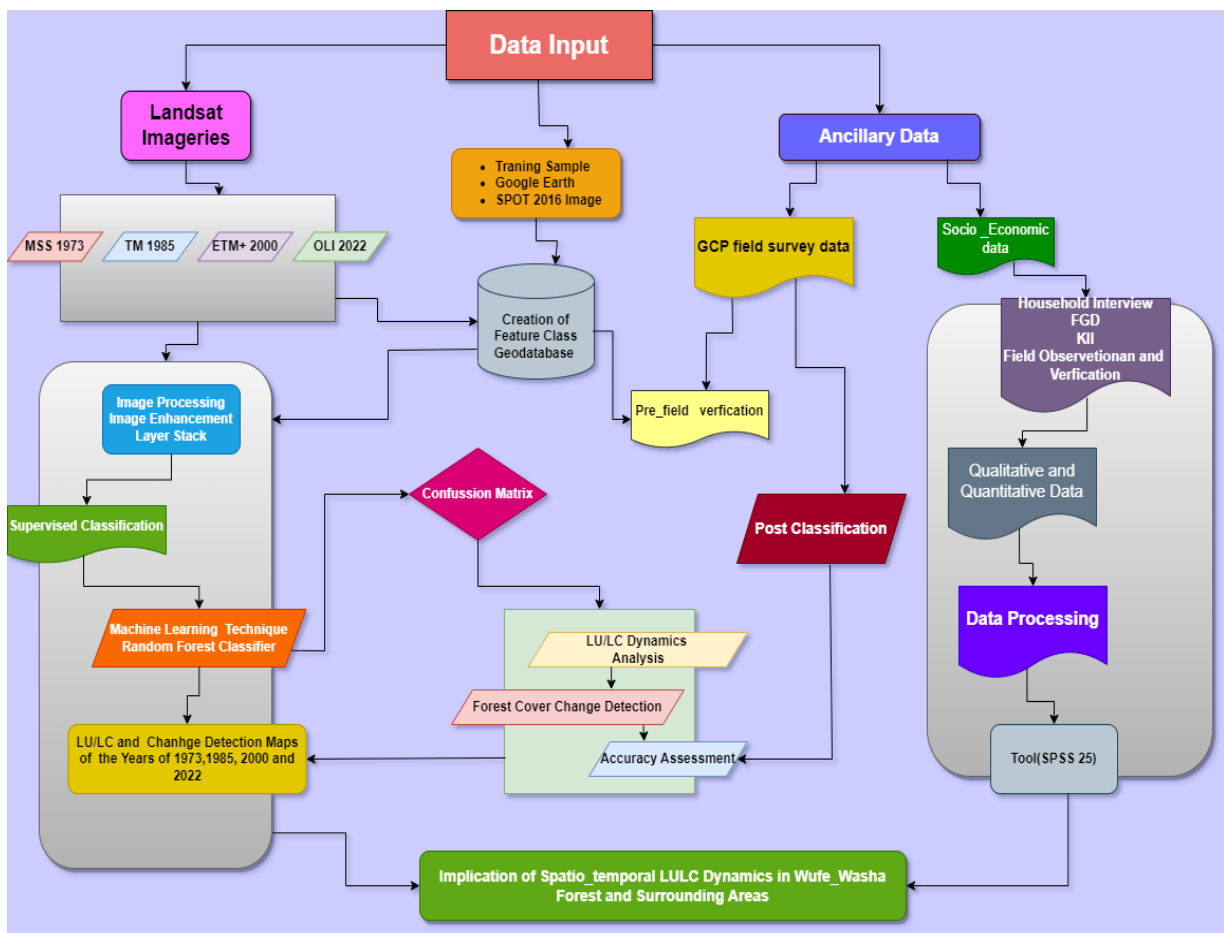


Figure 4: Analytical Framework of the LULC

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1. Spatiotemporal land use-land cover changes between 1973 - 2022

By employing visual interpretation techniques, identification and analyzing spectral reflectance values, patterns, color tones, and other pertinent factors, the satellite images of Wufe _Washa Forest and its surrounding environment were categorized into six distinct geographical characteristics. These include a forested area, shrubland, grassland, cropland, settlement, and bare lands.

4.1.1. Land uses- land cover between 1973 and 2022

4.1.1.1.LULC of 1973

After undergoing pre-processing, processing, and supervised classification, the Landsat MSS 1973 satellite imageries were classified into six distinct categories, revealing of the LULC class in the study area. The process involved several steps to convert raw satellite data into a meaningful representation of the study area. Pre-processing helped remove any noise or artifacts present in the images, followed by processing to enhance the image quality and extract useful information. Finally, supervised classification was performed, which involved training data set, an algorithm (RF) to classify each pixel in the image into one of several LULC categories, such as forest, settlement, cropland, grassland etc.

Table 6: LUILC classes, their corresponding areas (hectares) in 1973

Land use class	Pixel count	Area (m ²)	Area in hectare 1973	LULC class % 1973
Settlement	1971	7095600	709.56	3.14
Grassland	2892	10411200	1041.12	4.61
Forest	10360	37296000	3729.6	16.52
Bare land/Open area	12197	43909200	4390.92	19.45
Shrub land	16239	58460400	5846.04	25.89
Cropland	19056	68601600	6860.16	30.39
Sum			22577.4	

In this study site, six different LULC categories have been showed, namely settlement, grassland, forest, bare land, shrub land, and cropland. These categories have a combined area of 22,577.4 hectares. To enhanced recognize the changes in LULC over time, a satellite image was used to produce a LULC classification for the study area in 1973 (Figure 5). The results showed that the largest land use class was cropland, which covered an area of 6,860.16 hectares or 30.39% of the study area (Figure 4). This shows that agriculture was the dominant land use activity in the area during that period.

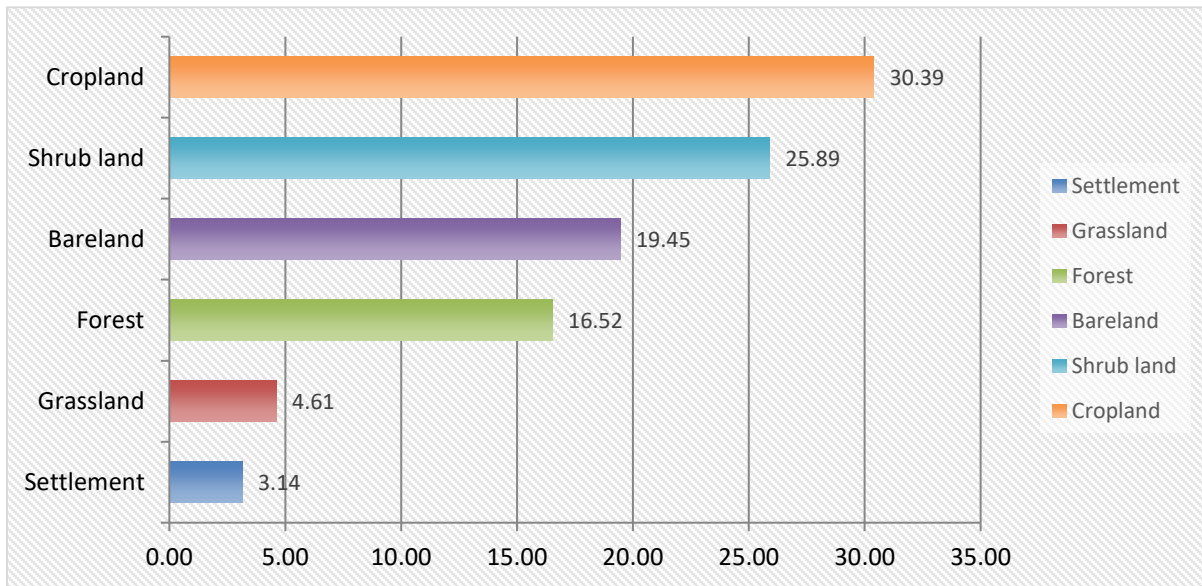


Figure 5: LULC and its corresponding area (%) in 1973

The second most significant land use/cover class was shrub land, which covered 5,846.042 hectares, accounting for 25.89% of the study area. Bare land was another category identified, covering 4,390.92 hectares or 19.45% of the study area. Forest, grassland, and settlement were less dominant land use/cover categories, covering 3,729.6 hectares (16.52%), 1,041.12 hectares (4.61%), and 709.56 hectares (3.14%), respectively.

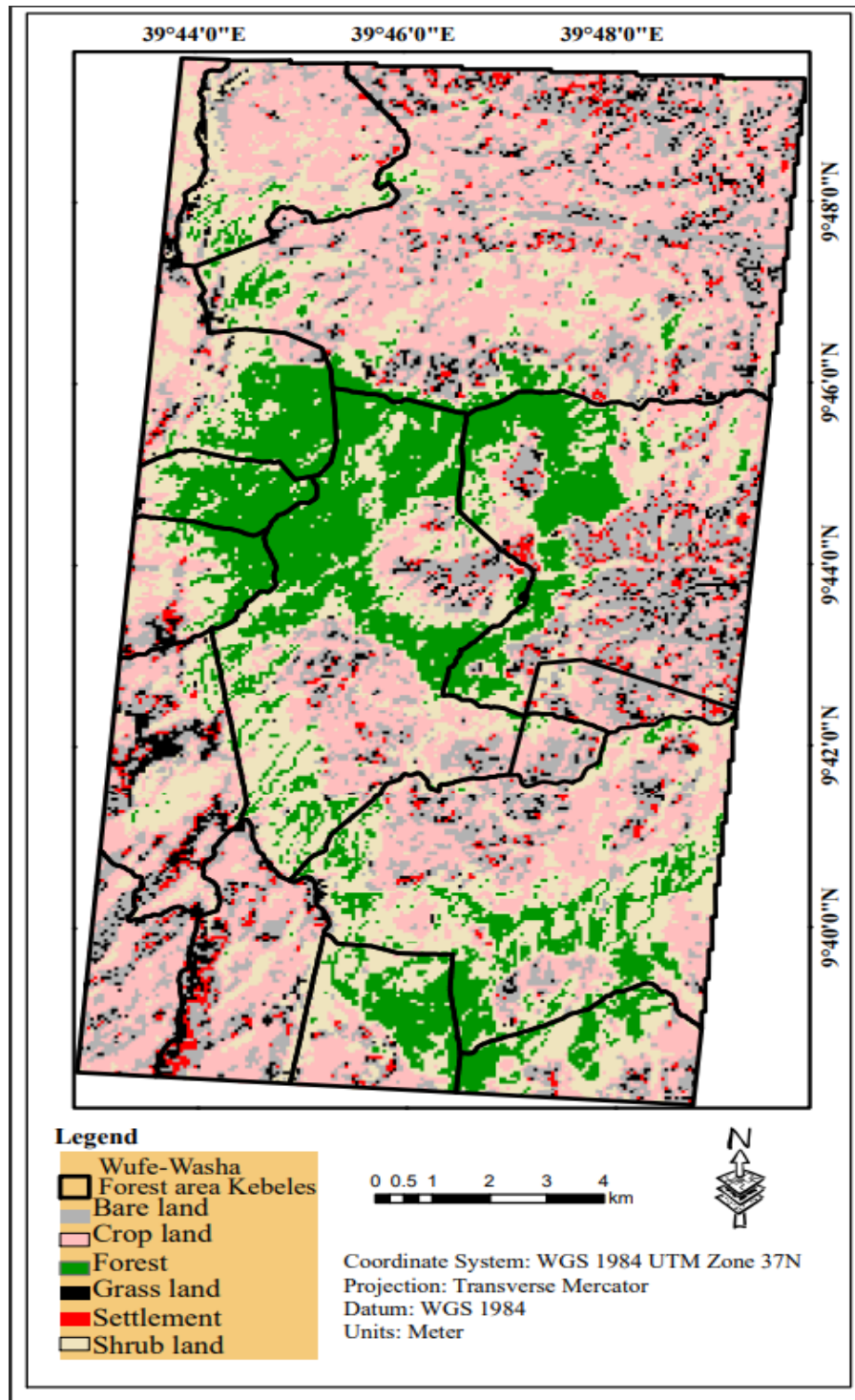


Figure 6: LULC classification maps of 1973

4.1.1.2.LULC for the year of 1985

As presented in table 7, the analysis of LULC carried out on 1985 using satellite Landsat TM + imagery, the main features of the study site were croplands and forests. These two land cover types accounted for a significant proportion of the total area, with croplands making up 37.27% (8413.83 ha) and forests comprising 22.97% (5185.35 ha). Besides these two dominant land cover types, there were other land cover categories observed in the area, including shrub, bare land, grassland, and settlements. Collectively, these land cover types represented about 40% of the study area, with shrub covering 20.33% (4588.92 ha), bare land covering 8.02% (1810.08 ha), grassland covering 7.64% (1725.66 ha), and settlements accounting for 3.78% (853.02 ha).

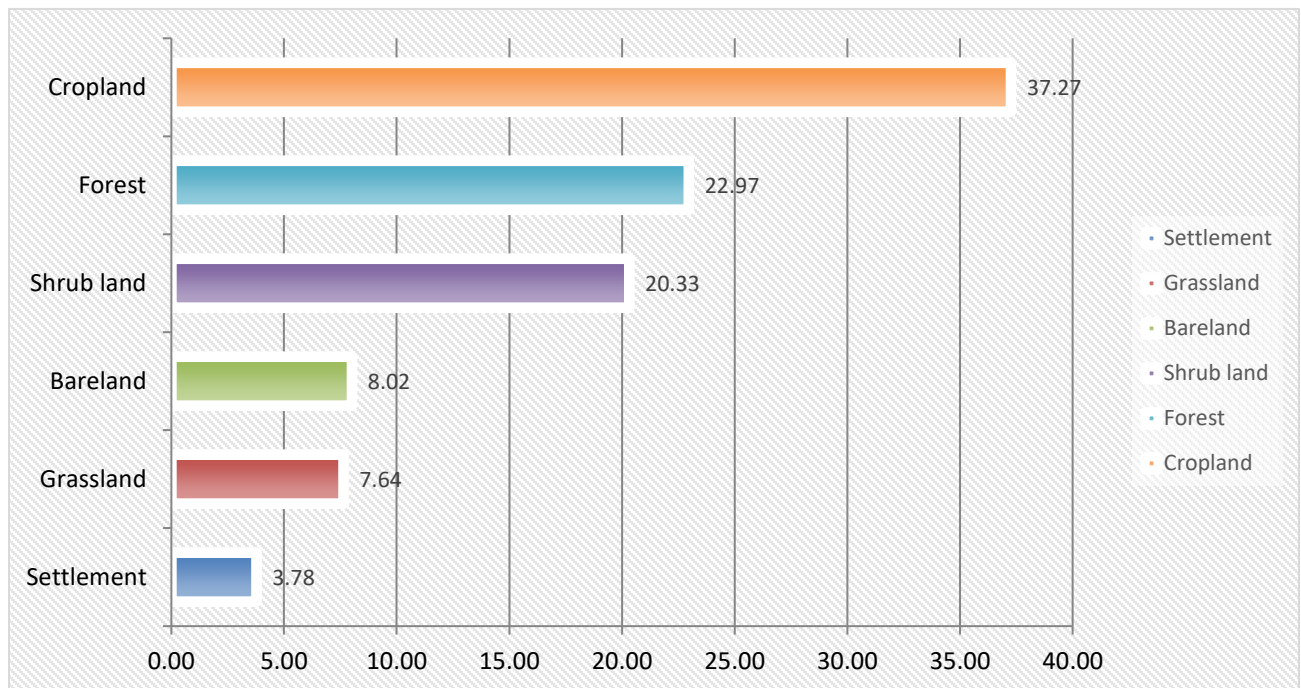


Figure 7: LULC class and their corresponding area (%) in 1985

Table 7: LULC classes, their corresponding areas (hectares) in 1985

Land use class	Pixel count	Area (m ²)	Area hectare 1985	LULC class % 1985
Settlement	9478	8530200	853.02	3.78
Grassland	19174	17256600	1725.66	7.64
Bare land	20112	18100800	1810.08	8.02
Shrub land	50988	45889200	4588.92	20.33
Forest	57615	51853500	5185.35	22.97
Cropland	93487	84138300	8413.83	37.27
Sum			22576.86	100.00

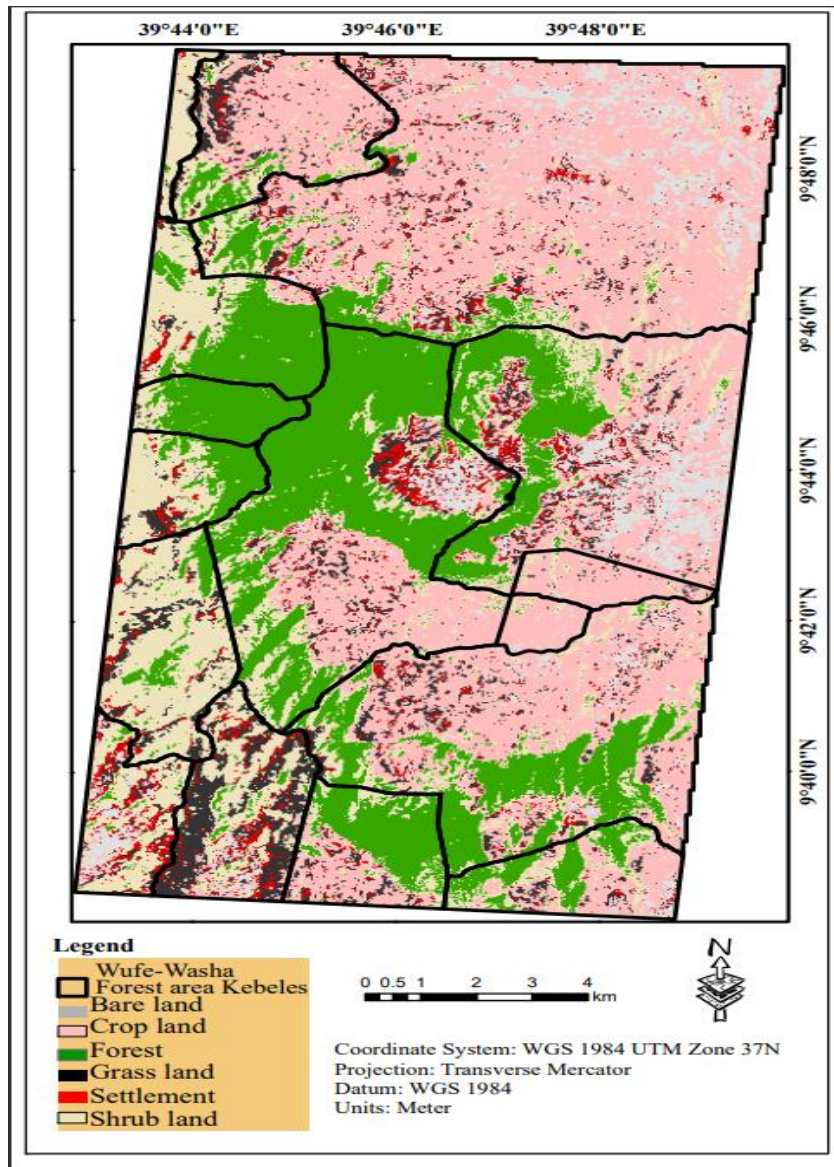


Figure 8: LULC classification maps of 1985

4.1.1.3. LULC the year of 2000

The land cover analysis that was carried out in the year 2000 using Landsat ETM+ satellite images indicated that the most dominant type of land cover in the study area was croplands. The analysis showed that these croplands occupied a vast area of 9908.82 ha, which represented 43.89% of the entire study area. Additionally, forests and bare land were found to be the second most extensive land cover types, covering 7538.04 ha (33.39%) and 1424.7 ha (6.31%), respectively.

Table 8: LULC classes, their corresponding areas (hectares) in 2000

Land use class	Pixel count	Area (m ²)	Area in hectare 2000	LULC class % 1985
Grassland	11017	9915300	991.53	4.39
Settlement	11602	10441800	1044.18	4.62
Shrub land	15830	14247000	1424.7	6.31
Bare land	18551	16695900	1669.59	7.39
Forest	83756	75380400	7538.04	33.39
Cropland	110098	99088200	9908.82	43.89
Sum			22576.86	

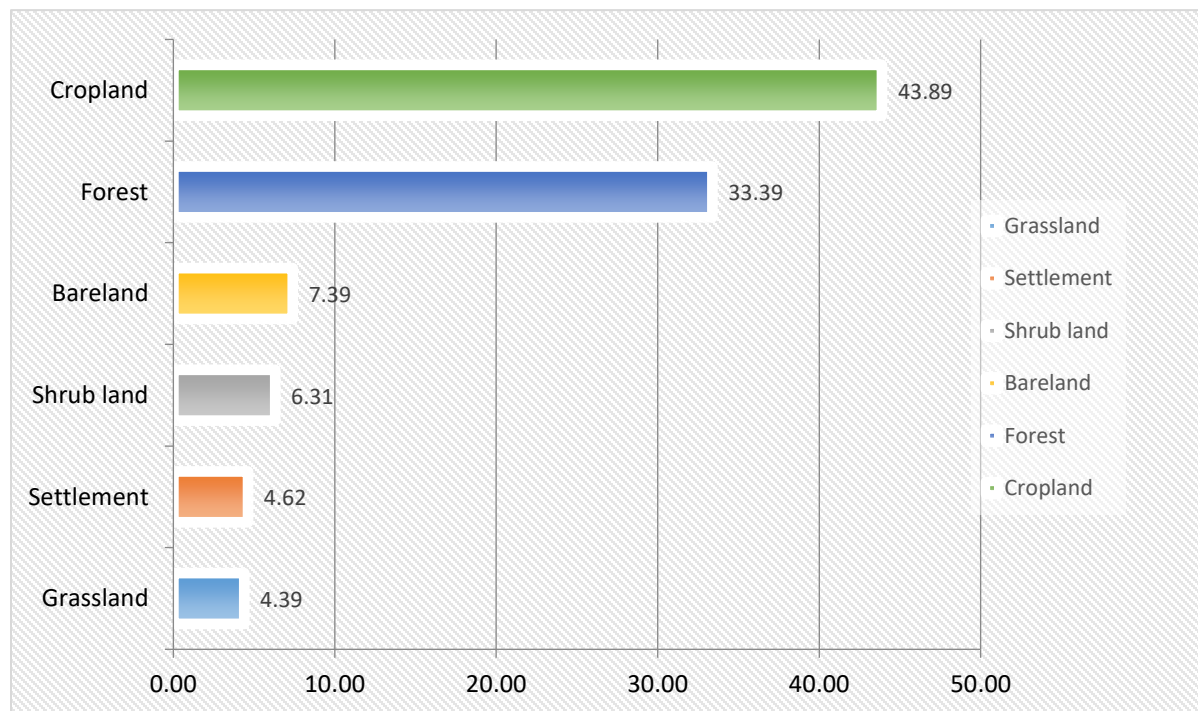


Figure 9: LULC class and their corresponding area (%) in 2000

Apart from these LULC types, the study also identified the presence of other land cover categories such as shrub land, settlements, and grassland. Collectively, these land cover types were estimated to cover 1424.7 ha (6.31%), 1044.18 ha (4.62%), and 991.53 ha (4.39%), respectively.

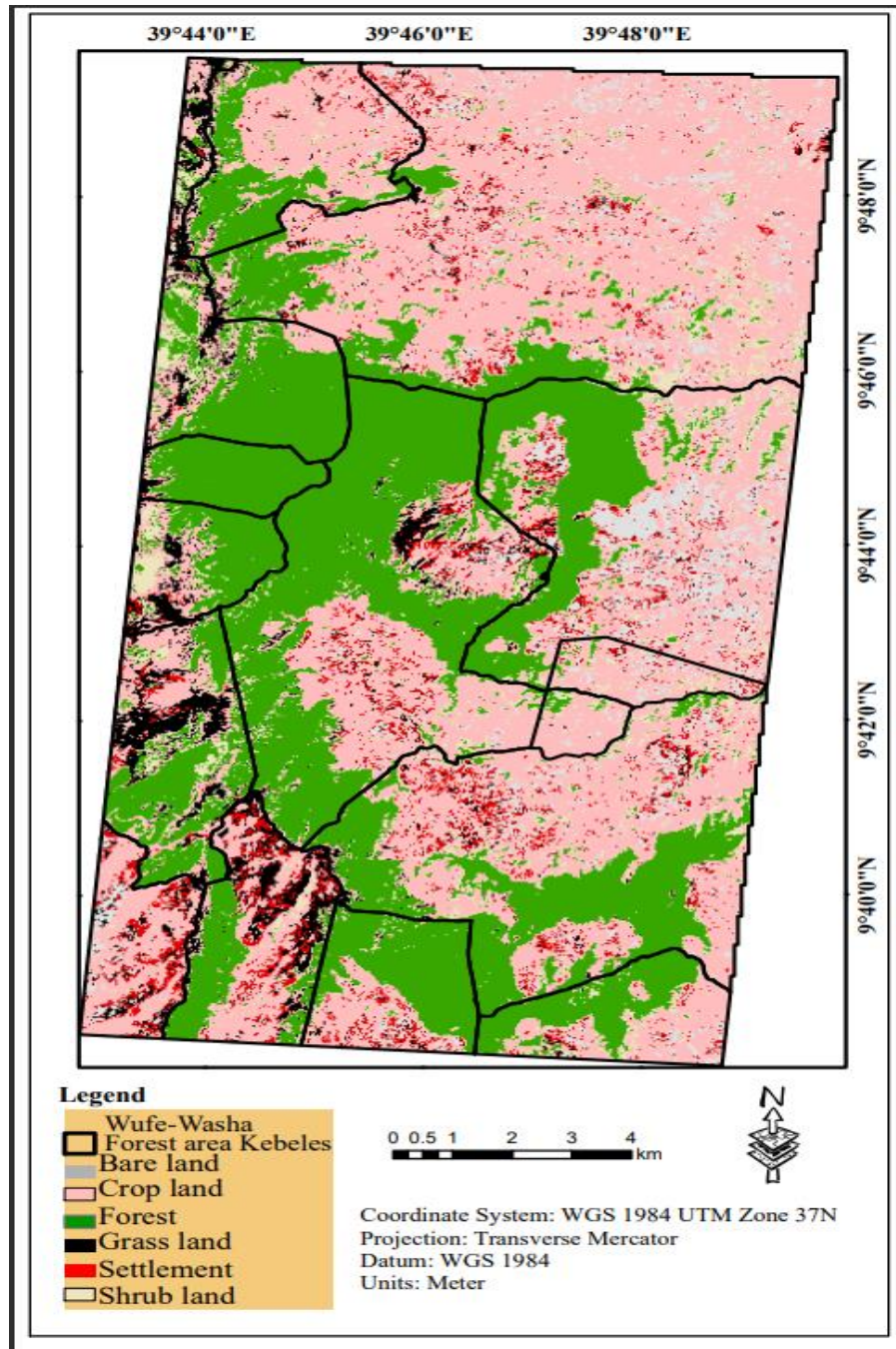


Figure 10: LULC class maps of 2000

Overall, the analysis revealed a diverse range of land cover types in the study area, with croplands occupying the most significant proportion of the land. The findings also emphasized cropland areas the dominant land use type and it increased its size from time to time.

4.1.1.4.LULC for the year of 2022

Table 9: LULC classes, their corresponding areas (hectares) in 2022

Land use class	Pixel count	Area (m ²)	Area in Hectare 2022	LULC class %
Grassland	1877	1689300	168.93	0.75
Shrub land	10491	9441900	944.19	4.18
Bare land	10905	9814500	981.45	4.35
Settlement	16143	14528700	1452.87	6.44
Forest	79918	71926200	7192.62	31.86
Cropland	131520	118000000	11836.8	52.43
Sum	250854		22576.86	

The above table (9), provides information about the distribution of land use and land cover classes in the study area in 2022. The largest area coverage is attributed to crop land, which encompasses an area of 11836.8 hectares, equivalent to 52.43% of the total area. This indicates that a significant portion of the study area is increased cropland size. The second-largest land use class is forest, which covers 7192.62 hectares or 31.86% of the total area. This suggests that the study area has a considerable amount of forest cover. Settlements, on the other hand, occupy a relatively smaller area of 1452.87 hectares or 6.44%.

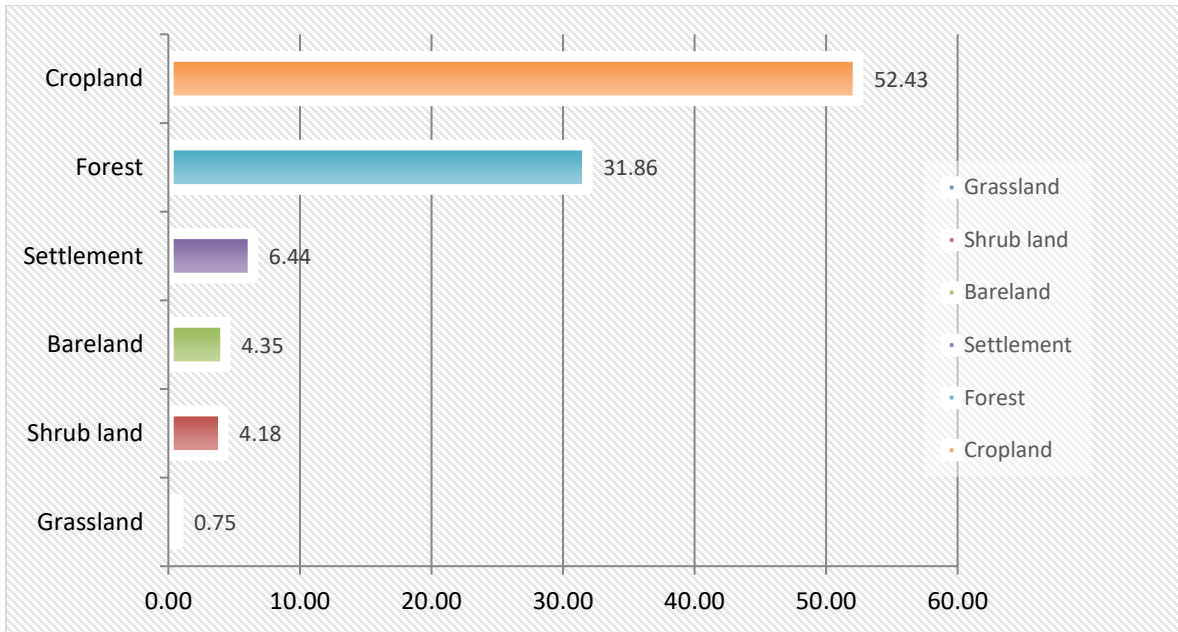


Figure 11: LULC Class and their corresponding areas (2022)

Moreover, the smallest areas in the study area are covered by bare land, shrub land, and grassland. Bare land covers an area of 981.45 hectares, which is 4.35% of the total area. Shrub land covers 944.19 hectares, which is 4.18% of the total area. Finally, grassland covers the smallest area of 168.93 hectares, which is only 0.75% of the total area. This suggests that the study area has limited areas covered by natural vegetation, and the land is predominantly used for agricultural and settlement purposes.

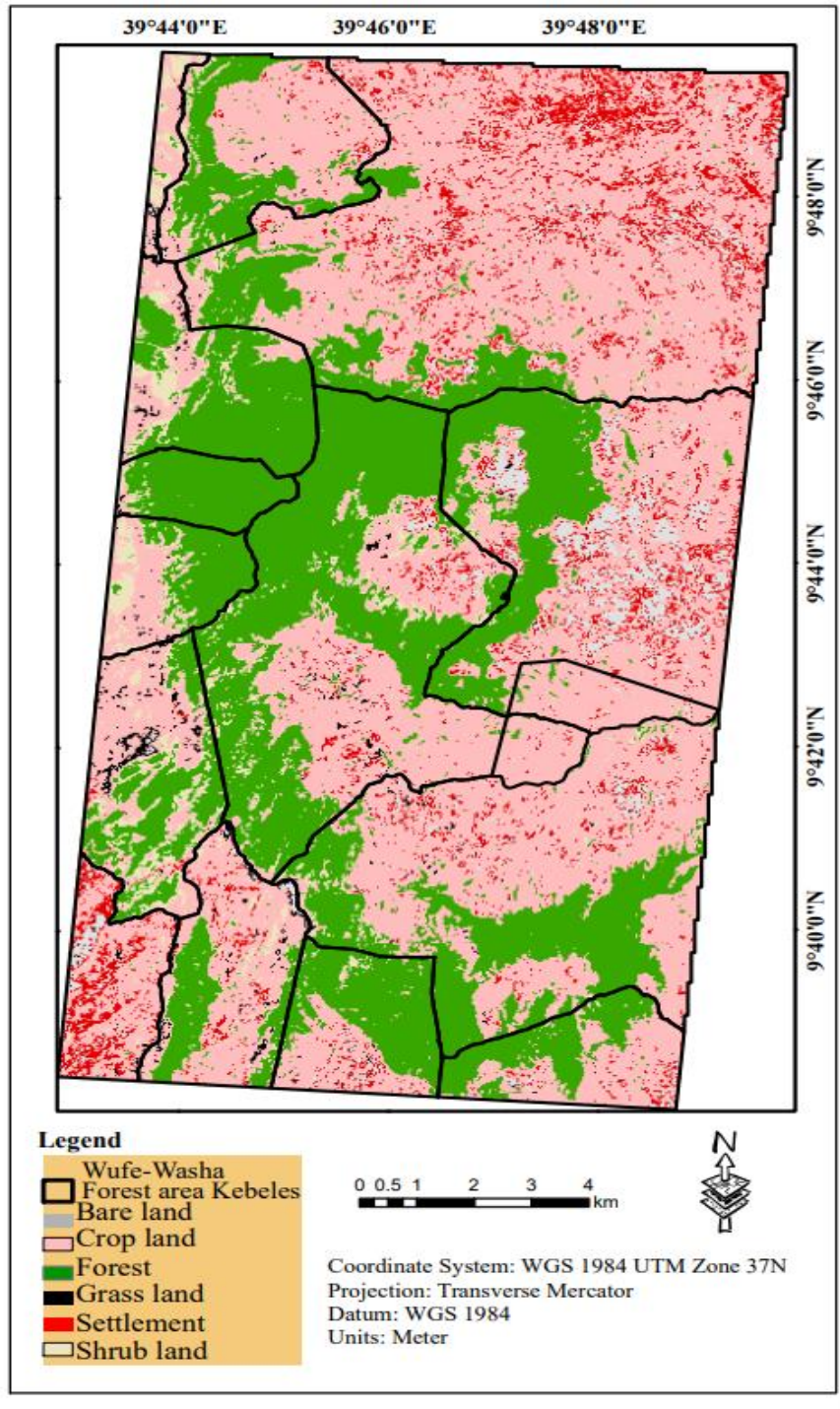


Figure 12: LULC classification map of 2022

4.2. LULC change detection

4.2.1.LULC Change between 1973 and 1985

The data presented in table 10 below, shows that change in land use in the Wufe-Washa forest and the surrounding areas between 1973 and 1985. It is clear that there was a significant decrease in the area of bare land and shrub land during this period. In particular, the area covered by bare land decreased by 2580.84 hectares, which translates to a decline of 58.78%. Similarly, the area covered by shrub land decreased by 1257.12 hectares, or 21.50%. This indicates that on average, the area of bare land decreased by 215.07 hectares or 4.90%, while shrub land decreased by 104.76 hectares or 1.79%.



Figure 13: LULC detection 1973 -1985

In contrast, the area covered by grassland, forest, crop land and settlement experienced a significant increase during the same period. The area covered by grassland increased by 684.54 hectares, which is a growth of 5.48%. The area covered by forest increased by 1455.75 hectares, which is a growth of 3.25%. Additionally, the area covered by crop land increased by 1553.67 hectares, which is a growth of 1.89%. Finally, the area covered by settlement increased by 143.46 hectares, which is a growth of 10.49%.

Table 10: LULC detection 1973 -1985

Land use class	Area In hectare - 1973	LULC % 1973	Area hector - 1985	LULC % 1985	change in ha 1973-1985	Change %	Change hectares / year	Change rate/ years
Bare land	4390.92	19.45	1810.08	8.02	-2580.84	-58.78	-215.07	-4.90
Cropland	6860.16	30.39	8413.83	37.27	1553.67	22.65	129.47	1.89
Forest	3729.60	16.52	5185.35	22.97	1455.75	39.03	121.31	3.25
Grassland	1041.12	4.61	1725.66	7.64	684.54	65.75	57.05	5.48
Settlement	709.56	3.14	853.02	3.78	143.46	20.22	11.96	1.68
Shrub land	5846.04	25.89	4588.92	20.33	-1257.12	-21.50	-104.76	-1.79
sum	22577.40		22576.86	100.00				

In general, the results imply that there has been a notable change in how the land in the area has been used over time. The fact that there is less bare land and shrub land suggests that people are using the land more for agriculture and building homes. However, based on feedback gathered from group discussions, the increase forest, crop land, and settlement could be due to natural regrowth of forests, reforestation efforts, or expansion of agriculture.

4.2.2.LULCC Detection between 1985 and 2000

The findings from analyzing the LULCC between 1985 and 2000 demonstrate that there has been a significant increase in the area covered by forest, settlement, and cropland. Specifically, there has been a remarkable increase of 2352.69 ha (45.37%) in forested areas, 191.16 ha (22.41%) in settlements, and 1494.99 ha (17.77%) in cropland. In contrast, the areas covered by shrub land, grassland, and bare land have decreased by -3164.22 ha (-68.95%), -734.13 ha (-48.94%), and -140.49 ha (-7.76%) respectively, with an average annual rate of change of -210.95 ha/year (-4.60 percent/year) for shrub land, -48.94 ha/year (-2.84 percent/year) for grassland, and -9.37 ha/year (-0.52 percent per year) for bare land.

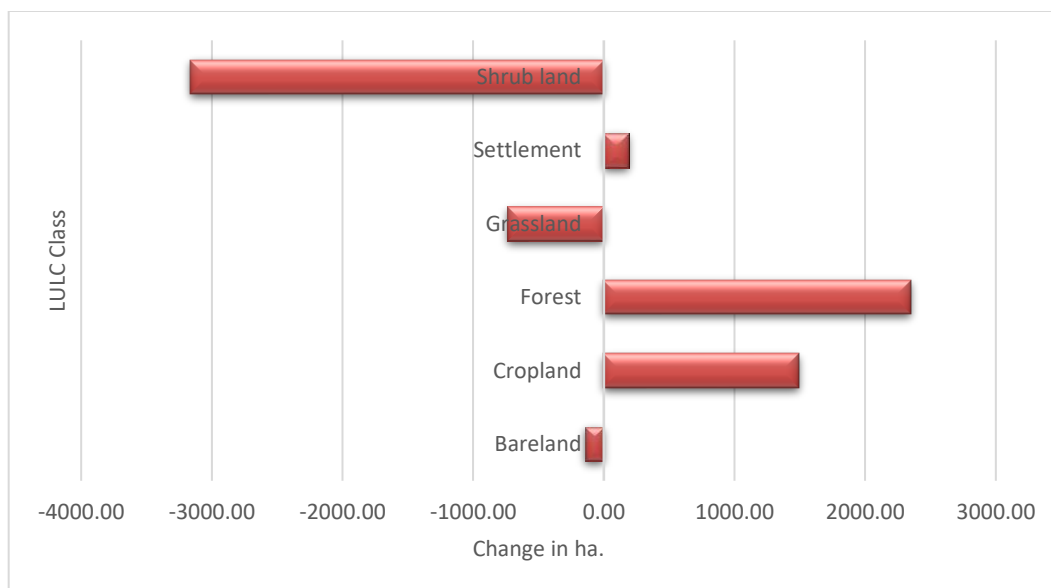


Figure 14: LULC detection 1985-2000

Over the course of 15 years, the expansion of forest, settlement, and cropland has been on average 156.85ha (3.02 percent per year), 12.74 ha (1.49 percent per year), and 99.67 ha (1.18 percent) respectively. These results suggest that there has been a shift in land use practices in the area, with more emphasis placed on agriculture and human settlements. Additionally, the increase in forested areas could be attributed to reforestation efforts or natural regrowth of forests. The decrease in shrub land and grassland, on the other hand, could be due to the expansion of cropland or other land use activities.

Table 11: Change detection 1985-2000

Land use class	Area ha 1985	LULC % 1985	Area in he.2000	LULC % 2000	Change in ha 1985-2000	Change %	Change ha/year	Change rate/year
Bare land	1810.08	8.02	1669.59	7.40	-140.49	-7.76	-9.37	-0.52
Cropland	8413.83	37.27	9908.82	43.89	1494.99	17.77	99.67	1.18
Forest	5185.35	22.97	7538.04	33.39	2352.69	45.37	156.85	3.02
Grassland	1725.66	7.64	991.53	4.39	-734.13	-42.54	-48.94	-2.84
Settlement	853.02	3.78	1044.18	4.63	191.16	22.41	12.74	1.49
Shrub land	4588.92	20.33	1424.70	6.31	-3164.22	-68.95	-210.95	-4.60
Sum	22576.86		22576.86					

4.2.3. LULCC Detection between 2000 and 2022

According to Table 12, there has been significant expansion of agricultural and settlement areas in the study area between 2000 and 2022. Specifically, cropland has expanded by 1927.98 ha (19.46 percent) at an average rate of 87.64 ha per year (0.88 percent year), while settlement has expanded by 408.69 ha (18.58 percent) at an average rate of 18.58 ha per year (1.78 percent/year) over the 22-year period. On the other hand, there has been a rapid decline in the areas covered by grassland, shrub land, forest, and bare land by -822.60 ha (-82 percent), -480.51 ha (-33.73 percent), -345.42 ha (-4.58 percent), and 688.14 ha (-41.22 percent) respectively.

Table 12: LULC change detection 2000-2022

Land use class	Area ha 2000	LULC % 2000	Area ha 2022	LULC% 2022	Change in ha (2000-2022)	Change %	Change ha/year	change rate/year
Bare land	1669.59	7.40	981.45	4.35	-688.14	-41.22	-31.28	-1.87
Cropland	9908.82	43.89	11836.80	52.43	1927.98	19.46	87.64	0.88
Forest	7538.04	33.39	7192.62	31.86	-345.42	-4.58	-15.70	-0.21
Grassland	991.53	4.39	168.93	0.75	-822.60	-82.96	-37.39	-3.77
Settlement	1044.18	4.63	1452.87	6.44	408.69	39.14	18.58	1.78
Shrub land	1424.70	6.31	944.19	4.18	-480.51	-33.73	-21.84	-1.53
	22576.86		22576.86					

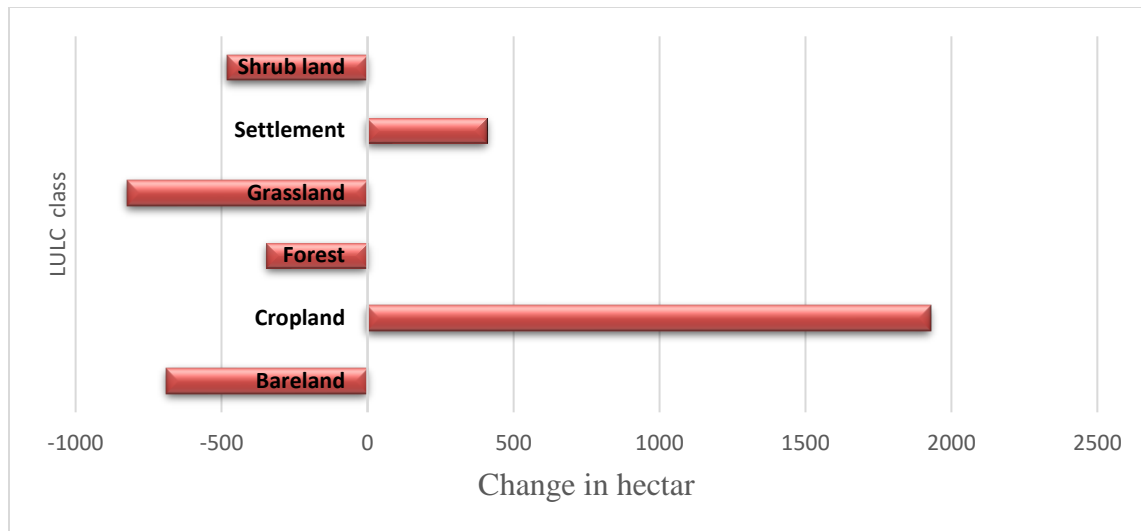


Figure 15: LULC detection 2000-2022

The average rate of change for grassland and shrub land is -37.39 ha per year (-3.77 percent/year) and -33.73 ha per year (-1.53 percent/year) respectively over the 22-year period. Additionally, forest and bare land have reduced by 345.42 ha (-4.58 percent) and 688.14 ha (-41.22 percent) at an average rate of -15.70 ha per year (-0.21 percent/year) and -31.28 ha with a -1.8% rate change per year, respectively. These results suggest that there has been a continued trend of expansion in agricultural and settlement areas, which has led to a significant reduction in the areas covered by grassland, shrub land, forest, and bare land.

4.2.4.LULCC the last 49 years (1973 – 2022)

According to the data presented in table 13, a substantial increase in land usage for Settlements, Croplands, and Forest lands between 1973 and 2022. The combined increase in these three categories is a noteworthy 14,794.38 hectares. Settlements experienced the most significant growth, with a gain of 6354.72 hectares, followed by Croplands, which gained 4976.64 hectares, and Forest lands, which gained 3463.02 hectares. On the other hand, there was a decline in the amount of land used for Shrub-land, Bare land/Open area, and Grassland. These three categories collectively lost 8255.51 hectares of land during the study period. Shrubland was the most impacted with a loss of 4901.85 hectares, followed by Bare land/Open area with a loss of 2481.57 hectares, and Grassland with a loss of 872.09 hectares.

Table 13: LULC between the end to initial (2022 – 1973) ha

LULC	Area ha 1973	Area ha 1985	Area ha 2000	Area ha 2022	Δ LULC (2022 – 1973) ha
Forest	3729.60	5185.35	7538.4	7192.62	3463.02
Shrubland	5846.04	4588.92	1424.70	944.19	-4901.85
Grassland	1041.02	1725.66	991.53	168.93	-872.09
Cropland	6860.16	8413.83	9908.82	11836.80	4976.64
Settlement	709.56	853.02	1044.18	1452.87	6354.72
Bare land/Open area	4390.92	1810.8	1669.59	981.45	-2481.57

The conversion of natural resource such as forests, shrub lands, and grasslands into settlements and croplands can lead to habitat fragmentation and loss of biodiversity. The loss of open areas and shrub lands can also affect soil quality and increase the risk of soil erosion. These changes can have significant consequences on ecosystems and human livelihoods (Gessisee et al., 2016). Moreover, the data obtained from field surveys, FGDs, and KIIs with residents and experts of various ages in the study area have revealed that the land use and land cover (LULC) pattern of the area, specifically the size of the Wufe-Washa forest, has undergone significant changes in the last four decades.

Table 14 illustrates that a vast majority of respondents (92.6%) have acknowledged these changes in the LULC of the Wufe-Washa forest and its neighboring areas. Recent studies have pointed out that changes in LULC have become a global environmental challenge, particularly in under developed countries such as Ethiopia, where natural resources are scarce and the population is rapidly increasing (Yohannies et al., 2021). In Ethiopia, numerous factors, including population growth, agricultural expansion, institutional factors and urbanization, have contributed to the substantial changes in land use and land cover (Neggassa et al., 2020). The study's results in the Wufe-Washa

forest are consistent with this trend. In addition, the information collected from the residents' responses in this study supports the spatial findings, indicating that there have been significant LULC dynamics in Wufe_Washa forest and its neighboring areas.

These changes are likely to have a significant impact on the forest ecosystem and its ability to provide ecosystem services such as water regulation, carbon sequestration, and biodiversity conservation (Getachew, 2018).

Table 14: LULCC opinions the past 49 years

Change in the land use/land cover in study area over 45 years?			
		Frequency	Percent
	Yes	203	92.6
	No	12	5
	Haven't information	4	2.4
	Total	219	100.0

Source: Own field survey, January 2023

As mentioned earlier, the growth of the population, expansion of agricultural land on the expenses of vegetation, and the occurrence of wildfires and other factors are significant driving forces behind the LULCC in the study area. These factors were clearly identified as major contributors during the KIIs with forest protection officers on the study region. The KII respondent of the North Showa Forest and Wildlife Protection Officer clearly stated that;

“The main cause of LULC change in the forest and neighboring areas is primarily attributed to uncontrolled population growth. This leads to an increased demand for farmland among the residents, which in turn compels people to illegally exploit forest resources, putting immense pressure on the forest ecosystem. Consequently, the study area has been confronted with several issues, such as declining crop yields, disruption of rainfall patterns, migration of wildlife from the forest, and loss of catchment water, among others”

Furthermore, per the 2021 report of the Amhara Regional State Forest and Wild Life Protection Authority the total population three kebeles in 2021 was 15,573 out of these, Wufe _Washa Genet kebele has the highest population with 6,473 people, followed by Keyit with 5,064 people and Mescha with 4,036 people respectively. In terms of gender, the male population in these three kebeles is 8,222, while the female population is 7,351. This indicates that the three kebeles are experiencing a significant population pressure due to the high number of residents living there.

Table 15: Population numbers of the three selected kebeles

Woredas	Kebeles	Male	Female	Total
Tarmaber	WW_Genet	3329	3144	6473
Basowoerena	Keyit	2581	2483	5064
Ankober	Mescha	2312	1724	4036
Total		8222	7351	15573

Source: Amhara Regional State Forest and Wild Life Protection Authority 2021

4.3. Forest cover change detection between 1973 and 2022

4.3.1. Forest Cover change between 1973 and 1985

Geospatial techniques employed to analyze the changes in forest cover in the study area, and the results presented in Table 16. The analysis indicates that the forest cover in the study area has undergone some variations over the years, from 1973 to 2022. Specifically, the forest cover exhibited notable changes between 1973 and 1985, during which it gained 1856.88 hectares of forest and lost only 409.32 hectares. The stable forest cover during this period was 3320.28 hectares. However, the dominant feature in the study area was non-forest, which covered 16990.92 hectares.

Table 16: Forest change detection of the study area

Classes	Area Hectare 1973 to 1985	Area Hectare 1985 to 2000	Area hectare 2000 to 2022
Non-Forest	16990.92	14808.87	14433.66
Gained For- est	1856.88	2582.64	605.16

Lost Forest	409.32	229.95	950.58
Stable Forest	3320.28	4955.4	6587.46

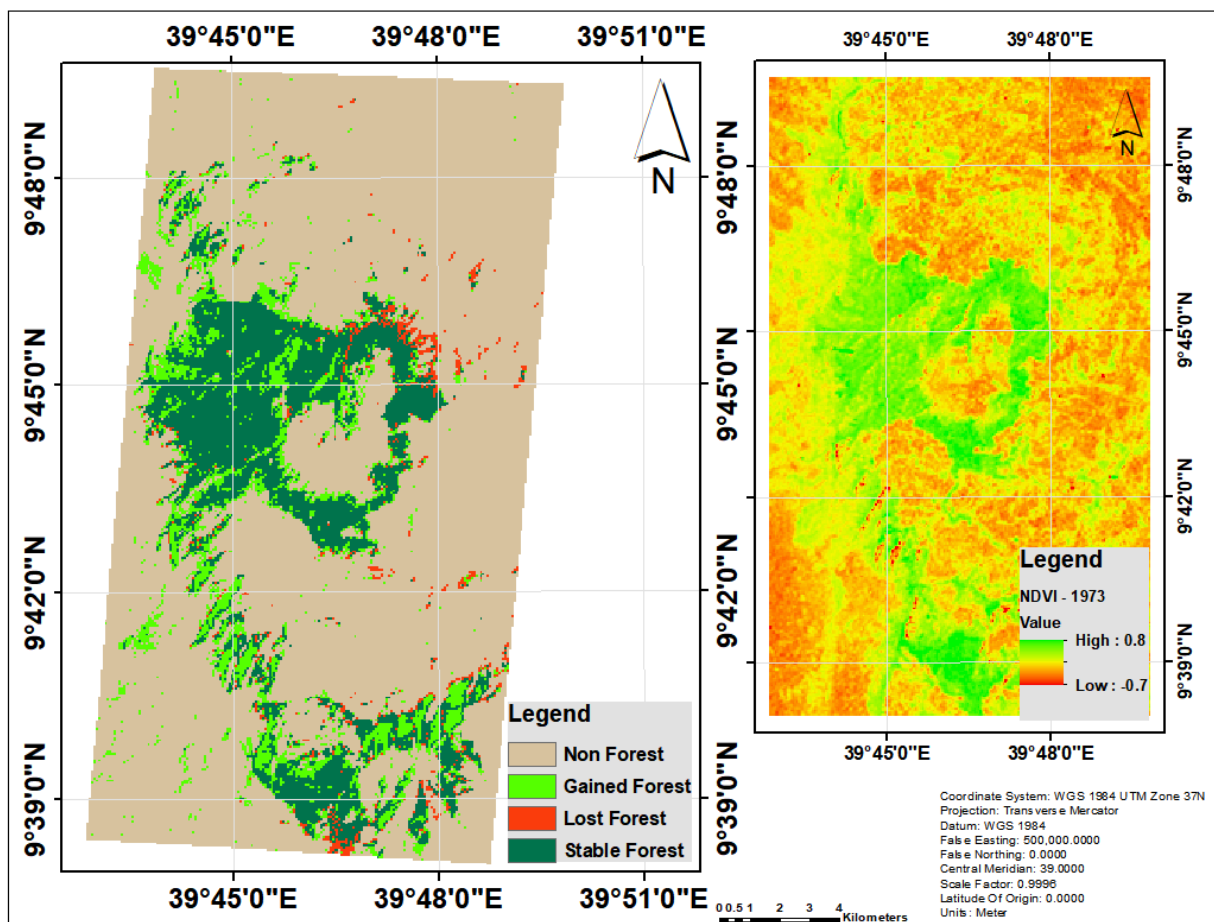
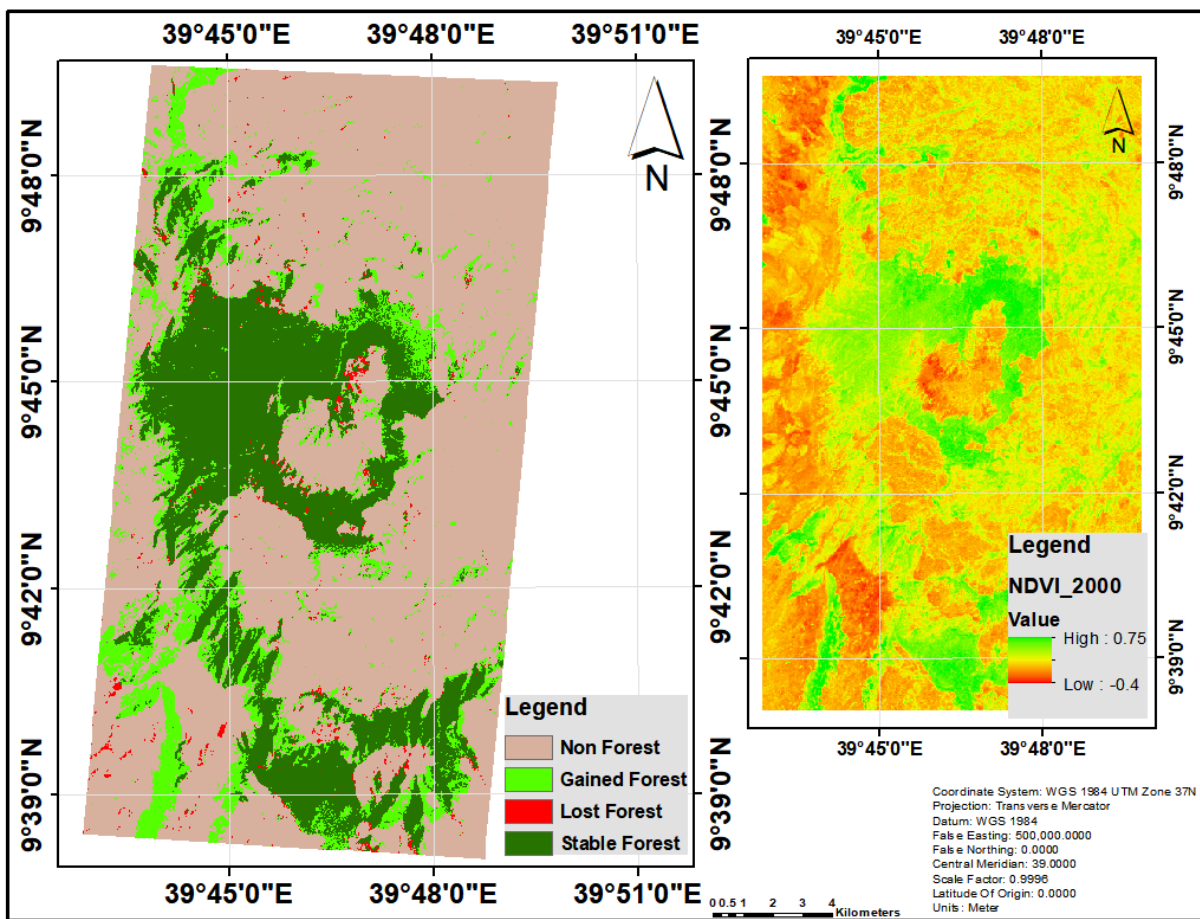


Figure 16: Forest change detection 1973-1985

Furthermore, the NDVI values of Wufe-Washa forest in the year 1973 was values ranged from -0.7 to 0.8, indicating a moderate to high level of vegetation cover. NDVI, or Normalized Difference Vegetation Index, is a widely used remote sensing tool that measures the amount and health of vegetation in a given area. In this case, the NDVI values suggest that the study area had a relatively healthy level of vegetation cover, despite the changes in forest cover observed over the years.

4.3.2. Forest Cover Change between 1985 and 2000

As shown in Table 16 and figure 16, Wufe Washa forest experienced changes in land cover between 1985 and 2000. During this period, the forest gained a significant amount of land which is 2582.64 hectares and, lost 229.95 hectares in the respective order. The majority of the land in the study area, however, was not covered by forest, with non-forest features accounting for a considerable amount of the land. Furthermore, the NDVI values for the study area ranged from -0.4 to 0.75, which suggests a moderate level of vegetation cover.



4.3.3. Forest Cover Change between 2000 and 2022

Table 16 presents data on the changes in land use in the Wufe_Washa forest from 2000 to 2022. The data shows that during this time, the forest area increased by 60516.58 hectares, decreased by 950.58 hectares, and remained stable at 6587.46 hectares. Additionally, the table indicates that there are 14433.66 hectares of non-forest geographic features in the region. Furthermore, Figure 17 displays the NDVI (Normalized Difference Vegetation Index) values for the year 2022, which ranges from -0.025 to 0.6. The NDVI is a measure of vegetation density and health, with higher values indicating more robust and healthy vegetation. To elaborate, the Wufe_Washa forest has undergone changes in its land use over the past 22 years, with both gains and losses in forest area. The non-forest geographic features in the region, which cover a significant amount of land, could potentially have an impact on the ecosystem of the forest. The NDVI values for 2022 suggest that the vegetation in the forest is generally healthy, although some areas may be less dense than others may.

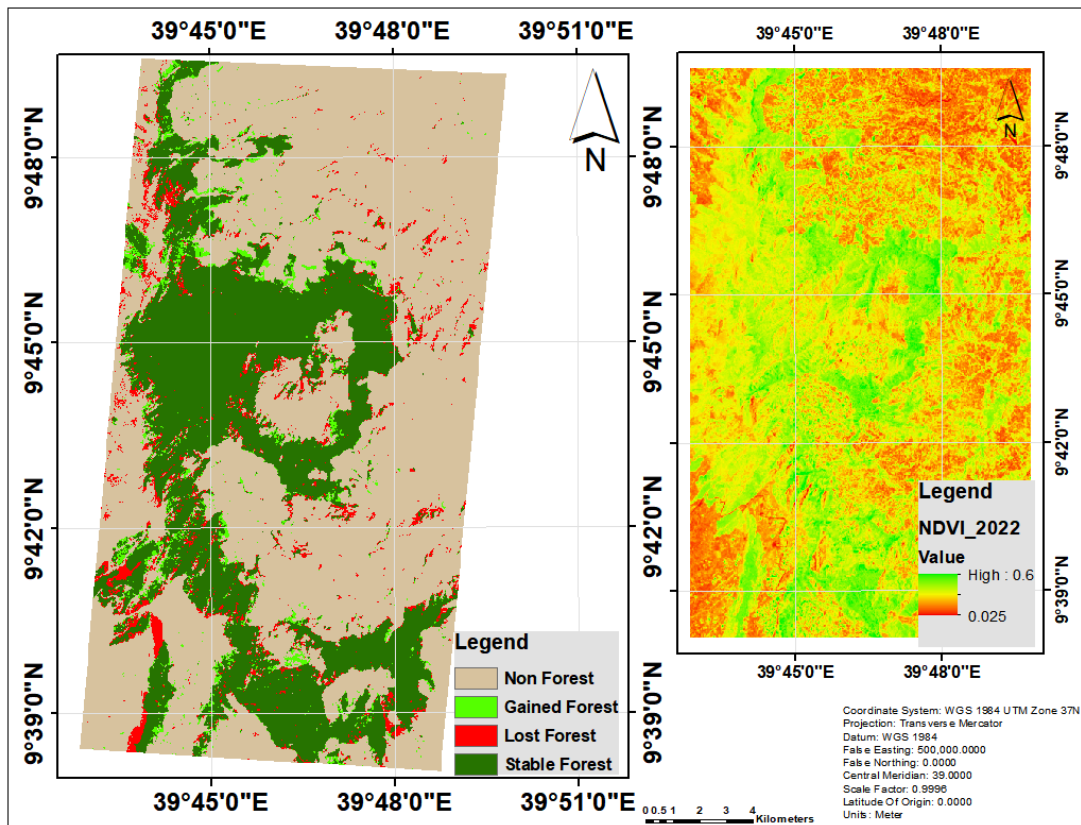


Figure 18: Forest change between 2000 and 2022

In general, the study area exhibited significant changes in its stable forest cover, with a considerable increase of 3,267.18 hectares of forestland from 1973 to 2022. However, this gain in forest cover was not uniform throughout the study period, as the forest suffered losses of 409.32 hectares from 1973 to 1985, 229.95 hectares from 1985 to 2000, and a significant decline of 950.58 hectares from 2000 to 2022.

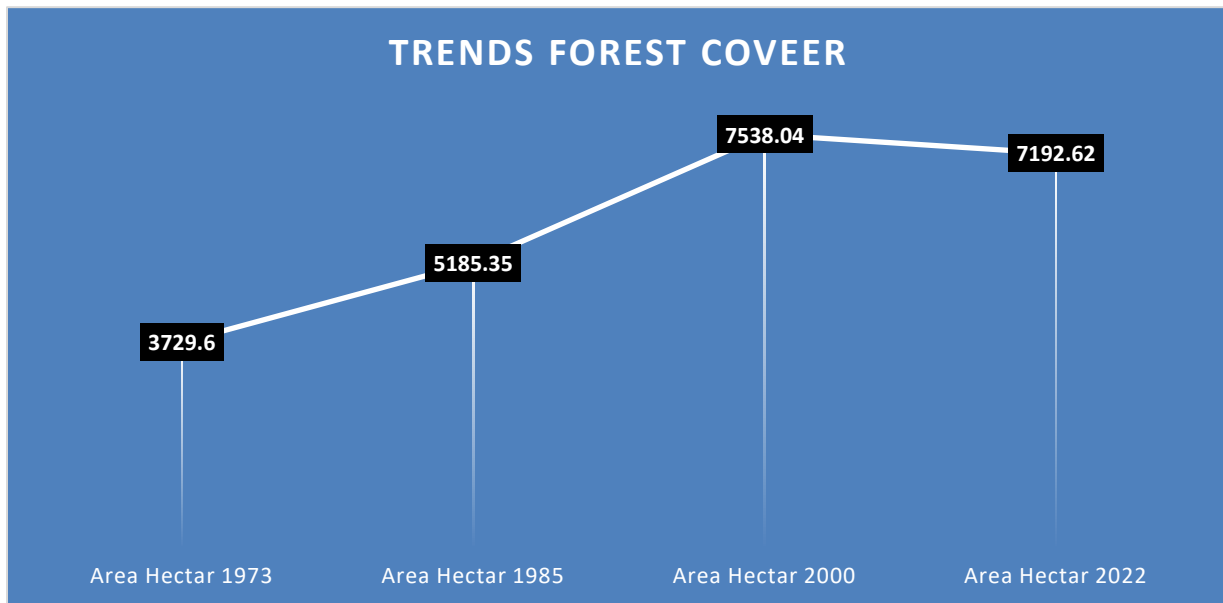


Figure 19: Trends of Forest cover change (1973-2022)

In other words, the table (16) presented on above in the study revealed that, the dominant land use features were non-forest, which further contributed to the diminishing size of the vegetation cover. Specifically, from 1973 to 1985, non-forest features occupied 16,990.92 hectares of land, while from 1985 to 2000, they covered 14,808.87 hectares, and from 2000 to 2022, they took up 14,433.66 hectares. This dominance of non-forest features in the study area had a detrimental impact on the forest cover, causing its decline over time.

Table 17: Summary of Wufe-Whash Forest change (2022-1973) ha

Year	1973	1985	2000	2022	Δ Forest cover (2022 – 1973) ha
Forest Cover ha	3729.60	5185.35	7538.4	7192.62	3,463.02

Similarly, table 17 indicates that the Wufe-Washa Forest has experienced a net increase of 3463.02 hectares of land from 1973 to 2022. However, recent evidence from satellite images analysis, FGDs, KIIs, and ground observations suggests that the forest is currently facing significant challenges such as a reduction in size due to deforestation, wildfire, and expansion of farmland around and within the forest. In recent years, Ethiopia has experienced significant deforestation, with an estimated loss of over 2 million hectares of forest between 2000 and 2010 alone (FAO, 2016). The Wufe-Washa Forest, located in Amhara regions, is no exception. In recent a study conducted by Ayalew (2018), found that the forest has been subjected to significant degradation due to human activities, including illegal logging, grazing, and cultivation. Furthermore, the expansion of farmland around and within the forest has also donated to the loss of forest cover. Yesuph et al., (2016), reported that the expansion of agricultural activities in the catchment area of the Wufe-Washa forest has led to increased soil erosion, sedimentation, and land degradation. This, in turn, has impacted the hydrological functioning of the forest, leading to reduced water availability and quality. In addition, the Wufe-Washa forest is also susceptible to wildfires, which can cause significant damage to forest ecosystems.

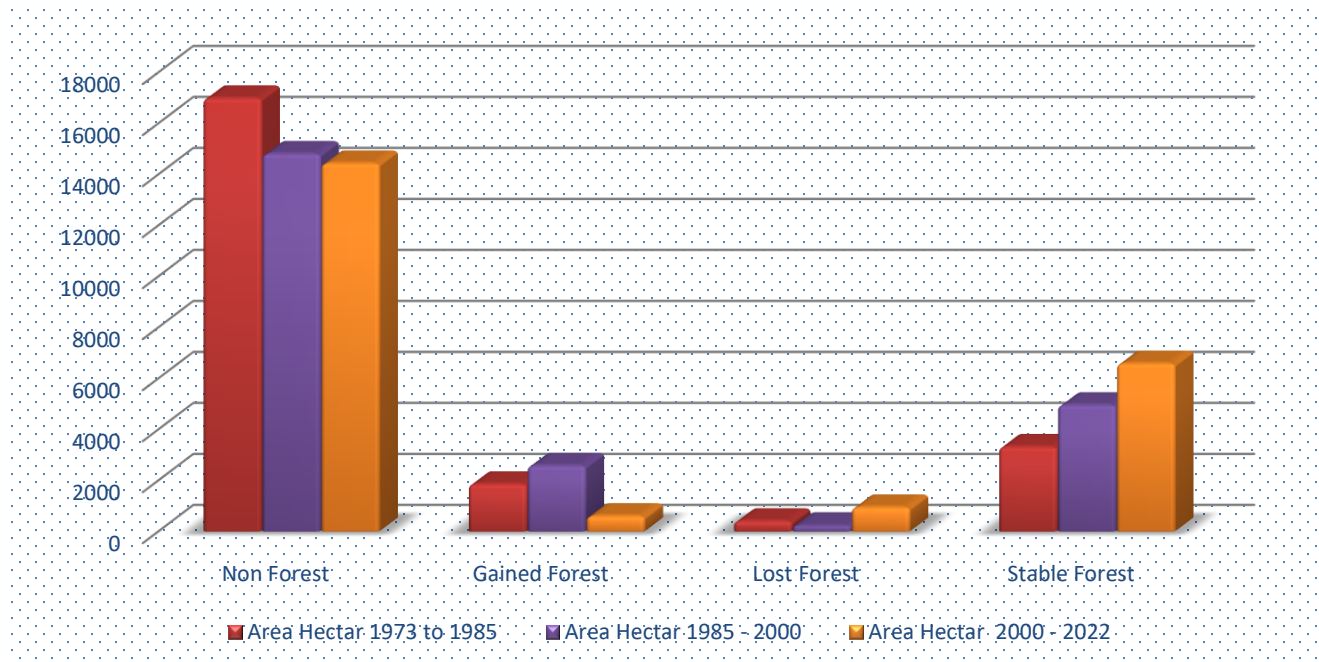


Figure 20: Graph Forest cover change (1973-2022)

Moreover, apart from the findings obtained through household surveys, deforestation emerges as a significant contributing factor to the modification of forested areas. One notable aspect relates to the demand for domestic energy, as evidenced in Table 18. The data reveals that a large proportion of participants are heavily rely on wood as their primary energy source for household purposes. Specifically, out of the total respondents, 141 individuals, representing 64.4% of the sample, reported wood as their main fuel choice.

Charcoal emerged as the second most prevalent energy source, with 33 households (15.1%) indicating its usage. The remaining participants reported utilizing animal dung or crop residuals, constituting 27 (12.3%) and 18 (8.2%) households, respectively. An in-depth examination of the table demonstrates that the majority of respondents who utilize wood for energy depend on natural forests as their primary source, accounting for 51.1% of all participants. Homestead trees ranked as the second most common source, adopted by 7.8% of respondents, while 5% reported purchasing wood from the market. The remaining 36.1% of participants abstained from using wood for energy and instead opted for crop residuals, animal dung, or charcoal.

Table 18: Energy sources of the households

Commonly used energy sources for your household			Source for household fire wood		
Biomass type	Frequency	Percent	Biomass type	Frequency	Percent
Wood	141	64.4	Homestead tree	17	7.8
Crop residuals	18	8.2	Natural Forest	112	51.1
Animal dung	27	12.3	From Market	11	5.0
Charcoal	33	15.1	Other	79	36.1
Total	219	100.0	Total	219	100.0

Source; Field survey January 2023

These findings suggest that the community's heavy reliance on wood for energy consumption has a significant impact on the forests in the area, both directly and indirectly. This dependence has led to forest degradation and has negatively impacted the biodiversity of the region.

In conclusion, while the Wufe-Washa forest has experienced a net increase in land over the past few decades, recent evidence suggests that the forest is currently facing significant challenges due to deforestation, farmland expansion, and wildfires. These challenges not only impact the forest ecosystem but also have significant implications for the livelihoods of nearby communities.

4.4. Classification Accuracy Assessments

Accuracy assessment is a crucial step in the classification process, as it helps to determine the level of accuracy of the classification results. In this study, post-classification accuracy assessment was carried out for the years 1973, 1985, 2000, and 2022. The overall accuracy of the classification results was found to be 88.70%, 89.65%, 87.73%, and 95% for the respective years. Additionally, the kappa coefficient values for the years 1973, 1985, 2000, and 2022 were 85%, 87%, 84%, and 93%, respectively. Further analysis showed that the producer's accuracy for shrub land in 1985, settlement in 2000, and grasslands in 2022 were the lowest, while the highest accuracy levels were achieved for forests, bare land, and cropland in 2022. The kappa statistics for 2022 had a value of 0.93, indicating a high level of agreement between the classification results and the ground truth.

The error matrix of 2022 showed that the producer's accuracy for forests, cropland, and bare land was 100%, while settlement had an accuracy of 91.67%, and shrub land and grassland had accuracies of 78% and 60%, respectively. The omission errors were found to be highest for grassland (40%), while there were no omission errors for forests, cropland, and bare land. The user's accuracy for forests, cropland, grassland, bare land, settlement, and shrub land was 100%, 94%, 100%, 94%, 100%, and 75%, respectively. The commission errors were found to be lowest for grassland, settlement, and forests at 0%, and 75% for shrub land. Overall, the results of the accuracy assessment indicate that the classification process was successful, with high levels of accuracy achieved for most land cover classes in 2022.

Table 19: Classification Accuracy Assessment Error Matrix for 2022 LULC classification

Land Class	Bare land	Crop land	Forest	Grassland	Settlement	Shrub land	Total sum	User Accuracy
Bare land	9	0	0	0	1	0	10	90.00%
Crop land	0	34	0	1	0	1	36	94.44%
Forest	0	0	16	0	0	0	16	100.00%
Grassland	0	0	0	3	0	0	3	100.00%
Settlement	0	0	0	0	11	0	11	100.00%
Shrub land	0	0	0	1	0	3	4	75.00%
Total sum	9	34	16	5	12	4	80	
Producer accuracy	100.00%	100.00%	100.00%	60.00%	91.67%	75.00%		

4.5. Drivers of the land use land cover change and its implication

LULCC are complex phenomena that result from the interplay of numerous factors. The commonly held belief that a few factors are solely responsible for these changes is not accurate. In reality, a multitude of interrelated factors are responsible for these changes (Lambin & Geist, 2007). In the specific case of Wufe-Washa forest and its surrounding area, LULCC, particularly forest cover changes, are driven by various factors. While natural processes may play a role in land cover changes, human-induced land use changes are the primary driving force globally, and their impacts are currently increasing at an alarming rate. Most of the factors are responsible for LULCC in Wufe-Washa forest and its neighbouring area are human-induced, resulting in the significant conversion of forest land into other land use units.

Scholars have identified two broad categories of reasons for land use and land cover changes: proximate (direct) and underlying (indirect or root causes). Proximate causes refer to the immediate actions that result in changes in land use and land cover. On the other hand, underlying causes refer to the fundamental drivers of land use and land cover changes, such as economic, social, and political factors (Geist & Lambin, 2002). Understanding these underlying factors is essential for developing effective strategies to mitigate land use and land cover changes and their impacts. According to a recent study by Lu et al. (2021), the primary underlying factors driving land use and land cover changes in China include population growth, urbanization, and economic development. Similarly, in Ethiopia, agricultural expansion, urbanization, settlement, and population growth have been identified as the primary underlying factors driving land use and land cover changes (Berihun, 2019).

4.5.1. Agricultural land expansion

According to Mekkonen et al. (2018), the growth of agriculture in the country of Ethiopia is one of the primary causes of land cover change, particularly the destruction of natural forests. From 1973 to 2022, there will be an increase in agricultural land, according to the study regions' results for detecting changes in land use and land cover. The conversion of other LULC classifications into agricultural lands is the implication of increased agricultural land in terms of area coverage. Agricultural land expansion at the expense of other LULC types, to meet

the demand for food from the ever-increasing human population, and the building of homes for newlyweds are two additional factors that have led to changes in land use and land cover.



Source: Field observation by the researcher, January 2023

Figure 21: Farmland expansions near to the forest Mescha kebele

The respondents also note that because the region may be crucial for farmland, the activity is more likely to spread to other areas of different LULC, such as grazing land and forest land, and as a result, the majority of private pasture land is converted to agricultural use. Additionally, this activity spread to uplands covered with forest. As a result, the amount of forest in the area is steadily declining due to the growing conversion of forest land for cultivation and the continued infringement of farming towards the boundaries of mountain forests.

4.5.2. Deforestation

Based on (FAO, 2015) findings, the reason for the substantial reduction in forest area in Ethiopia are deforestation for agricultural purposes, a distressing and accelerating phenomenon. The surge in population and extensive agricultural practices has created a high demand for firewood, contributing significantly to this disturbing trend. Deforestation is also a major driver of changes in LULC within the study area. The forest cover in this region has exhibited an unstable pattern over time. Between 1973 and 1985-2000, there was an increase in forest size by 1,856.88 and 2,582.64 hectares, respectively. However, from 2000 to 2022, there was a noticeable decline of 950.58 hectares of forest land, as detected through methods examining land use and forest cover changes.

Moreover, in addition to the quantitative data collected, qualitative insights were gathered through focus group discussions with local elders in the study area. These discussions revealed that human activities have exerted both positive and negative impacts on the forests. For instance, between 1973 and 1985, as well as from 1985 to 2000, the government actively participated in tree planting efforts, leading to an increase in the number of trees within the area. However, during the period between 2000 and 2022, the forests were consistently affected by human activities, as well as natural occurrences such as recurring wildfires. The elders expressed their concerns about the continuous decline in forest coverage, with deforestation and the conversion of forests into cultivated and grazing lands becoming increasingly severe.

Furthermore, the quantitative data collected, focus group discussions were conducted with elders in the study area to gain qualitative insights into the state of the forests. The discussions revealed that human activities have had a significant impact on the forests, particularly in the period between 2000 and 2022. The elders reported that there has been a continuous decline in forest coverage in the area, with deforestation and conversion of forests into cultivated and grazing lands becoming increasingly severe.

4.5.3. Demographic Factor

Land use and land cover change is a complex phenomenon that is influenced by a variety of factors, including demographic pressures. In Ethiopia, population growth and increasing demand for food, fuel, and other resources have put significant pressure on the country's land resources, leading to

widespread LULCC (Kindu .2017). The population of Ethiopia has been rapidly increasing in recent years, with estimates suggesting that the country's population may reach 210 million by 2060 (United Nations, 2021). This demographic pressure has led to an expansion of agricultural lands, as farmer's clear forests and other natural habitats to make way for crops and livestock. Additionally, the growing demand for fuelwood has led to deforestation and forest degradation, further exacerbating land use and land cover changes in Ethiopia.

According to Amhara Regional State Forest and Wild Life Protection Authority unpublished document 2021 stated that, the last 28 years in three kebele woredas namely Taramaber, Baso Worena and Ankober the population of these woredas increased an alarming rate. In 1995, the population was 143,526. In 2007, it increased to 281,921, and in 2021, it was 347312.

The difference between 2021 and 1995 is 124966 people in the total of 347312 people. Over the past 28 years, the population has increased by 49.18%, an average of 1.76% per year.

Table 20: Demographic information of the selected woredas

Woreda	1999(2007)			2013(2021)			Sum difference 1995-2021
	Male	Female	Total	Male	Female	Total	
Ankober	33,791	33570	67361	38,790	37,720	76,510	73196
Baso Worena	56868	55305	112,173	61924	59006	120,930	119
Taramaber	37197	37323	74520	42812	41669	844481	51651
Total	127,856	126,198	254,054	143,526	138,395	281,921	124966

Source, Amhara Regional State Forest and Wild Life Protection Authority 2021

The pressure on resources and land use is high, so improving productivity is critical. Alternative income sources can also help alleviate this pressure. Making resources available and raising public awareness can also help.

4.5.4. Economic Factor: market price increment of for forest product

In addition to deforestation, the primary factor contributing to the change in land use and land cover in the Wufe-washa, market-oriented forest products for construction of new settlement houses and building. This has led to a surge in demand for forest resources, which has resulted in deforestation and the conversion of forested land into other uses such as agriculture and settlement.



Source; Field observation by the researcher January 2023

Figure 22: Forest products for construction of new settlement Wufe-Washa Genetet Kebele

The rise in market price of forest products has created economic incentives for individuals and communities living near the Wufe-Washa forest to exploit forest resources for their own economic gain. This has resulted in unsustainable harvesting of timber and non-timber forest products such as fuelwood, charcoal, and medicinal plants. As a result, the forest has been degraded

and fragmented, leading to the loss of biodiversity, soil erosion, and water scarcity (Lambin et al., 2003, Neggassa et al., 2020).

4.5.5. Institutional Factor

Land use and land cover change in Ethiopia are influenced by institutional factors, which include policies, laws, regulations, and institutional frameworks. These factors determine how land use and management are practiced and decided. They also affect the governance and enforcement of these practices and decisions (Bewket, 2015). However, sometimes the governance structures may be ineffective, leading to weak enforcement of land use and management regulations. This can worsen the causes of land use and land cover change. Moreover, a lack of coordination among different institutions involved in land use and management can make it difficult to achieve a coherent and integrated approach to land use planning and implementation.

Therefore, institutional factors have a strong impact on land use and land cover change in Ethiopia. These factors consist of policies, laws, regulations, and institutional frameworks that shape land use and management practices. But the impact of these factors also depends on the governance, enforcement, and coordination of these practices. Addressing these institutional issues is important for reducing the causes of land use and land cover change in Ethiopia. (Tefferu, 2011).

KIIs and FGDs have been conducted to gather evidence about the factors leading to the illegal deforestation of Wufe Washa forest in Ethiopia. From the discussion indicate that, institutional factors have played a significant role in this environmental degradation. Specifically, during the regime changes that occurred in 1974, 1991, and 2018, the government lacked the ability to enforce laws and regulations effectively, which enabled people living around the forest to expand their farmland and grazing areas. The forest ranger's experience of serving under four different governments sheds light on the issue. He explained that;

'Lack of law enforcement allowed the locals to take advantage of the political instability and encroach upon the forest land. Consequently, the forest cover has decreased, and the ecosystem's biodiversity has been threatened. These institutional factors are among the main drivers of the illegal deforestation of Wufe-Washa forest. Therefore, there is an urgent need for more effective measures to be implemented to combat this problem. The government must strengthen

its law enforcement capabilities to prevent the encroachment of the forest land. Additionally, alternative livelihood options must be provided to the people living around the forest to minimize the dependency on forest for economic gain. The conservation of the Wufe-Washa forest is critical for sustaining the region's ecological balance and maintaining the welfare of its inhabitants'.

4.5.6. Implication of LULC dynamics on the study area

Land use and land cover dynamics have profound implications for the Wufe-Washa forest and its surrounding regions, as they impact various aspects of the ecosystem and local communities. The Wufe-Washa forest, situated in the uplands of Ethiopia, plays a vital role in supporting the livelihoods of nearby communities and providing essential ecosystem services like water regulation, carbon sequestration, and biodiversity conservation. Unfortunately, the forest is facing multiple threats due to human activities, resulting in changes in land use and land cover patterns.

One of the primary implications of these land use and land cover dynamics on the Wufe-Washa forest and its neighboring areas is the issue of deforestation. Deforestation is a significant problem in Ethiopia, driven by factors such as population growth, expansion of agriculture, and demand for fuel wood. In the context of Wufe-Washa, deforestation has caused a loss of forest cover and fragmentation of the remaining forest patches. This, in turn, has led to a decline in biodiversity, increased soil erosion, and a reduction in the availability of water resources in the region. The loss of forest cover and fragmentation have severely impacted the biodiversity of the Wufe-Washa forest and its neighboring areas.

Deforestation has led to the destruction of habitat for many plant and animal species that live in the forest. As a result, the number and diversity of these species have decreased. Some of these species are unique to the region, meaning they do not exist anywhere else on the planet. The loss of biodiversity has wider ecological consequences, as it disturbs the fragile equilibrium of the ecosystem and affects the stability of the whole region

Furthermore, land use practices such as agriculture and grazing have contributed to soil degradation and reduced soil fertility in the area surrounding Wufe-Washa. Unsustainable agricultural practices, including overuse of land and improper soil management, have led to a decline in soil

quality. Consequently, this has caused reduced agricultural productivity and an increased occurrence of soil erosion. Soil erosion further exacerbates the problem of deforestation, as it accelerates the loss of fertile topsoil, degrades the quality of water resources, and negatively affects local communities' livelihood. During my conversation with a key informant who is an expert on natural resources and resides in the Wufe Washa forest area, he shared some valuable insights. He explained that,

“Due to the ongoing deforestation activities in and around the forest, the local inhabitants have been negatively impacted. These activities have led to the degradation of agricultural land, resulting in a decline in agricultural yields and a negative impact on the livelihoods of the locals. Furthermore, he pointed out that the ecosystem of the forest and surrounding areas have been affected by climate change, leading to an expansion of aridity and an increase in the frequency of wildfires. The temperatures and precipitation levels have fluctuated significantly in the past 20 years, and rainfall patterns have changed, occurring later or earlier than usual with minimal amounts. In light of these changes, farmers in the highland areas have shifted their focus towards cultivating crops such as teff, sorghum, and maize, which are typically grown in arid areas

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The primary objective of this research was to explore the implications of dynamic changes in land use and land cover on the Wufe-Washa forest and its surrounding regions. Additionally, the study sought to investigate the historical patterns of these changes, their underlying reasons, and the consequences they have had on the forest and the local community. To analyze the spatial dynamics of these alterations, various techniques were employed, including GIS, remote sensing, and machine learning, specifically utilizing the random forest classifier, in conjunction with field observations. Qualitative data such as interviews and discussions with key informants and focus groups were also employed to examine the causes and implications of the land use and land cover dynamics in the study area.

By analyzing raster data, the study identified six major types of land use and land cover for the Wufe-Washa forest and its surrounding area based on Landsat satellite images from 1973, 1985, 2000, and 2022. These types included forest, shrub land, bare land, grassland, settlement, and crop land. Furthermore, change detection analysis was conducted by comparing classifications from different time series raster images at specific intervals.

The study utilized the LULC classification method to analyze changes in land use and land cover across three comparison periods (1973-1985, 1985-2000, and 2000-2022). The findings revealed significant variations in spatial distribution and area coverage among different land use categories. Forest land experienced fluctuation throughout the three periods, with a 39.03% increase of 1553.67 hectares and a yearly change rate of 3.25% during 1973-1985, a 45.37% increase of 2352.69 hectares and a yearly change rate of 3.02% during 1985-2000, and a 4.58% decrease of 345.42 hectares and a yearly change rate of -0.21% during 2000-2022.

On the contrary, cropland and settlements exhibited continuous increments over the three comparison periods. Cropland expanded by 22.65% or 1553.67 hectares with a yearly change rate of 1.89% during 1973-1985, by 17.77% or 1494.99 hectares with a yearly change rate of 1.18% during 1985-2000, and by 19.46% or 1927.98 hectares with a yearly change rate of 0.88% during

2000-2022. Similarly, settlements increased by 20.22% or 143.46 hectares with a yearly change rate of 1.68% during 1973-1985, by 22.41% or 191.16 hectares with a yearly change rate of 1.49% during 1985-2000, and by 39.14% or 408.69 hectares with a yearly change rate of 1.78% during 2000-2022. Grassland shows variations across different periods, initially experiencing a 65.75% increase of 684.54 hectares with a yearly change rate of 5.48% during 1937-1985, followed by a significant decline of 42.54% or -734.13 hectares with a yearly change rate of -2.84% during 1985-2000, and a further decrease of 82.96% or -822.60 hectares with a yearly change rate of -3.77% during 2000-2022.

The remaining two land cover classes, scrubland and bare land, consistently decreased throughout the three consecutive comparison periods. Shrubland diminished by 21.50% or -1257.12 hectares with a yearly change rate of -1.79% during 1973-1985, by 68.95% or -3164.22 hectares with a yearly change rate of -4.60% during 1985-2000, and by 33.73% or -480.51 hectares with a yearly change rate of -1.53% during 2000-2022. Bare land also exhibited a continuous decline, with a 58.7% decrease of -2580.84 hectares and a yearly change rate of -4.90% during 1973-1985, a 9.37% decrease of -140.49 hectares and a yearly change rate of -0.52% during 1985-2000, and a 41.22% decrease of -688.14 hectares and a yearly change rate of -1.87% during 2000-2022.

Furthermore, a post-classification accuracy assessment was conducted for the years 1973, 1985, 2000, and 2022 to evaluate the precision of the land use and land cover classifications. The results of the assessment indicated that the overall accuracy of the classifications for the respective years were 88.70%, 89.65%, 87.73%, and 95%. Moreover, the kappa coefficient values were found to be 85%, 87%, 84%, and 93% for the same years, respectively.

In general, the study revealed that machine learning classifiers like random forest algorithm performed well in achieving high accuracy results, particularly in identifying forest and vegetation geographic features. In addition, that in the study find, the transformation of Wufe-Washa forest's land cover is due to a multitude of complex and interconnected factors, with human activity being the primary contributor to the massive conversion of forested land into other land uses. The study shows that deforestation and agricultural expansion are the main immediate causes of LULCC in the area. However, underlying factors such as population growth, shortage of farming and grazing lands, demand for wood, inadequate government policy implementation, and political instability

also play a significant role. The study further reveals that the changes in land use and land cover have adverse impacts on both the biophysical resources and the livelihoods of the community in the study area. Field surveys and observations have identified loss of biodiversity, land degradation, and reduced soil fertility and vegetation as some of the biophysical impacts of the LULCC.

5.2. Recommendation

After conducting comprehensive analyses of land change detection statistics and survey data gathered from the local community a recommendation has been identified. These recommendations are absolutely indispensable in safeguarding and conserving the esteemed Wufe-Washa forest.

First and foremost, it is imperative that the government, NGOs, and forest administration or workers embrace the utilization of advanced technologies such as Geographic Information Systems (GIS), remote sensing, and machine learning approaches for assessing Land Use and Land Cover Change (LULCC). Adopting this integrated approach will yield accurate and up-to-date information regarding the dynamic changes in land use and cover. Furthermore, it will enable the production of highly precise LULC maps and facilitate an in-depth evaluation of the extent to which resources are being conserved effectively and efficiently.

The second recommendation highlights the utmost significance of forest conservation, specifically emphasizing the delineation and preservation of the existing forest boundaries. Forest conservation serves as the cornerstone for maintaining the delicate ecological balance and ensuring the sustainable utilization of natural resources. Protecting the integrity of the current forest cover against degradation and deforestation is of paramount importance. One highly effective strategy to achieve this goal involves the meticulous delineation of forest boundaries and steadfast commitment to their preservation.

Thirdly, promoting and fostering the development of non-agricultural economies, with particular emphasis on eco-tourism, should be accorded the highest priority. This strategic approach holds the potential to alleviate the mounting pressures exerted on the park's precious natural resources while simultaneously bestowing significant economic benefits upon the local community.

The fourth recommendation accentuates the pivotal role played by active participation from the local community in the successful implementation of conservation measures. Without their

wholehearted involvement, the effectiveness of any conservation efforts is bound to be limited. To accomplish this, it is of paramount importance to enhance the knowledge and awareness levels of local communities regarding the principles and practices of participatory forest management (PFM).

Lastly, the final recommendation underscores the imperative nature of recognizing the ecological significance embodied by the esteemed Wufe-Washa forest. This extraordinary forest stands as a haven for a rich tapestry of diverse flora and fauna, boasting the presence of numerous endemic species. Consequently, it is highly recommended that this magnificent forest be designated as a national park.

Furthermore, the national park status offers remarkable opportunities for scientific research, education, and eco-tourism, all of which have the potential to significantly contribute to both the local and national economy. Additionally, it serves as a powerful instrument for raising awareness regarding the profound significance of safeguarding biodiversity and embracing the sustainable utilization of our precious natural resources

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APPENDIX 1

SURVEY QUESTIONNAIRES

Addis Ababa University

School of Graduate Studies

Three kebeles from the Wef-Washa Forest proposed to be done individually in this study: Kebeles are, Wef-Washa Genete, Keyit, and the Mescha Kebeles.

Title of paper: Implication of land use/ land cover dynamics on Wef_Washa Forest.

This survey's goal is to gather information on the factors that have an impact on the forest cover and the land use of Wef_Washa forestland and its surrounding area. Policy makers and development professionals were anticipated to benefit from the information generated regarding the scope and patterns of changing land use and land cover, as well as the effects on local communities and the biophysical environment.

The information provided will remain confidential, and your responses will only be used for this study. As a result, your input as a stakeholder to fill out this questionnaire is highly appreciated. You are kindly requested that there will be no need to identify yourself or write your name in the answers you provided. Any information you provide will be kept private. Your assistance is, therefore, crucial to achieving the study's intended purpose.

Identification of the Respondents (Household head)

Code No. _____

Keble Name: _____ *Village:* _____

Date of interview: _____

Part one Household Characteristics

1.1 Demographic Characteristics

Sex: I) Male II) Female

1.2. Age: _____

1.3. **Marital Status of the household:** I) Married II) Unmarried III) Divorced IV) Widowed

1.4. Education Level:

I) Illiterate II) Read and Write III) Grade 1st -8th IV) Grade 9th - 12th V) above 12th grade

1.5. **Family size:** male _____ female _____ total _____

Part II Economic Activity

Direction; Circle or fill in the blanks for the following questions; choosing more than one alternative is possible wherever necessary.

2.1. **Do you have a farmland?** 1) Yes 2) no

If your answer is 'yes', what is the estimated total size of your farmland? _____

I) Less than 1 ha II) 1-2ha III) 3-4ha IV) above 4ha'

2.2. **What is your major economic activity?**

I) Crop production II) animal rearing III) Mixed farming IV) others, specify _____

2.3. **Means of farmland acquisition**

I) Distribution II) Redistribution III) Inheritance IV) Inheritance and Redistribution V) Gift

VI) Others, specify _____

2.4. **Do you think that your farmland is getting smaller or bigger?**

I) Smaller II) Bigger III) None

2.5. If your answer is ' bigger' what are the reasons behind the increments?

I) Cultivation of forest land II) Cultivation of grazing land III) Others, specify

2.6. If your answer to Q No.2.5 above is 'decreasing', what are the root causes?

I) Share with my children II) Land redistribution III) Land taken away by government

IV) Others specify

2.7. Do you own livestock? 1) Yes 2) No

2.8. If "Yes", what number of livestock do you own?

I) cow _____ II) oxen, _____ III) sheep _____ IV) goat _____ v) donkey VI) others specify _____

2.9) what is the trend of your livestock holding?

I) Increasing II) Decreasing III) No change

2.10. How do you feed your livestock? I) Free grazing on communal grazing land II) Cut and carry from communal pasture land III) Own grazing land IV) Others (specify) _____

2.11. How do you see the size of grazing land overtime?

I) Increasing II) Decreasing III) Remain the same

2.12. If your answer is ' decreasing', what are the reasons?

I) Expansion of farm land II) Degradation of grazing land due to over grazing III) Grazing land changed to area closure IV) Other (specify) _____

2.13. What are the most commonly used energy sources for your household?

I) Wood. II) Animal dung III) Crop residues IV) Charcoal V) Others specify _____

2.13. If your answer is wood where are the sources?

I) Own homestead tree II) Natural forest III) From market

Part III. Land use land cover change: its pattern, drivers, and impacts

3.1) Have you noticed any change in the land use/land cover in your locality over the past 48 years or so? I) Yes II) No

3.2) If “Yes” what major changes occurred in your locality in the past 48years? Give your opinion as (1= increasing, 2= decreasing, 3 = no change and 4=don’t know).

Land use type	1970s to 1985	1985s to2000	Since 2000
Cultivation land			
Settlement			
Grazing land communal			
Plantation Forest			
Forest			
Shrub land			
Bare land			

3.3) what are the factors that drive the alterations in land use/land cover.

I) Wood prices and availability II) Population increase III) Expansion of agricultural land IV) Introduction of new development projects VI) Climate change VII) Others, specify_____

3.4. List the problems you personally faced due to increases in land use/cover change. List them in order of importance.

3.5. Following the land use/land cover change, which environmental problems become very common in your area? I) Soil erosion II) Degradation of watersheds III) Change in local climate IV) Lack of grazing land IV) Lack of trees to hang beehives IV) Others, specify_____

3.6. What kind of land use land cover conversion have you seen in Wefe -Washa Forest and its surrounding? I) Forest land to agricultural land. II) Forest land to grazing land. III) Grazing land to agricultural land IV) Bush/wood land to grazing land

APPENDEX 2

የዳሰሳ ጥናት መጠይቅ ናሙና ቅጽ

በዚህ ጥናት ከወፍ ዋሻ አካባቢ እና አዋሳኝ የሆኑት ሦስት የገጠር ቀበሌዎች ማለትም ወፍ ዋሻ-ገነቴ ከጣርማ በር ወረዳ ፣ ቀየት ከቦሰና ወረዳ እና መስጫ ቀበሌ ከአንኮበር ወረዳ በተናጠል እንዲደረግ ሃሳብ ቀርቦአል። የዚህ ጥናት ርዕስም “የመሬት አጠቃቀም እና ሽፋን ለተለዋዋጭነት አንድምታ በወፍዋሻ ደን ላይ የሚል ሲሆን የዚህ የዳሰሳ ጥናት አላማ በዋናነት በአዲስ አበባ ዩኒቨርሲቲ፣ ልማት ጥናት ኮሌጅ እና የአካባቢ እና ዘላቂ ልማት መማሪያ ትምህርት ክፍል የሁለተኛ ዲግሪ ጥናታዊ ፅሁፍ ማሟያ የመመረቂያ ፅሁፍ እና፤

በዚህም ዳሰሳ በወፍ ዋሻ ደን እና አካባቢው የደን ሽፋን ፣ የመሬት አጠቃቀምን የሚመለከቱና የደን ሽፋን ለተለዋዋጭነት እንዲሁም አንድምታ ለተለዋዋጭነቱ እና አንድምታ ጋር ምክንያት እና እያደረሰ ያለውን ነባራዊ ሁኔታ ለመጠየቅ የቀረበ መጠይቅ ነው።

ስለዚህም የእርስዎ ምላሾች ለዚህ ጥናት ብቻ ጥቅም ላይ ይውላል። በዚህ ምክንያት ይህንን መጠይቅ ለመሙላት እንደ ባለድርሻ አካል ለምታደርጉልኝ ትብብር በጣም አመሰግናለሁ።

በመልስዎ ውስጥ እራስን መለየት ወይም ስምዎን መጻፍ አስፈላጊ አለመሆኑን በትህትና እገልጻለሁ። የሚያቀርቡት ማንኛውም መረጃ በሚስጥር ይጠበቃል።

የጥናት ግቦቹን ለማሳካት የእርስዎ እርዳታ ወሳኝ ነው።

ምላሽ ሰጪዎችን መለየት

መለያ ቁጥር _____

ቀበሌ _____ መንደር _____

የቃለ መጠይቅ ቀን _____

ክፍል አንድ የመጠይቅ ተሳታፊዎች መረጃ

ለሚከተሉት ጥያቄዎች ክፍት ቦታዎችን ያክብቡ ወይም ይሙሉ።

- 1.1. የስነ ህዝብ ባህርያት
- 1.2. ጾታ 1) ወንድ 2) ሴት
- 1.3. እድሜ _____
- 1.4. የጋብቻ ሁኔታ 1) ያገባ 2) ያላገባ 3) የፈታ 4) የሞተበት
- 1.5. የትምህርት ሁኔታ 1) ያልተማረ 2) ማንበብ እና መጻፍ 3) ከ1ኛ-8ተኛ ክፍል

4)ከ9ኛ-12ተኛ 5)ከ12ኛ በላይ

1.6. የቤተሰብ ብዛት :- ወንድ _____ ሴት _____ አጠቃላይ _____

ክፍል ሁለት

አቅጣጫ :- ለሚከተሉት ጥያቄዎች ክፍት ቦታዎችን ያክብቡ ወይም ይሙሉ:: አስፈላጊ ከሆነ ከአንድ በላይ አማራጮችን መምረጥ ይቻላል

2.1. የእርሻ መሬት አለዎት?

- 1)አለኝ
- 2)የለኝም

መልስዎ አዎ ከሆነ የእርሻ መሬትዎ ስንት ሄክታር ይገመታል? _____

2.2. የእርስዎ ዋና የኢኮኖሚ እንቅስቃሴ ምንድነው?

- 1) የሰብል ምርት
- 2) እንስሳት እርባታ
- 3) የተደባለቀ እርሻ
- 4) ሌሎች ካሉ _____

2.3. የእርሻ መሬቶችዎ የተገኙበት ሁኔታ?

- 1) በመንግስት አዋጅ
- 2) በውርስ
- 3) በስጦታ
- 4) ሌሎች ካሉ _____

2.4. የእርሻ መሬትዎ እየቀነሰ ወይም እየጨመረ ነው ብለው ያስባሉ?

- 1) እየጨመረ
- 2) እየቀነሰ

3) ባለበት ነው

2.5. መልስዎ ትልቅ ወይም እየጨመረ ነው ከሆነ ለጭማሬው ምክንያቶች ምንድን ናቸው?

- 1) ጫካ በመመንጠር
- 2) የግጦሽ መሬትን ወደ ግብርና መሬት በመለወጥ
- 3) ሌሎች ካሉ ይገለጹ _____

2.6. ለጥያቄ ቁጥር 2.5 የሰጡት መልስ እየቀነሰ የሚል ከሆነ ዋናዎቹ ምክንያቶች ምንድን ናቸው?

- 1) ከልጆች ጋር የመሬት ክፍፍል ማድረግ
- 2) የመሬት መልሶ ክፍፍል (የመሬታ አዋጅ)
- 3) የመሬት መራቆት እና መሽርሽር
- 4) በመንግስት መነጠቅ
- 5) ሌሎች ካሉ ይገለጹ _____

የመሬት አጠቃቀም የመሬት ሽፋን ለውጥ : ሂደት ፤ መንስኤዎች ተጽእኖዎች

3.1 ላልፏት አርባ አምስት ዓመታት እና ከዚያ በላይ በቀዳሚ እና በአካባቢዎ ላይ የመሬት አጠቃቀም/ የመሬት ሽፋን ለውጥ : እንዳደረገ ምን ዓይነት ለውጥ አስተውለዋል?

- 1) ለውጥ አድርጎአል
- 2) ለውጥ አላደረገም

3.2. መልስዎ "አዎ ለውጥ አድርጎአል " ከሆነ ባለፉት 45 ዓመታትና ከዚያ በላይ ውስጥ በአካባቢዎ ምን ዋና ለውጦች ተከስተዋል?

(1 = እየጨመረ፣ 2 = እየቀነሰ፣ 3 = ምንም ለውጥ የለም እና 4 = አላውቅም) በማለት አስተያየትዎን ይሰጡ።

የመሬት አጠቃቀም /ሽፋን ዓይነት	1970ዎቹ እስከ 1985	1985ዎቹ እስከ2000	ከ2000 በሁ-ዋላ
የእርሻ መሬት			
ሰፊ/ የመኖሪያ መንደሮች			
የግጦሽ መሬት			

የቁጥቋጠ መሬት			
ጫካ			
የተራቆተ/ ባዶ መሬት			

3.3 በመሬት አጠቃቀም/የመሬት ሽፋን ላይ ለውጦች እንዲፈጠሩ ያደረጉ ምክንያቶች ምንድን ናቸው?

- 1) የእንጨት እና የግንባታ አቃዎች ገበያ ዋጋ መጨመር
- 2) የህዝብ ቁጥር መጨመር
- 3) የእርሻ መሬት መስፋፋት
- 4) አዳዲስ የልማት ፕሮጀክቶች መገንባት
- 5) የአየር ንብረት ለውጥ
- 6) ሌሎች ምክንያቶች ካሉ ይግለጹ _____

3.4 በጥቅሉ፣ እረስዎ በአካባቢው መኖር ከጀመሩበት ጊዜ ጀምሮ በአካባቢው

ስለ መሬት አጠቃቀም/የመሬት ሽፋን ተለዋዋጭ ለውጦች ምን ምን አስተያየቶች አሉዎት?

3.5 በመሬት አጠቃቀም/ሽፋን መለወጥ እና መጨመር ምክንያት ያጋጠሙዎትን ችግሮች

ይዘርዝሩ _____

3.6 በወፍ ዋሻ ደን እና አካባቢው ምን አይነት የመሬት አጠቃቀም/ የመሬት ሽፋን ቅየራ አይተዋል?

- I) የደን መሬት ወደ እርሻ መሬት
- II) የደን መሬት ወደ ግጦሽ መሬት
- III) የግጦሽ መሬት ለእርሻ መሬት
- IV) ቡሽ / የእንጨት መሬት ወደ ግጦሽ መሬት መቀየር

4 የቡድን ውይይት መጠይቅ

4.1 በወፍ ዋሻ ደን እና አካባቢው ለሚደረገው የመሬት አጠቃቀም /የመሬት ሽፋን ለውጥ ዋና መንስኤ ምንድን ነው?

4.2 በጥናቱ አካባቢ የመሬት አጠቃቀም ለውጦች ምክንያቶች ምንድን ናቸው?

4.3 በጥናቱ አካባቢ ለደን መጨፍጨፍ መንስኤዎች ምንድን ናቸው?

4.4 የደን ውድመቶችን ለመቆጣጠር የአካባቢው ማህበረሰብ የሚወስዳቸው እርምጃዎች ወይም ተግባራት ምን ምን ናቸው?

4.5 የመሬት አጠቃቀም /የመሬት ሽፋን ለውጥ በአዎንታዊ ወይም በአሉታዊ መልኩ ያደረሰቱን ተፅዕኖዎች ለመቋቋም፤ ለመቆጣጠር በመንግስትም ወይም መንግሥታዊ ባልሆኑ ድርጅቶች ምን ዓይነት ጣልቃገብነት እና ጥረቶች ተደርገዋል?

4.6 የመሬት አጠቃቀም /የመሬት ሽፋን ለውጦች በአካባቢው ላይ ምን ዓይነት ተፅዕኖዎች አድርሰዋል?

5 ለቁልፍ መረጃ ሰጪ ሰዎች የሚደረግ መጠይቅ

የመሬት አጠቃቀም እና የመሬት ሽፋን ለውጥ ሂደት ምን ዓይነት ነው?

በጥናቱ አካባቢ ለመሬት አጠቃቀም የመሬት ሽፋን ለውጥ ዋና ዋና ምክንያቶች ምንድን ናቸው?

በደን እና አካባቢው ላይ የመሬት አጠቃቀምን የሚቀይሩ ምክንያቶች ምንድን ናቸው?

በጥናቱ አካባቢ ለደን መጨፍጨፍ መንስኤዎቹ ምንድን ናቸው?

APPENDEX 3

Customized codes for forest and LULC Change detection studies using R studio software

```
#Forest Change Analysis 2000-2022
```

```
rm (list = ls ())
```

```
library (raster)
```

```
library(rgdal)
```

```
library(sf)
```

```
library(terra)
```

```
library(caret)
```

```
library(randomForest)
```

```
library(e1071)
```

```
library (RStoolbox)
```

```
forest2000 <- rast("C:/Users/user/Desktop/WOFWASHA/WOFWASHA/Data/w2000/Output/ForestCoverWofWasha2000.tif")
```

```
forest2000
```

```
## class      : SpatRaster
```

```
## dimensions : 709, 425, 1 (nrow, ncol, nlyr)
```

```
## resolution : 30, 30 (x, y)
```

```
## extent     : 578355, 591105, 1065045, 1086315 (xmin, xmax, ymin, ymax)
```

```
## coord. ref.: WGS 84 / UTM zone 37N (EPSG:32637)
```

```

## source    : ForestCoverWofWasha2000.tif

## name      : category

## min value :    1

## max value :    6

lgnd = c(" Non forest", "forest")

plot(forest2000,main= "Wofwasha Forest Cover in 2000 GC", plg=list(legend= lgnd))

forest2022 <- rast("C:/Users/user/Desktop/WOFWASHA/WOFWASHA/Data/w2022/Out-
put/ForestCoverWofWasha2022.tif")

forest2022

## class     : SpatRaster

## dimensions : 709, 425, 1 (nrow, ncol, nlyr)

## resolution : 30, 30 (x, y)

## extent    : 578355, 591105, 1065045, 1086315 (xmin, xmax, ymin, ymax)

## coord. ref.: WGS 84 / UTM zone 37N (EPSG:32637)

## source    : ForestCoverWofWasha2022.tif

## name      : category

## min value :    1

## max value :    6

lgnd = c(" Non forest", "forest")

plot(forest2022,main= "Wofwasha Forest Cover in 2022 GC", plg=list(legend= lgnd))

```

Class Name	Pixel count	Area (m ²)	Area Hectar 2022
Non-Forest	170936	153842400	15384.24
Forest Cover	79918	71926200	7192.62

Forest cover change analysis 2000 to 2022

```
change2000_2022 <- (forest2000*10) + forest2022
```

```
#plot(change2000_2022)
```

```
lgnd = c(" Non forest", "Gained forest", "Lost forest", "Stable forest")
```

```
plot(change2000_2022, type= "classes", main= "Forest Cover Change 2000 to 2022 GC",
```

```
col=c( "gray", "yellow", "red", "green"), plg=list(legend= lgnd), cex=1, bty="o",
box.lwd=2, bg="light grey", )
```

```
## Warning in plot.window(...): "box.lwd" is not a graphical parameter
```

```
## Warning in plot.xy(xy, type, ...): "box.lwd" is not a graphical parameter
```

```
## Warning in title(...): "box.lwd" is not a graphical parameter writeRas-
ter(change2000_2022, 'C:/Users/user/Desktop/WOFWASHA/WOFWASHA/Data/timeSeries
Change Analysis/forest_coverChange2000-2022.tif', overwrite = TRUE)
```

```
write.csv(change2000_2022, 'C:/Users/user/Desktop/WOFWASHA/WOF-
WASHA/Data/timeSeries Change Analysis/forest_coverChange2000-2022.csv')
```



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