MODELING SPATIAL AND TEMPORAL URBAN GROWTH PATTERNS AND TRENDS BY USING GEOSPATIAL TECHNOLOGIES, THE CASE OF AMBO TOWN, OROMIA, ETHIOPIA

Gemechu Alemu Eticha

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

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Geoinformatics Engineering

Office of Graduate Studies
Adama Science and Technology University

August19, 2021
Adama, Ethiopia

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APPROVAL SHEET

we, the advisors of the thesis entitled "Modeling Spatial and Temporal Urban Growth Patterns and Trends by Using Geospatial Technologies" and developed by Gemechu Alemu, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Examiners of the thesis by Gemechu Alemu have read and evaluated the thesis entitled "Modeling Spatial and Temporal Urban Growth Patterns and Trends by Using Geospatial Technologies" and examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geoinformatics Engineering.

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DECLARATION

I hereby declare that this Master Thesis entitled "Modeling Spatial and Temporal Urban Growth Patterns and Trends by Using Geospatial Technologies" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Gemechu Alemu	________________________	________________
Name of the Student	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled “Modeling Spatial and Temporal Urban Growth Patterns and Trends by Using Geospatial Technologies” prepared under our guidance by Gemechu Alemu submitted in partial fulfillment of the requirements for the degree of Mater’s of Science in Geoinformatics Engineering. Therefore, we recommend the submission of the revised version of the thesis to the department following the applicable procedures.

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LIST OF ACRONYMS

ANN	Artificial Neural Network
ArcGIS	Aeronautical Reconnaissance Coverage Geographic Information System
CA_MARKOV	Cellular automata and Markov Model
DEM	Digital Elevation Model
ERDAS	Earth Resources Data Analysis System
ENVI	Environment for Visualizing Images
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organization
GCP	Ground Control Points
GIS	Geographic Information System
LCM	Land Change Modeler
LULCC	Land Use and Land Cover change
LULC	Land Use and Land Cover
MCE	Multi Criteria Evaluation
MLP	Multilayer perceptron
MSS	Land sat multispectral scanner
OLI	Operational Land Imager
RMSE	Root Mean Square Error
Sentinel	Security the nation through infrastructure enhancements locally
SVM	Support vector machine
TM	Thematic Mapper
UN-Habitat	United Nation Human Settlement Program
UN	United Nations
USGS	United States Geological Survey
UTM	Universal Transverse Mercator

ABSTRACT

Understanding and quantifying the spatiotemporal dynamics of urban land use and land cover changes and its driving factors over space and time is essential to put forward the right policies and monitoring mechanisms on urban growth for decision making. Thus, the objective of this study was to analyze the Spatio-temporal dynamics of urban areas in Ambo town by applying geospatial and land-use change modeler tools. The change detection of multiple Landsat images was conducted to map and analyzed the extent and rate of land use/land cover change in the Ambo town between 1990 and 2021. Image classification was using support vector machine algorism and the simulation of built-up area based on the past trend using land change modeler. Subsequently, the urban growth extent of the area was forecasted for the years 2030, 2040, and 2050 on the land change modeler using Multi-Layer Perceptron neural network, with the combination of Markov chain method, together with drivers representing proximity, biophysical, and socioeconomic variables and finally the relationship between population growth and urban built-up area expansion were analyzed using regression analysis. Overall, the results show there were extensive LULC changes in Ambo town over the Study Period (31years). Agriculture land and grassland were dominant classes at the beginning but declined with the continuous increase of urban land area. The coverage of grassland and agricultural land was 41.45% and 33.94% of the total area at the beginning of the study timeframe respectively. After 31 years, grassland and forest area dramatically dropped to about 14.58% and 8.63% respectively. By contrast, the proportion of the urban class was 2.93% in 1990, this figure rose to just over 16.65% in 2021. Agriculture decreases by negative net change59.31% in the last period. LULC Classes that contribute more net change in a built-up area for three decades (1990-2021) were grassland that contributes (765Ha), agriculture land (612Ha), forest area (34 Ha), barren land (9Ha) and water body contribute (6.4Ha). In the next coming 30 years, it will be expected that urban built-up land area is increased from 19.97% to 26.90%,33.27%, and 38.42% of the total area coverage according to prediction at 2030,2040 and 2050 respectively. As the study reveals also the relationship between population growth and urban built-up area expansion was also a positive correlation. The success of this research in generating a future urban land-use map for 2030, 2040, and 2050, together with the other significant findings, demonstrates the usefulness of spatial models as tools for sustainable city planning and environmental management.

Keywords: *land use/land cover; urban growth prediction; spatiotemporal; geospatial technologies*

CHAPTER ONE: INTRODUCTION

According to Clark (1982) Urban area commonly refers to towns and cities an urban landscape. Urban development is the process of the emergence of the world dominated by cities and by urban values. It is important to draw a clear distinction between the two main processes of urban development; urban growth and urbanization. Urban growth is a spatial and demographic process and refers to the increased importance of towns and cities as a concentration of population within a particular economy and society. Urbanization is the physical growth of urban areas from rural areas as a result of population immigration to an existing urban area. Although the two concepts are sometimes used interchangeably, urbanization should be distinguished from urban growth. Whereas urbanization refers to the proportion of the total national population living in areas classified as urban, urban growth strictly refers to the absolute number of people living in those areas (https://en.wikipedia.org/wiki/Urbanization).

There are many reasons why urbanization processes have been a hot research area for several decades. One of the most important reasons for such an interest is that the size and spatial configuration of an urban area directly impact energy and material flows such as carbon emissions and infrastructure demands, and thus has direct or indirect consequences on the proper functioning of Earth as a system and the quality of life of urban inhabitants.

1.1 Background of the Study

Globally, more people live in urban areas than in rural areas, with 54 percent of the world's population residing in urban areas in 2014. In 1950, 30 percent of the world's population was urban, and by 2050, 66 percent of the world's population is projected to be urban. There is significant diversity in the urbanization levels reached by different regions. The most urbanized regions include Northern America (82 percent living in urban areas in 2014), Latin America and the Caribbean (80 percent), and Europe (73 percent). In contrast, Africa and Asia remain mostly rural, with 40 and 48 percent of their respective populations living in urban areas. All regions are expected to urbanize further over the coming decades. Africa and Asia are urbanizing faster than the other regions and are projected to become 56 and 64 percent urban, respectively, by 2050 (Nations, 2014).

More recently, the world's urban population is estimated to be about 54.5 percent (World Population Prospects, 2019). Urban growth and urban built-up area expansion in large cities and small towns are increasing leading to urban sprawl. Recent studies made by various researchers indicate that the expansion of cities and towns has a positive correlation with different factors (Reis et.al, 2015; Shiferaw and Tesfaw, 2017). Despite the economic benefits, the rapid rates of urbanization and unplanned expansion of cities have resulted in several negative consequences (Reis et.al, 2015).

Most cities in developing countries are expanding horizontally following the routes of roads and railway networks, the urban sprawl is moving to unsettled peripheries at the expense of agricultural lands and areas of natural beauty and other surrounding ecosystems (Bekalo, 2009; Shiferaw and Tesfaw, 2017). Such dynamism in urban land cover can be caused by demographic, economic, or industrial factors. Currently, these are the major environmental concerns that have to be analyzed and monitored carefully for effective land use management and planning. Furthermore, the rapid urban growth and the associated urban land cover changes attracted many researchers to study and monitor the changes (Bekalo, 2009). There is no information on the extent and patterns of changes that occurred in Ambo over time. Besides, there are no extensive studies conducted related to urban growth and its impacts. Urban planners and decision-makers should consider the potential of geospatial tools to detect, monitor, and evaluate urban land cover changes.

Urban areas are complex geographic dimensions with a mixed combination of various surface cover types that exhibit a unique spectral signature (Melesse et al.; Shiferaw and Tesfaw, 2017). Remote sensing has been the best cost-effective mechanism of data acquisition for a wide range of applications ever since the launch of Landsat-1 in 1972 (babuS, 2007; Kumar and Bhanderi, 2007). Different scholars have applied many land-use modeling techniques with varying theoretical bases, assumptions, and inputs to model and predict land-use change. Several scholars have reviewed and applied these techniques in the different study areas. Bedassa uses CA and CA MARKOV to predict the urban land use/land in the case of adama city (Regassa et al, 2020). Nugusa also conducted Modeling Spatial and Temporal Urban Growth Patterns and trends by using Geospatial technologies in the Case of Modjo Town and predict urban growth using Multi-Layer Perceptron (MLP) neural network and Markov (Nugusa, 2019). Ahmed and Ahmed (2012) conducted a comparative study on different models for predicting land-use change and concluded that a combination of Multi-Layer Perceptron (MLP) neural network and Markov Chain produced the most accurate land-use change prediction. Understanding the rapid growth dynamics, developments of urban sprawl, and quantifying the spatial extent of urbanization requires a geospatial tool (Araya and Cabral, 2010).

There is no information on the extent and patterns of changes that occurred in Ambo over time. Besides, there are no extensive studies conducted related to urban growth and its impacts. Urban planners and decision-makers should consider the potential of geospatial tools to detect, monitor, and evaluate urban land cover changes.

1.2 Statement of the Problem

Urbanization and urban growth are complex systems concerning social, economic, technological, and political forces interacting together. According to the Global Risk Report (2019), the world is experiencing an unprecedented transition from predominantly rural to urban living. By 2050, the world urban population is expected to nearly double, making urbanization one of the 21st century's most transformative trends (UN-Habitat III, 2016).

This is mainly due to uncontrolled population growth resulting in serious problems, like scarcity of food, informal settlements, environmental pollution, destruction of ecological structures, and unemployment (Maktav and Erber, 2005). This kind of uncontrolled, haphazard, human settlements will lead to urban sprawl. Bureau‘s World Population Data Sheet (2002), indicates the average standard of urbanization for Africa, in general, was 33% in 2002, Ethiopia had only 15% of its population reside in urban areas. According to the US Environmental Protection Agency (2013), unplanned urban growth brings long-lasting and irreversible impacts such as degradation, loss, and fragmentation of habitat, loss of water resources, heat island effect, air quality degradation, greenhouse gas emission, and climate change. Rapid urbanization poses considerable social and environmental challenges to city authorities and planners.

Unmanaged population growth, increasing social inequality, economic disparities, and poverty all increase the potential of conflict. Poor urban planning and housing development lead to the construction of informal settlements that lack access to basic infrastructure and provide poor living conditions (Bekalo, 2009; Nugusa, 2019).

Ambo town is among the fast-growing urban centers in Ethiopia. The town has attractive Potential that contributed to its accelerated growth. Hence the expansion of the town is becoming irregular, uncontrolled, and often resulting in the creation of slums. In nearly after 15 years the population of Ambo town will double itself. This is a short doubling time when compared with the doubling time of Ethiopia, which is 23 years. The small doubling time is due to the large influx of people from the rural area to Ambo town due to seeking for an urban job, educational opportunity for that the Ambo Agricultural College is upgraded to

University level, decentralized administration system and Ambo being the capital town of the Zonal Administration.

The other factor for short doubling time is different facilities like education which attract people especially students from other places to attend high school, preparatory education and technical education in the town. This is especially true of the presence of different privately owned colleges that render training in several fields or professions in the town. The majority of trainees are not only from the town and the surrounding rural hinterlands rather come from other parts of Oromia (Ambo municipal, 2021).

So, these have partly increased the population of the town that would make the doubling time of Ambo town to be shorter (Ambo townland administration offices, 2021). Road network problem, Incompatibility, Urban deterioration, and poor urban quality, Lack of services for the center, Lack of market hierarchy, Inefficient and uncoordinated utilization of potential site and resources, Inadequacy of pedestrian walkways, Inefficient traffic management, Sanitation emergency associated with lack of waste collection system and disposal site for both solid and liquid waste, Growing pollution and land erosion, Illegal settlement, Unplanned fencing and' kiosks' on streets, Unplanned quarrying and deforestation, Lack of focus to urban redevelopment renewal and upgrading in the built-up areas, especially original settlements and inner-city are Problems Identified from the public forum (Ambo townland administration offices, 2021).

Because of the different activities and processes that take place in the urban ecosystem every day, the subject of urbanization and urban sprawl has drawn attention from ecologists, urban planners, civil engineers, sociologists, administrators, policymakers, and finally to common urban or rural residents (Dejene, 2016). Rapid urbanization poses considerable social and environmental challenges to city authorities and planners (Bekalo, 2009; Abebe, 2013).

Generally, the issues of Urban land use and land cover changes of Ambo town become the most basic problems of societies in economic, social, and environmental confusion which leads to health problems, cultural disturbance, uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands and protected Forest lands (Ambo townland administration offices, 2021).

So far in Ambo town the study related to urban land use dynamics is not conducted and low level of geo-information to figure out the extent and pattern of the change in the study area, there is also still a serious shortage of geospatial information to predict the future growth and dynamics of the town. This in turn can negatively affect the decision-making process of urban, regional, and environmental planners (Nugusa 2019; Regassa et al., 2020). Quantifying changes in land use and land cover and modeling of it for the future time is, therefore, important in Ambo town for monitoring and resolving the negative consequences. This could be useful for better land use management, environmental development and serve as a guide for decision-makers and citizens who want to create a healthy, affordable, and sustainable urban future in the study area.

1.3 Objectives of the Study

1.3.1 General objective

The general objective of this study was to analyze the Spatio-temporal dynamics of the buildup area in ambo town under the influence of urbanization from 1990 - 2050 using geospatial tools.

1.3.2 Specific objectives

Specifically, the study aspires to:

- Assess land use/land cover changes of the study area from 1990 – 2021;
- Analyze buildup area dynamics within the selected time;
- Predict the extent of buildup area based on the past trend in 2030, 2040, and 2050;
- Compare the trends of population growth and buildup area expansion in the study time frame.

1.4 Research Questions

1 What is the land use/land cover change trend of the study area?

2 What is the dynamic of buildup in the study area in spatial and temporal scales?

3 How the buildup area does change in 2030, 2040, and 2050 under the condition of business as a usual scenario?

4 How can the relationship between the trends of the population growth and built-up land expansion in the study area be explained?

1.5 Significance of the Study

The study aims to analyses land use/land cover dynamics and predicts future urban growth modeling that has gained prominence in recent years. Some significance's of study on urban land use and land cover change and future urban growth modeling: To form and implement land and policies regarding existing and future land use; Planning, management, and monitoring of natural resources and LULC is an input parameter in many fields as geology, hydrology, demography, environment, etc.

Therefore, it is expected to provide basic information on the status and dynamics of the urban land use/land cover of the area and the potential of Remote sensing data for such purpose. It is also expected to identify the rate of population growth and urban land cover changes in different times and provide greater importance to the research community, urban planners, stakeholders as well as decision making groups in terms of understanding the impacts of urban expansion and land use land cover changes in Ambo town.

1.6 Scope of the Study

This study deals with west shoa zone Ambo in the Oromia Regional State, Ethiopia. This research focuses mainly on urban growth LULC change analysis from 1990_20201and prediction of the future urban growth modeling at (2030, 2040, and 2050) using Geospatial technologies and giving hints about the importance of developing land use land cover change map for urban planning in Ambo town.

1.8 Limitations of the Study

The present study was an attempt with all possible efforts to attain required inputs in the form of primary and ancillary data collection, interpretation, and analysis. However, the study has encountered the following limitations: time constraint, financial constraint, data availability, and quality constraint.

1.9 Structure of the Thesis

The thesis was organized into five chapters. The first chapter deals with the introduction to the research and mainly addresses the statement of the problem research objective, research questions, the significance of the study, and limitations. Chapter two contains a review of related literature, it describes the main concept used in the study i.e. urban land use /land cover and its national and international experiences of the diverse study of land-use changes and modeling techniques. Chapter three deals with the description of the study area, materials and methods of data collection, and data analysis technique. Chapter four contains results and interpretation of data analysis and the last chapter includes the conclusion and recommendation.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature regarding urbanization and urban growth, land-use/land-cover changes, advances in remote sensing technology in analyzing urban growth, classification methods, geospatial tools, and their application in monitoring urban growth patterns and driving forces of urban growth and urban modeling techniques. Definition of basic terms:

Urbanization: is the process of urban expansion but, Different researchers define urbanization in various ways, some researcher defines, urbanization process is mainly linked to economic growth, commercialization, and industrialization, as well as rural-urban migration and globalization, while other researchers define urbanization is the link of population growth and urban built-up area expansion (Buhaug and Urdal, 2013).

Urban growth: is a spatial and demographic process that refers to the increased importance of towns and cities as a concentration of people within a particular economy and society (Bhatta et al., 2010).

Land use: The purpose for which land is used by humans.

Land cover: The physical surface of the earth including natural and artificial features.

GIS: is a tool used to capture, store analyze and display both spatial and non-spatial data.

Modeling: The kind of process creating the representation of reality or probability that represents reality.

Remote sensing is the art or science of acquiring information about the earth‘s surface at distance by recording reflectance using a sensor.

2.2 Theoretical Frameworks of Urban LU/LC Change and Future Urban Growth Modeling

To understand the evolution of various land-use systems, to analyze dramatic changes of land use/land cover at global, continental, and local levels, and further to explore the extent of future changes, the current geospatial information on patterns and trends in land use/land cover are already playing an important role. Remotely sensed imageries provide an efficient means of obtaining information on temporal trends and spatial distribution of urban areas needed for understanding, modeling, and projecting land changes (Elvidge, et al., 2004).

2.2.1 Forms of urban expansion

Urban expansion takes place in different forms. The major forms are the positive effects (orderly) form of urban expansion properly laid out in simple geometric forms, of urban expansion such as the center of the market area, center for production and distribution of goods and services, an opportunity for access to employment, economic development, full facilities, and technology development. The other forms are negative effects (disorderly) of urban expansion are loss of prime agricultural farmland, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, overexploitation of natural resources, and conflict (Atlas of Urban Expansion—2016 Edition | Lincoln Institute of Land Policy).

2.2.2 Consequences of urban expansion

The rapid rate of urban growth leads to rapid changes in land use and cover than ever before, particularly in developing nations, are often characterized by unrestrained urban rambling, land degradation, or the transformation of agricultural land to other uses and resulting in a massive cost to the environment (Sankhala et al., 2014). The negative effects (disorderly) urban expansion highly increase the land use and land cover changes and becomes many problems such as uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands, and loss of fish and wildlife habitat, loss of prime agricultural farmland, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, overexploitation of natural resources and conflict (Alexander, 1995; Rosenfeld, 1994).

2.2.3 Factors of LU/LC change and urban expansion

There are several factors of urbanization, such as Economic development, innovation of technology, the industrial revolution, emergence of large manufacturing factors, job opportunities, availability of infrastructures, and migration. Generally, the causes of urbanization and urban expansion are groups into three major classes.

1. **Demographic factors:** Demographic effects include rural to urban migration and natural population growth in the city, the level of urbanization, and the rank of the city/town in the country‘s urban hierarchy. Natural population growth is a major element in urban growth for all countries, and migration of rural to urban contributes fast growth of urban population in many developing countries (Gugler, 1996)
2. **Economic factors:** Economic effects include the level of economic development, the difference in household incomes, exposure to globalization, the level of foreign

direct investment, the degree of employment, the level of financial markets, the level and effectiveness of property taxation, and the presence of high inflation and acute shortage of housing (Angel et al).

3. **Natural/environment factors:** Natural /environmental effects include those of climate, slope, mountain barriers, and the existence of drillable water aquifers. In addition, the minor causes such as Redevelopment and rebuilt up of inner cities again cause displacement of citizens (Cernea, 1995).

2.3 Urbanization

2.3.1 Definition of urbanization and urban growth

Urbanization refers to the growth of towns and cities, often at the expense of rural areas, as people move into urban centers in search of jobs with the expectation of a better life, enabling cities and towns to grow. It can also be termed as the progressive increase in the number of people living in towns and cities. It is highly influenced by the notion that cities and towns have achieved better economic, political, and social mileages compared to the rural areas (Bhatta et al., 2010). Urban growth is a spatial and demographic process that refers to the increased importance of towns and cities as a concentration of people within a particular economy and society (Bhatta et al., 2010). There are at least three different and widely studied concepts of urban growth in the urban and regional planning literature, related to population change, economic performance, and the spatial expansion of urban areas (Reis et al., 2015). The socio-demographic dimension of urban growth focuses on demographic trends and migration.

2.3.2 World urbanization

United Nations World Urbanization Prospect (2014) indicated that the percentage of the urban population in 1950 was 30 percent which increased to 54 percent in 2014 and is estimated to be 66 percent by 2050. More recently, the world's urban population is estimated to be about 54.5 percent (Areas et al., 2016). According to United Nations World Urbanization Prospect (2019), the percentage of the urban population in 1950 was 30%, which was increased to 54% in 2014, and is estimated to be 66% by 2030. The highest urban population is found in the developed world, rapid urbanization and expansion have been the characteristics of cities and towns in the developing world in the past 20 years from 1995-2015, taking a considerable area of their surroundings (Balram and Suzana Dragicevic; Gugsa, 2017) Contrary to this, a vast majority of the population in the third world remain residing in rural areas. By now Asia and Africa are the least urbanized, sharing 48 and 40 percent of their population urbanized, respectively.

2.3.3 Urbanization in Africa

According to The state of African cities (2008), Africa used to be, and perhaps is still, the least urbanized continent, with growth rates of cities close to, if not the fastest in the world. But, today, in virtually every part of the continent, new cities have emerged, while the old ones have drastically expanded, some of which have become mega-cities. By 2030, for the first time in history, more of the continent's people will be living in urban areas than in rural regions and by 2050 an estimated 1.23 billion people, or 60% of all Africans will be city dwellers Currently, even if the level of urbanization in Africa is low, the rate of urbanization is high due to the population growth, which is one of the most important driving forces of changes in any urban system. If the urban population swells, the city must expand upward or outward. Along with economic development and technologies (mainly transport and communication) revolution, rapid urban growth can be characterized by the development of suburban expansion and redevelopment in city centers (United et al., 2016). Freire et al. (2014) indicated that Africa's urbanization faces four major challenges:

1. Inadequate infrastructure and services, housing shortage, traffic and transport management problems, violence and other social crisis are highly pronounced,
2. Weakness in administration, institutions, and overall planning capacity,
3. Urban sprawl with encroaching upon environmental sensitive areas, major agricultural areas, and areas which are not suitable for development,
4. Rapid population growth with low-level of economic activities based on inadequate capital.

If well managed, cities offer important opportunities for economic and social development. Cities have always been focal points for economic growth, innovation, and employment (Barney, 2001).

2.3.4 Urbanization in Ethiopia

Although urbanization processes took place prior to the 20th century in Ethiopia, most of the Ethiopian towns originated due to geographical, political, and economic factors (MUDH, 2015). However, it is one of the least urbanized countries in the world, well below the Sub-Saharan Africa average of 37 percent. According Ministry of Urban Development and Housing State Report (MUDH, 2015), the level of urbanization in Ethiopia remained low until recent decades that saw an expansion of roads and telecommunications infrastructure and the country's multi-faceted participation in the global arena. The country's level of urbanization was about 5% in the 1950s and only reached 10% in the 1970s. However, by 1984, when the first census was conducted, the level of urbanization was increasing to 13%. The level of urbanization was estimated at 19% in 2014, having grown by 6% between 1984 and 2014, reflecting an average increase of 2% in the level of urbanization per decade. However, this is set to change dramatically (MUDH, 2015).

2.4 Land Use Land Cover (LULC)

The land is the most important usual resource, which comprises soil and water and the associated flora and fauna, thus involving the total ecosystem. Knowledge of the spatial distribution of land use and land cover is essential for planning and management activities. Land use is characterized by the planning, activities, and inputs people undertake in a certain land cover type to produce change or maintain it (Basudeb, 2011).

Although the terms Land cover and land use are often using interchangeably, their actual meanings are quite distinct. It is important to distinguish this difference and the information that can be ascertained from each source. Land cover corresponds to the physical condition of the ground surface, for instance, forest, grasslands, etc., while land use reflects human activities such as the use of the land, for instance, industrial zones, residential zones, etc. Land cover refers to a feature of the land surface, which may be natural, semi-natural, managed, or man-made. They are directly observable by remote sensors. Land use, on the other hand, refers to the activities on land or classification of land according to how it is being used. Not directly observable, inferences about land use can often be made from land cover (Basudeb, 2011).

Land Use Land Cover Change (LULCC) is a very complicated process, affected by natural and human dimensions. The natural environment is a dominant factor in a way, while human dimensions are repulsive factors. The research on LULCC is a basic precondition of regional LUCC monitoring, driving factor analysis, and even LULCC prediction. RS (remote sensing) and GIS (geographic information systems) are believed as the most advanced means to obtain land use information because they are real-time, impersonal, and have wide coverage (Sankhala et al., 2014).

2.4.1 Purpose of land use land cover

Remote sensing data can provide land cover information rather than land use information. The properties measured with remote sensing techniques related to land cover, from which land use can be inferred, particularly with ancillary data or a prior (already known) knowledge (Basudeb, 2011). According to (Basudeb, 2011) Land use application involves both baseline mapping and subsequent monitoring since timely information is required to have knowledge on the state of use of the current quantity of land and to identify the land-use changes from time to time. This knowledge helps to develop strategies to balance conservation, conflicting uses, and developmental pressure. Issues driving land-use studies include the removal or disturbance of productive land, urban encroachment, and depletion of forest. In addition, a reason for developing and maintaining a land cover monitoring study is to provide a consistent view of the stock and state of our natural and built resources as they change through time. Knowledge of land use and land cover is important for many planning and management activities concerning the surface of the earth. The survival of the human race depends on its living in harmony.

Land use land cover change (LULCC) detection is very essential for a better understanding of landscape dynamics during a known period having sustainable management. Land use land cover changes are a dynamic, widespread, and accelerating process, mainly driven by natural phenomena and anthropogenic activities, which in turn drives changes that would impact the natural ecosystem. Land use and land cover change, as one of the main driving forces of global environmental change, is central to the sustainable development debate. Land use/land cover change has been reviewed from different perspectives to identify the drivers of land use/land cover change, their process, and consequences (Zahra et al, .2004).

Changes in land cover are examined by environmental monitoring researchers, conservation authorities, and departments of municipal affairs, with interests varying from tax assessment to reconnaissance vegetation mapping. Governments are also concerned with the general protection of national resources and become involved in publicly sensitive activities involving land-use conflicts (Basudeb Bhatta, 2014).

According to (Basudeb Bhatta,2014) explanation, land use applications of remote sensing include natural resource management, wildlife habitat protection, baseline mapping for geographic information system (GIS) input, urban expansion or encroachment, routing and logistics planning for seismic/exploration/resources extraction activities, damage delineation (tornadoes, flooding, volcanic, seismic, fire, and terrorist activities), legal boundaries for tax and property evaluation and target detection_ identification of landing strips, roads, clearings, bridges, and land or water interface. Purpose of urban land use/land covers change study and mapping:

- To interpret Landsat images using different Geospatial technologies.
- To learn about the different types of land cover in their GLOBE Study Site.
- To gain a spatial or landscape perspective of their local area.
- To estimate change based on past and present LULC and forecast the future LULCC in magnitude using temporal remote sensing data.
- Check the accuracy of classification knowing the environment using ground truth (GCP).

2.4.2 Urban land use the land cover of image classification

Image classification refers to the extraction of differentiated classes or themes, usually, land cover and land use categories, from raw remotely sensed digital satellite data (Weng, 2012). Image classification using remote sensing techniques has attracted the attention of the research community as the results of classification are the backbone of environmental, social, and economic applications (Lu and Weng, 2007). Because image classification is generated using remotely sensed data, many factors cause difficulty to achieve a more accurate result. Some of the factors are the characteristics of a study area, availability of high resolution remotely sensed data, ancillary and ground reference data, Suitable classification algorithms and the analyst‘s experience, time constraints.

Image classification refers to grouping image pixels into categories or classes to produce a thematic representation. Classification is the most important aspect of image processing to GIS. Image classification operations that include image restoration, image pre-processing, enhancement, compression, spatial filtering, and pattern recognition are applied to image data. Various image classification methods can be applied to extract land cover information from remotely sensed images (Lu and Weng, 2007). However, their application depends on the methodology and type of data to be used. Some of these methods are artificial neural networks, support vector machines, fuzzy sets, and expert systems. In a more specified way, image classification approaches can be categorized as supervised and unsupervised, or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel, and per-field.

2.4.3 Land use land cover change detection

Change detection is the process of identifying differences in the state of objects or phenomena by observing them at different times by using remote sensing techniques (Singh, 1989). Change detection has a wide range of applications in different disciplines such as change analysis, forest management, vegetation phonology, and seasonal changes in pasture production, risk assessment, urban expansion, and other environmental changes (Singh, 1989). A change detection research to be good, it should provide the following vital information: area change and rate of changes, the spatial distribution of changed types, change trajectories of land-cover types, and accuracy assessment of change detection results.

2.4.4 Supervised image classification algorithms

Classification of Supervised Learning Algorithms According to (Taiwo, 2010), the supervised machine learning algorithms which deal more with classification includes the following: Linear Classifiers, Logistic Regression, Naïve Bayes Classifier, Perceptron, Support Vector Machine; Quadratic Classifiers, K-Means Clustering, Boosting, Decision Tree, Random Forest (RF); Neural networks, Bayesian Networks and so on.

1. **Linear Classifiers:** Linear models for classification separate input vectors into classes using linear (hyperplane) decision boundaries (Elder, n.d). The goal of classification in linear classifiers in machine learning is to group items that have similar feature values, into groups. Timothy Jason Shepard, (1998) stated that a linear classifier achieves this goal by making a classification decision based on the value of the linear combination of the features. A linear classifier is often used in situations where the speed of classification is an issue since it is rated the fastest classifier (Taiwo, 2010).
2. **Logistic regression:** This is a classification function that uses a class for building and uses a single multinomial logistic regression model with a single estimator. Logistic regression usually states where the boundary between the classes exists, also states the class probabilities depend on distance from the boundary, in a specific approach. This moves towards the extremes (0 and 1) more rapidly when a data set is larger. These statements about probabilities make logistic regression more than just a classifier.
3. **Naive Bayesian (NB) Networks:** These are very simple Bayesian networks that are composed of directed acyclic graphs with only one parent (representing the

unobserved node) and several children (corresponding to observed nodes) with a strong assumption of independence among child nodes in the context of their parent (Good, 1951). Thus, the independence model (Naive Bayes) is based on estimating (Nilsson, 1965). Bayes classifiers are usually less accurate than other more sophisticated learning algorithms (such as ANNs).

4. **Multi-layer Perceptron:** This is a classifier in which the weights of the network are found by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard neural network training. Other well-known algorithms are based on the notion of the perceptron. Perceptron algorithm is used for learning from a batch of training instances by running the algorithm repeatedly through the training set until it finds a prediction vector that is correct on all of the training sets. This prediction rule is then used for predicting the labels on the test set (Kotsiantis, 2007).
5. **Support Vector Machines (SVMs):** These are the most recent supervised machine learning technique. Support Vector Machine (SVM) models are closely related to classical multilayer perceptron neural networks. SVMs revolve around the notion of a marginal on either side of a hyperplane that separates two data classes. Maximizing the margin and thereby creating the largest possible distance between the separating hyperplane and the instances on either side of it has been proven to reduce an upper bound on the expected generalization error (Kotsiantis, 2007).
6. **K-means:** According to Bishop (1995) and K means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. K-Means algorithm is be employed when labeled data is not available. The general method of converting rough rules of thumb into highly accurate prediction rules. Given a weak learning algorithm that can consistently find classifiers (rules of thumb) at least slightly better than random, say, accuracy 55%, with sufficient data, a boosting algorithm can provably construct a single classifier with very high accuracy, say, 99% (Rob Schapire,n.d) Machine Learning Algorithms for Classification.
7. **Decision Trees:** Decision Trees (DT) are trees that classify instances by sorting them based on feature values. Each node in a decision tree represents a feature in an instance to be classified, and each branch represents a value that the node can assume. Instances are classified starting at the root node and sorted based on their feature

values. Decision tree learning, used in data mining and machine learning, uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value. More descriptive names for such tree models are classification trees or regression trees (Friedman, 2001).

2.5 LULC change prediction modeling techniques

Land Use Land Cover Change (LU/LCC) modeling is a rapidly growing scientific field because land-use change is one of the most important ways that humans influence the environment (Sankhala and Singh, 2014).

Modeling means the process of creating a representation of reality; it could be a map, graph, picture, or mathematical representation. Land use land cover change modeling is defined as the process of creating maps based on the history of land use land cover, existing information, and assumptions of the future. Modeling urban growth plays a significant role to understand the impacts of the changes that occur through time. The Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler (LCM), Earth trend, Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (Eastman, 2006). It is difficult to compare the performance of the numerous models because LU/LCC models can be fundamentally different in a variety of ways. For example, some models, such as GEOMOD, simulate change between two land categories (Silva and Clarke 2002) while others, such as CA_MARKOV, can simulate change among several categories (Pontius and Malanson 2005). However, it is difficult to compare which one gives a more accurate representation (Wu and Webster 2000; Chang, 2006).

1. Land Change Modeler (LCM)

Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI SELVA that is used to the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation (Eastman, 2012). Land Change Models are important tools for environmental and geomatics research concerning LUCC (Pontius, 2015). Monitoring and analysis of changes in LULC are needed to provide information on existing land use patterns and changes for decision-makers to support sustainable development (Fan, 2007). LULCC models are used to improve and/or better understanding the alteration of land use that is induced by human activities (Brown, 2004). In LCM, tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, habitat and biodiversity impact assessment, and planning interventions (Eastman, 2012).

In IRDRISI Run Transition Sub-Model panel is where the actual modeling of transition sub-models is implemented. Three methodologies are provided for modeling: a Multi-Layer Perceptron (MLP), Similarity-Weighted Instance-based Machine Learning (SimWeight), and Logistic Regression. Multi-Layer Perceptron and SimWeight procedures perform best in modeling transitions (Eastman, 2012). The MLP option can run multiple transitions, up to 9, per sub-model. But SimWeight and Logistic Regression can only run one transition per sub-model. Both MLP and SimWeight use half of the samples (change pixels) for training and the other half for validation. MLP generates predicted class memberships for each of the validation pixels at each iteration and reports the aggregate accuracy as well as a skill score. The skill score represents the difference between the calculated accuracy using the validation data and expected accuracy if one were to randomly guess at the class memberships of the validation pixels. SimWeight calculates the mean transition potential among validation pixels that changed (i.e., went through the transition) and the mean transition potential among pixels that did not change (persisted). These express the hit rate and false alarm rate respectively. The difference between them yields the Peirce Skill Score a value between 0 and 1 Logistic Regression. This model undertakes binomial Logistic Regression and prediction using the Maximum Likelihood method.

2. Earth Trend Modeler (ETM)

Earth observation image time series provide a critically important resource for understanding both the dynamics and evolution of environmental phenomena. As a consequence, Earth Trends Modeler (ETM) is focused on the analysis of trends and dynamic characteristics of these phenomena as evident in time-series images. Further, the system is highly interactive, with the process of exploration largely being an active process. The trends and dynamics emphasized include Inter-annual trends, Seasonal trends, Cyclical components, Irregular but recurrent patterns in space/time (recurrent patterns in space/time including a unique form of Wavelet analysis), Teleconnections (analysis of climate patterns of variation between widely separated areas of the globe), and variability such as the coupled ocean-atmosphere (Eastman, 2012)

3. GEOMOD

GEOMOD is the model that has been used frequently to analyze baseline scenarios of deforestation (Pontius and Chen, 2006). It is a grid-based land-use and land-cover change model, which simulates the spatial pattern of land change forwards or backward in time. Simulates the change between exactly two land categories denoted as 1(non-developed and 2 (developed), but 1 and 2 could represent any two categories for any particular application (Pontius, 2006). The minimum input requirements are the beginning time, the ending time, an image of the beginning time for two land cover types that must be denoted by 1 and 2, and an estimate of the number of cells of each of the two categories at the ending time and Suitability map. GEOMOD is used to Predicts land selected land classes in the future using a land use/cover map. Its advantages need only a one-time land use map for calibration and its disadvantage can simulate change only in two categories (Pontius and Chen, 2008). GEOMOD has been designed such that it can take maximum advantage of data that can vary highly in availability, completeness, precision, currency, and accuracy (Silva and Clarke 2002).

4. Cellular Automata (CA)

Cellular Automata is, in general, a collection of cells, of an arbitrary shape, arranged in a grid-like structure. These cells can "hold" different values from time to time - binary being the simplest of the forms. All the cells change their states simultaneously, i.e., at the same time according to some rule - which may be fixed at the beginning or may vary from time to time. These rules are applied to the system at a regular discrete time interval (Eastman, 2012). The cellular Automata (CA) model explains Change in urban areas over time using the variables such as extent of urban areas, elevation, slope, and roads. Its advantage allows each cell to act independently according to rules and its disadvantage is doesn't include human and biological factors (Agarwal et al., 2002).

5. Markov chain model

A Markov chain is a random process having a property characterized by memoryless transition from one state to another on a state space take place such that it depends only on the present state and not on the past states that the process went through. A random process could be termed as a Markov chain when in a series of events, any event that is about to occur depends only on the present state and eventually forms a kind of a chain.

A Markov chain model is a stochastic process that analyses the probability that one state will change to another one – i.e., the state of a system at time t2 is predicted from the state the system is in at time t1 (Thomas and Laurence, 2006). Future prediction using Markov chain modeling is generally done by analyzing two qualitative land cover images taken on different dates (Moghadam and Helbich, 2013).

The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix, stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012). Markov Model used to explain Land use change using Multi-Temporal Land Use/ cover Maps. Its strength is considered both spatial and temporal change and its weakness is no sense of Geography (Agarwal et al, 2002).

6. **CA-Markov Model**

The Markov model can quantitatively predict the dynamic changes of landscape patterns, while it is not good at dealing with the spatial pattern of landscape change. On the other hand, Cellular Automata (CA) has the ability to predict any transition among any number of categories (GIL et al., 2005). Combining the advantages of Cellular Automata theory and the space layout forecast of Markov theory, the CA- Markov model performs better in modeling land cover change in both time and spatial dimensions.

CA-MARKOV Used to explain Spatio-Temporal dynamic modeling and Predicts land use/cover in the future using Multi-Temporal Land Use/ cover maps and Suitability maps. The strength of CA-MARKOV is creating the data is easy, CA add a spatial dimension to the model, and can simulate change among several categories. Its weakness is Socioeconomic factors are not considered and calibrating the model with MCE is too time-consuming compared to other methods (Adhikari & Southworth, 2012).

2.6 Geospatial technologies useful for urban LULC change analysis

Remote Sensing, GIS, and IDRISI are now providing new tools for advanced ecosystem management. With the advancement of technology, reduction in data cost, availability of historic spatiotemporal data and high-resolution satellite images used for urban planning, geography, earth science, transportation planning, environmental planning, disaster management, urban expansion change analysis, and modeling

1. Remote Sensing According to Lambin (2004), the definition of Remote Sensing (RS) is as follows: Remote sensing is the science and art of obtaining information about the

Earth's surface through the analysis of data acquired by a device which is at a distance from the surface‖. Remote sensing is an essential tool of land change science because it facilitates observations across larger extents of Earth‘s surface than is possible by ground-based observations by using of cameras, multispectral scanners.

2. Geographic Information System (GIS) GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced information (Maguire, 1991). GIS also allows the integration of these data sets for deriving meaningful information and outputting the information derivatives in map format or tabular format. GIS support any operation on geographic information: acquisition, editing, manipulation, analysis, modeling, visualization, publication, and storage. GIS has four basic subsystems: input, storage, analysis, and output.
3. IDRISI IDRISI is the industry leader in raster, covering the full spectrum of GIS and remote sensing needs from a database query, to spatial modeling, to image enhancement and classification. Special facilities are included for environmental monitoring and natural resource management, including land change modeling and time series analysis, multi-criteria and multi-objective decision support, uncertainty and risk analysis, simulation modeling, surface interpolation, and statistical characterization (IDRISI Selva Manual version 17.02). One advantage of using IDRISI for land-use change modeling is that in one software package you have: 1) the data, 2) the simulation model, and 3) the statistical techniques of goodness-of-fit (Pontius, 2002)

2.7 Emperical Literature Review Summary

Researches on land use and land cover change in Ethiopia involved different regions and disciplines depending on the availability of data and tools to perform analysis (Alemayo, 2019; Regassa et al., 2014; Heregeweyn et al., 2012). However, most of the studies have focused on deforestation, the expansion of cultivated land to land degradation, river catchments and watersheds, natural ecosystems, and forests as well as the associated consequences. While urban growth and its impacts are relatively studied in larger and megacities (a metropolitan area of more than ten million people) worldwide(Atalel, 2014). Urban growth and modeling studies in cities of developing countries like, Ethiopia, were limited. However, few studies have been reported relatively such as Regassa et al (2014); Nugusa (2019); Heregeweyn et al (2012); Bekalo (2009); Getu(2014); Alemayo(2019).

Bekalo (2009) identified a significant increase of urban areas from 34% in 1986 to 51% in 2000 in Addis Ababa, Ethiopia by the expense of agricultural land and vegetated areas driven by population growth. Land use and land cover changes in response to urban growth were also reported by some studies that, an expansion of urban areas annually from 1957 to 2009 has been identified by Haregeweyn et al (2012) in the urban fringe of Bahir Dar area as a consequence of increasing population. Regassa et al (2014) have done the thesis entitled: "Analysis of Urban Expansion and Modeling of LULC Changes Using Geospatial Techniques in case of Adama city. This study investigates The conversion of crop land to build-up areas could be related to the increment of population and faster economic development in Adama City. Urban areas increased through all study periods 7.6% (1973-2000) and 13.44% (2000-2010). Crop land which highly contributes to urban area decrease in a net change of loss of 3.03% (1973- 2000) and 12.89% (2000-2010) at this period forestland contribute to urban area. The study also predicted the future land use/land cover using CA and CA MARKOV accordingly the prediction indicates a build-up of 60.27% in predicted map 2040. Nugusa (2019) reported a significant conversion of agricultural land to the built-up area in Mojdo town. The researcher also predicted the future urban extent using MLP and MARKOV. This study describes the coverage of agricultural land as 88.25% of the total area at the beginning of the study timeframe 1990. In the following 29 years, it dramatically dropped to about 66.34%. By contrast, the proportion of urban class was 0.93% in 1990, this figure rose to just over 15.94% in 2019 and other studies reveal the same result means the continuous decline of agricultural land to buildup area which needs proper planning to overcome the negative effect of urbanization.

From most of these studies it is evident that population pressure is one of the major drivers of land use and land cover changes through destruction of agricultural area, forest, and vegetation cover for urban expansion as discussed by Regassa et al (2014); Atalel (2014) and Nugusa (2019).

CHAPTER THREE: MATERIALS AND METHODS

This chapter deals with the study area presents the accessible data, methods, techniques, approaches, and materials used to attain the research objectives. It explains the data sources and types, methods of data collection, image classification techniques employed, and change detection methods used, accuracy assessment, and list of software packages used in this research.

3.1 Description of the Study Area

3.1.1 Location of the town

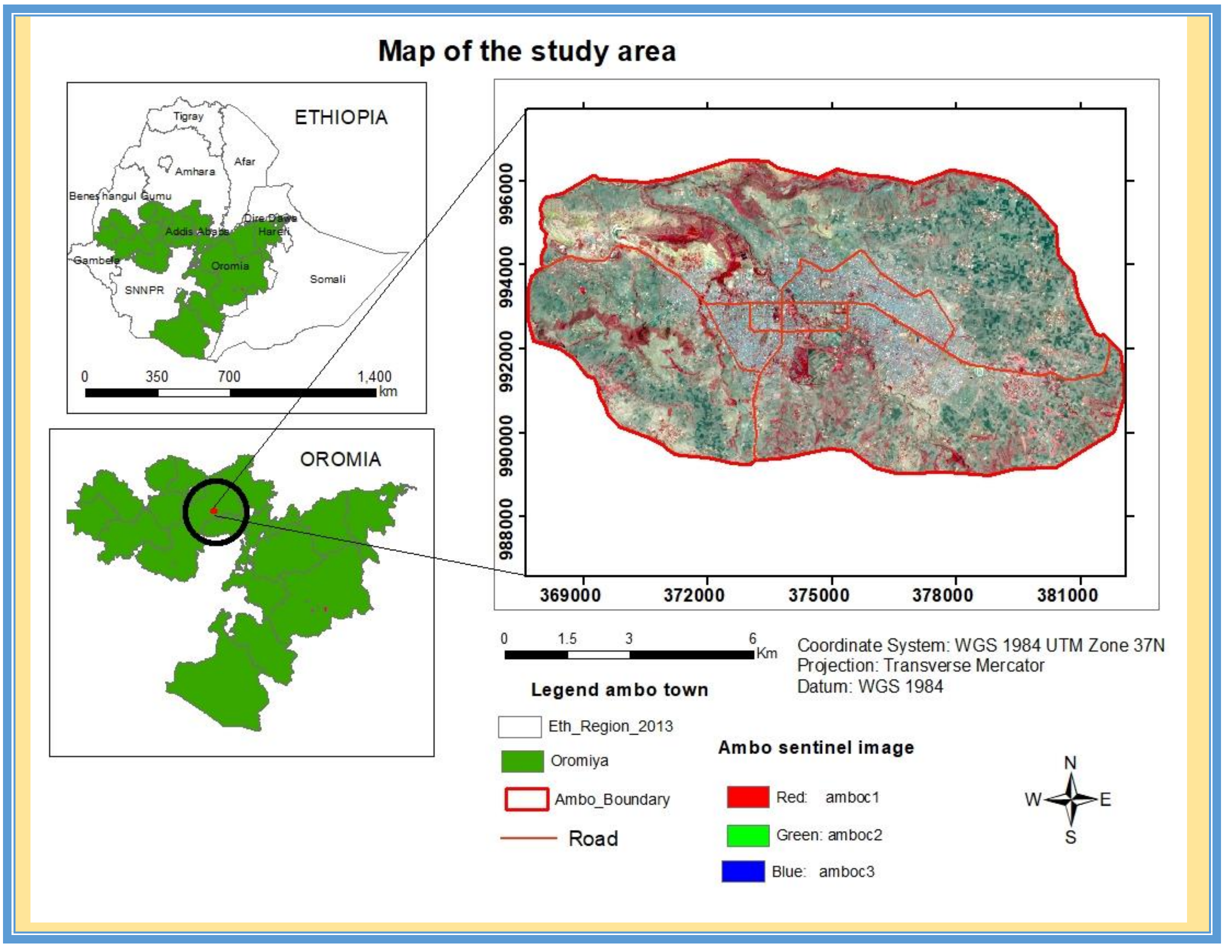


Figure 3.1: Location map of the study area

Ambo town is located in the west of the Oromia Regional state and it is the Zonal town of West Shoa Zone. The geographical (Astronomical) location of Ambo town is approximately between 8º 56'30'' N - 8º 59'30'' N latitude and between 37º47'30" E - 37º 55'15" E longitude and an elevation of 2101 meters *(topographic map sheet obtained from Ethiopian Mapping*

Agency and topographic surveyed map). Relatively Ambo town is located 114 km faraway west of Finfinnee, 60km northwest of Weliso town, and 12kms East of Guder town.

Ambo town was established in 1889 and covers 8587 hectares of land. It is one of the oldest towns in Ethiopia. Owning its strategic location, it has been serving as the administration, transportation, and commercial center of West Shoa Zone. Ambo town has three kebeles and now the town is expanding outwardly and included certain farmers' kebeles such as Awwaro and Illamu Mujja in the east direction, Sankalle Farisi in the west, Gosu kora in the south, and Liban kisose in the north direction (Ambo Municipality, 2009).

3.1.2 Topography

As the town is located on the Shewa plateau land, most of the existing built-up areas of the town are almost gentle slopes & undulated while some hill slopes and mountains are also seen in the town. Along the course of the rivers and streams, steep slopes & gullies are also observed. Concerning the altitude of the town, the town's altitude ranges from 1872 meters above sea level (MSL) to 2362 MSL *(as obtained from the base map prepared and 1: 50, 000 Scale map of Ethiopian Mapping Authority).* As regards the proposed expansion, most of the proposed Expansion areas are characterized by flat, gentle slopes and undulated plains towards Awwaaroo & Illaammuu Muujjaa in the eastern direction, Oddoo Liiban Kisoosee in the Northern and Goosuu Qooraa in the southern. But some of the slopes in the Sanqallee Farisii in the Western direction have higher slopes and also have manmade barriers such as Ambo Mineral Water Factory, Sanqallee Police Training Centre, and Sanqallee Gypsum Factory (Ambo Municipality, 2021).

3.1.3 Slope of the land surface

The land surface terrain of the majority part of the surface of the town has a slope gradient of less than 20 percent. The slope classification of Ambo is largely dominated by terrain with flat to undulating and steep slopes. From different urban experiences under normal conditions, urban areas with slopes greater than 20% are not recommended for construction activities. However, this situation doesn't be taken as a rule in the case of Ambo town. In the case of Ambo town to have a wide area for construction purposes slope up to 35% can be taken as a maximum limit of elevation (Ambo municipality, 2021).

3.1.4 Climate

According to the data obtained from the National Meteorological Agency of Ambo branch which is located in Ambo University 10 years of consecutive meteorological data was taken and the following result is observed on the temperature, rainfall, humidity, and wind direction.

Temperature: The mean annual temperature, the mean annual maximum and mean annual minimum temperatures of the town are reckoned to be about 18.87^{o}C, 23.76 ^{o}C & 10.67^{o}C, respectively, which is the characteristics of a warm temperate climate which is locally called Weina Dega (Badda Daree).

Rainfall: The mean annual rainfall is about 987.78mm. The highest rainfall concentration occurs from June to September. Thus Low infiltration of rainwater, storm water occurrence, and inundation of Low gradient areas, and incidence of sheet and gully erosion are some of the problems in the town & surrounding areas (Ambo town municipality, 2021).

Humidity: The mean monthly relative humidity of the town varies from 64.6% in August to 35.8% in December, which is very comfortable for human life.

3.1.5 Vegetation cover

In the study area, there are almost no remains of endogenous natural vegetation cover. Ambo and its surrounding areas are dominated by eucalyptus trees, which are owned by individuals. The eucalyptus trees are found distributed in all directions of the town and its surroundings. Other trees observed in the town and its surrounding areas are acacias, cordial (locally Wanza, Wadeessa), Tid/scientifically Junipers/and coniferous forest trees are other trees found distributed in the town and its surrounding. Along the riverbanks, in the Ambo Palace, in the known hotels (Ambo Ethiopia Hotel, Jibatena Mecha Hotel), in the churches, and some other government offices we find vegetation, which keeps the urban environment to be green (Ambo municipality, 2021).

3.1.6 Geological construction materials

In the town and its surrounding area, there are various geological construction materials. The available geological construction materials in the Ambo area include different rocks, sand, and red clay. The rocks and other construction materials are found at the beds of the known rivers in the town, in the Sanqallee and Farisii of the Western and northwestern part of the town.

3.1.7 Mineral Potential

Even though the number of minerals and the types of minerals are not deeply and highly studied in the country, and in Ambo town there are some mineral resources which are known and used by the people of the town & its surrounding. Mineral resources that should be considered while dealing with the existing situation and future development of Ambo town are the mineral water resources and limestone deposits in the area. The abundant hot water springs are an additional one (Ambo municipality, 2021).

3.1.8 Population size

The population and housing census conducted in 1994/1986 and 2007/1999 by Central Statistical Authority are considered here to see the trend of the population size of the town under study. Ambo town is the capital town of West Shewa Zone with a population size of more than 67,514 in 2009/2001 including the population of expansion areas. According to the 1994 and 2007 population and housing census of CSA, the total population of the town was 27,636 and 50,267 respectively.

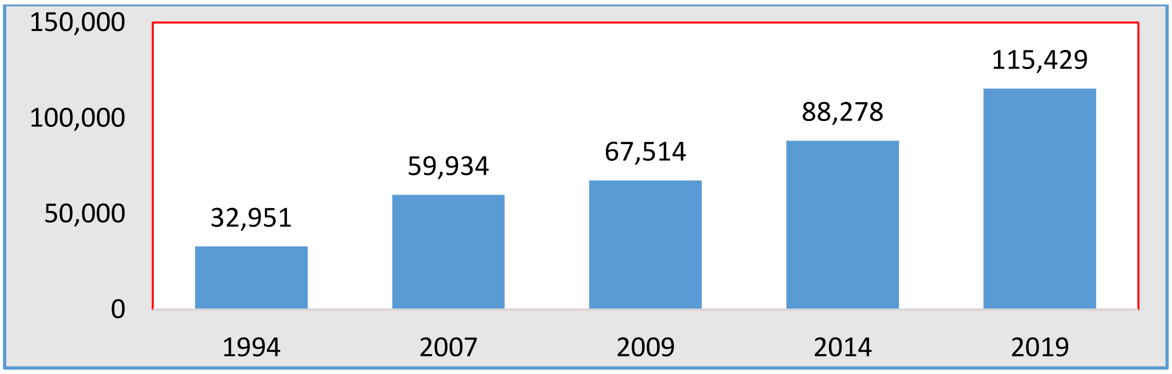


Figure3.2: Population growth as Computed based on Census reports of 1994 and 2007 (Ambo Municipal, 2021)

Between 1994 and 2007 the population size of the town was growing on average at 4.6 percent per annual. But between 2007 and 2009 population of Ambo town growth rate increased to 5.5 percent and its number was grown to 67,514. To project the current (2009) population size of the town to the end of the planning period (2019) an attempt has been made to examine the growth rate of the town experienced during 1994-2009. The growth rate observed during 1994-2007 and 2007-2009 appears to be high (4.6% and 5.5%) when compared to the average annual growth rate of the urban population at the national level, which was 4.11% during the inter-censual period (1984-1994). According to the report produced by CSA in 1994, migrants constituted about 56.8% of the total population of Ambo town indicating the fact that more than half of the residents of the town to be migrants from other areas. The data on the area of the previous residence of the migrants showed the number of migrants from rural areas (51.7%) slightly greater than that of the urban centers (48.3%).

3.2 Materials and Software Used

There are several different kinds of software, methods, strategies, and techniques to process input data to generate the required output with desired quality. The methodology integrates remote sensing and GIS tools as well as urban growth modeling using CA MARKOV and LCM embedded in IDRISI software.

Table3.1: materials and software used

Software used	Its functions
ArcGIS 10.8	visualization, map layout and accuracy assessment for classification, Post classification tabulation
ERDAS (2015)	Digital image preprocessing, layer stacking, radiometric correction, and delineation of area of interest (AOI) or subset
ENVI (5.3)	For scan line removal and Image classification
IDRISI (17.2)	For change analysis, multi-criteria and multi-objective decision support, simulation modeling, and prediction for the future LULC map.
Google Earth	Visualization and verification of classification and point data collection for accuracy assessment of 1990,2005 and 2015 map
Microsoft office(2013)	Writing, chart preparing, graphs, and statistical analysis
Handle GPS	Collect Ground Controls Points (GCPs)

3.3 Data Used in This Research

The research was conducted using Landsat and Sentinel images as the prime remote sensing data due to the availability of images for an extensive period of time as compared to other satellite types. Two Landsat images (Landsat 5TM and Land sat 7TM) and two sentinel images (2015, 2021) were obtained from the United States Geological Survey (USGS) online data portal. Sentinel-2 is a system of two polar-orbiting satellites that will contribute to the continuity and improvement of the SPOT and Landsat series of multispectral missions, and ensure the delivery of high-quality data and applications for operational land monitoring, emergency response, and security services.

Sentinel-2 Multispectral imaging for (Drusch et al., 2012):

- Land cover, land use, and land-use change detection maps;

- maps of biogeophysical variables such as leaf chlorophyll content, leaf water content, leaf area index (LAI);
- risk mapping;
- Acquisition and rapid delivery of images to support disaster relief efforts

Table 3.2: Characteristics and properties of the Landsat images used

Acquisition Date	Path/Row	Landsat/Sentinel data	Sensor	Spatial Resolution	Number Bands
10/1/1990	169/54	Landsat 5	TM	30 m	7
25/02/2003	169/54	Landsat 7	TM+	30 m	8
20/03/2015	169/54	Sentinel	ESA 2A	10 m	12
10/6/2021	169/54	Sentinel	ESA 2B	10m	12

Basically, the satellite images were selected based on the availability of data and quality. For this reason, this study uses Landsat 30m resolution and sentinel image 10m. Several ancillary data were also collected for this research. Digital Elevation Model was obtained from the geospatial institution bureau. Vector data of roads, administrative boundaries, and population data were also obtained from the Ambo land administration office. All of the datasets used in the study were geometrically calibrated using WGS 1984_UTM zone 37 North projections.

3.4 Methodology

For this study, standard image processing techniques such as image extraction, rectification, restoration, classification, categorical map generation, accuracy assessment, reclassification, change detection, and LULC Prediction were done. The lansat and sentinel image were classified by using supportive vector machine in ENVI software. After LULC map production statistical change analysis were accomplished in land change modeler (LCM) in IDRISI software.The projection of land use land cover for the entire period of study were predicted based on the past trend by using MLP Neural network and Markov chain. The flow chart of the study was described in the following figure 3.3.

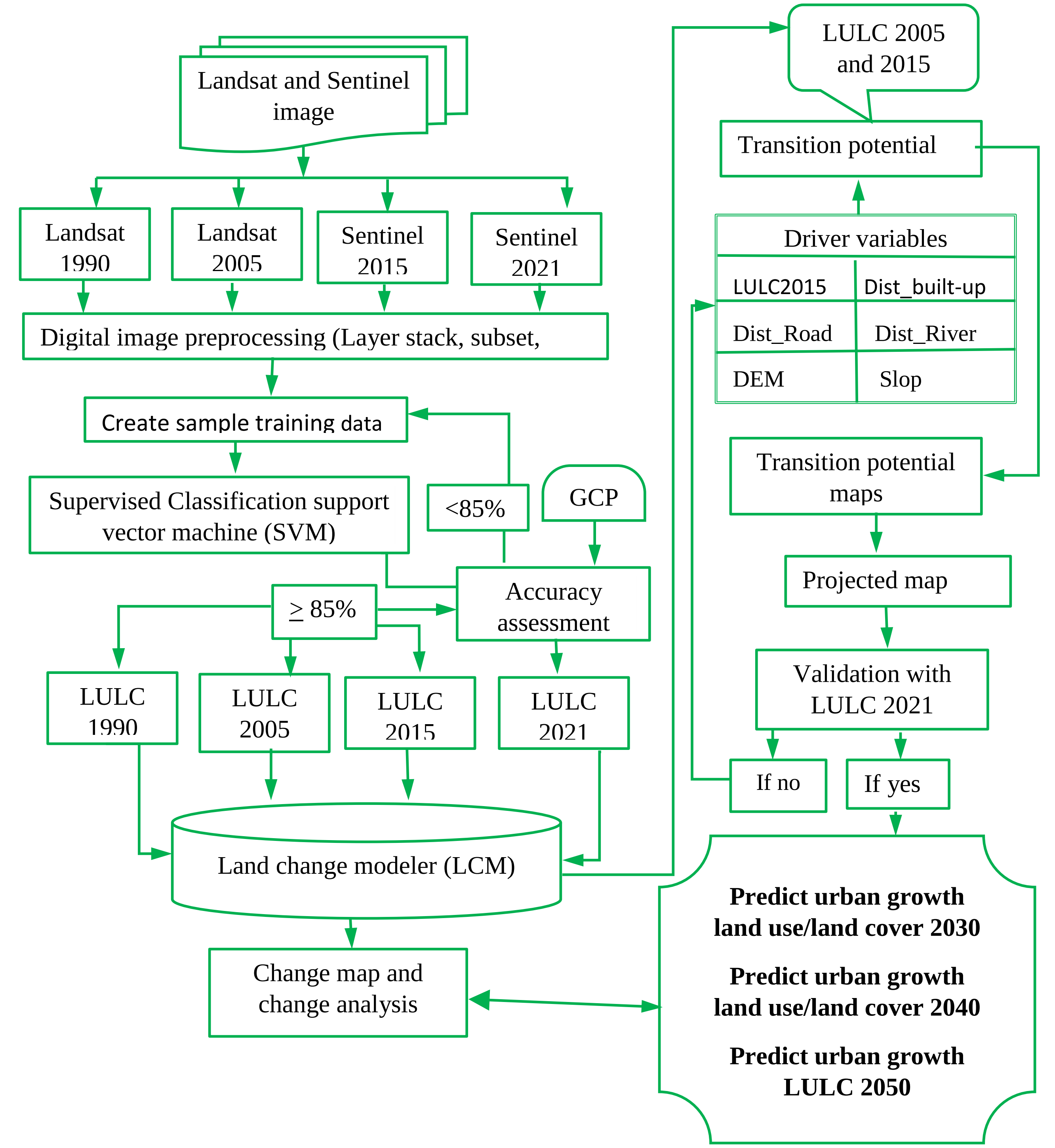


Figure:3.3. Flow chart methodology1

3.5 Image Pre-Processing

Image preprocessing activity was necessary to provide a data set to be used to extract spatial information, as satellite images were subject to geometric and radiometric distortions. It was including mosaic construction, sub-setting of the image based on the boundary of the study area, and projection was performed for all images to be ready for use. Radiometric correction includes the process of haze reduction, removal of atmospheric noise, brightness inversion, and histogram equalization to make more representatives of the ground truth conditions based on the sensors. Pan sharpening has been applied for Landsat (2005) to improve the resolution of all bands to panchromatic image (band 8) and the resolution increased to 15m. These activities were done to produce a corrected image as close as possible, both geometrically and radiometrically to the radiant energy characteristics of the original scene and to improve visible interpretability of the image by increasing apparent distinction between the features in the scene.

3.5.1 Sub-setting of study area images

The first step in image pre-processing is image extraction. Some irrelevant parts of the image can be removed and the image region of interest is focused. Taking out the project area from the whole part of the image is important to reduce the size of the image file to include only the area of interest (AOI). This does not only eliminate the extraneous data in the image. But it speeds up processing due to the smaller amount of data to process. This is important when utilizing multiband data Such as Landsat TM imagery. This reduction of data is known as Subsetting. In this stage ERDAS IMAGINE and Arc GIS Software were important. In this process, each Landsat scene was clipped through by the project area (Ambo town shapefile). It has to be done after layer stacking or composite image.

3.6 Data Analysis Techniques

The analysis has conducted the map of urban built-up areas based on the satellite images and using other ancillary data. By delineating with the town boundaries, the spatial patterns of urban growth trends were analyzed and predicted urban growth at 2030, 2040, and 2050. Another analysis was the population figures for Ambo town for the period under investigation and investigated the relationship between built-up areas and population change for the period under investigation. The methodologies are described in detail in the methods (figure 3).

3.6.1 Image classification

Image Classification Image classification is the process of sorting pixels into a finite number of individual classes or categories of data, based on their DN (pixel) values. Classification of remotely sensed data is used to assign corresponding levels concerning groups with homogeneous characteristics to discriminate multiple objects from each other within the image. The level is called class (Basudeb Bhatta, 2011). Classification is the most popularly used information extraction technique in digital remote sensing.

Based on the major land use/land cover of the study area the following land class was classified from the satellite image. According to the Laotian Ministry of Agriculture and Forestry guideline (Thongphanh et al., 2006), the definition of each land class is described in the following table 3

Table 1.3: Nomenclature of land use land covers classes.

Land classes	Land-cover types	*Description*
C1	Agriculture land	*cropland with permanent crops, farming, and fallow field*
C2	Barren land	*Open spaces with little or no vegetation, beaches, dunes sands, bare rocks*
C3	Buildup area	*Includes all developed areas, roads and transport infrastructures, buildings, housing units, commercial and residential areas, and under construction areas*
C4	Forest land	*Natural and manmade forests, Woodland shrubs, sparsely planted trees*
C5	Grassland	*Grasses, shrubs, bushes*
C6	Waterbody	*Consists of areas with surface water seized in the form of a river, lake, or pond, which may be permanent or seasonal.*

3.6.2 Classification algorithm

Each image was classified into a set of spectral classes using the Support Vector Machine (SVM) algorithm in ENVI software. SVM is a non-parametric classifier. Unlike parametric classifiers such as maximum likelihood which assumes that the data is normally distributed, non-parametric classifiers do not base classification on a normality assumption or statistical parameters (Phiri and Morgenroth, 2017). Because highly heterogeneous land covers data (e.g., Urban areas) are unlikely normally distributed, the distribution of land cover surfaces is associated with various uncertainties which prevent their description based on data distribution (Lu and Weng, 2007). In this respect, non-parametric classifiers provide better results as compared to parametric classifiers in complex landscapes.

3.6.3 Sample size and sample point data used for classification accuracy assessment

Reference sample data depends upon two types of sampling units, i.e., pixels (points) and polygons (patches) but this research used point sample data for accuracy assessment. Various mathematical theories develop to determine adequate sample sizes for Classification of Accuracy Assessment but no standardized consent reach yet regarding the adequate sample size determination.

3.6.4 Accuracy assessment

Accuracy assessment is an essential and crucial part of studying image classification and thus LULCC detection is used to understand and estimate the changes accurately. It reveals the extent of correspondence between what is on the ground and the classification results. It is important to be able to derive accuracy for individual classification if the resulting data are to be useful in change detection analysis (Cagalton and Green, 2009). Overall accuracy was calculated by dividing the sum of the correctly classified sample units by the total number of sample units. Accuracy Assessment is a kind of process to compare the classification with ground truth or other data. It allows evaluating a classified image file (Eastman, 2009). Usually, this data is known as ground-truth data that has been collected in the field. It is not typical to ground-truth every pixel of the classified image. Therefore some reference pixels are generated. Reference pixels are points on the classified image. Each point of reference pixel represents a specific geographic coordinate of the image. These reference pixels are randomly selected (Congalton, 1991). The randomly selected points within the classified image list two sets of classes. The first set of class values represents the actual land cover type. The second set of class values are known as reference values.

Various mathematical theories develop to determine adequate sample sizes for Classification of Accuracy Assessment but no standardized consent reach yet regarding the adequate sample size determination. For this research, Congal-ton and Green (2009) were used. For the accuracy assessment overall kappa which is a statistical measure of overall agreement between two categorical items (Cohen‘s kappa,) and conditional kappa which includes, user‘s accuracy, producer‘s accuracy, and overall accuracy were calculated. An error matrix is a square assortment of numbers defined in rows and columns that represent the number of sample units assigned to a particular category relative to the actual category as confirmed on the ground.

The rows in the matrix represent the remote sensing derived land use map, while the columns represent the reference data that will be collected from fieldwork. The error matrix tables produce many statistical measures of thematic accuracy including overall classification accuracy, percentage of omission and commission error, and kappa coefficient-an index that estimates the influence of chance (Congalton and Green, 1999).

3.6.4.1 Overall accuracy

Overall Accuracy is essentially told us out of all of the reference sites what proportions were mapped correctly. The overall accuracy is usually expressed as a percent, with 100% accuracy being a perfect classification where all reference sites were classified correctly. Overall accuracy is the easiest to calculate and understand but ultimately only provides the map user and producer with basic accuracy information. The diagonal elements represent the areas that were correctly classified. To calculate the overall accuracy you add the number of correctly classified sites and divide it by the total number of reference sites.

3.6.4.2 Omission Error

Errors of omission refer to reference sites that were left out (or omitted) from the correct class in the classified map. The real land cover type was left out or omitted from the classified map. The error of omission is sometimes also referred to as a type I error. An error of omission in one category will be counted as an error in commission in another category. Omission errors are calculated by reviewing the reference sites for incorrect classifications in columns for each class and adding together the incorrect classifications and dividing them by the total number of reference sites for each class.

3.6.4.3 Commission error

Commission errors are calculated by reviewing the classified sites for incorrect classifications by going across the rows for each class and adding together the incorrect classifications and dividing them by the total number of classified sites for each class.

3.6.4.4 Producer accuracy

Producer's Accuracy is the map accuracy from the point of view of the mapmaker (the producer). This is how often are real features on the ground correctly shown on the classified map or the probability that a certain land cover of an area on the ground is classified as such. The Producer's Accuracy is a complement of the Omission Error, $Producer's\ Accuracy\ = 100\% - Omission\ Error$.

3.6.4.5 User accuracy

The User's Accuracy is the accuracy from the point of view of a map user, not the map maker. The User's accuracy essentially tells us how often the class on the map will be present on the ground. This is referred to as reliability. The User's Accuracy is the complement of the Commission Error, $\text{User's Accuracy} = 100\% - \text{Commission Error}$. The other way of the User's Accuracy is calculated is by taking the total number of correct classifications for a particular class and dividing it by the row total.

3.6.4.6 Kappa coefficient

The Kappa Coefficient is generated from a statistical test to evaluate the accuracy of classification. Kappa essentially evaluates how well the classification performed as compared to just randomly assigning values, i.e. did the classification do better than random. The Kappa Coefficient can range from -1 to 1. A value of 0 indicated that the classification is no better than a random classification. A negative number indicates the classification is significantly worse than random. A value close to 1 indicates that the classification is significantly better than random (Jennes et al (2007). Kappa is a statistical measure of overall agreement between two maps (e.g. output of classified/simulated map and ground truth/reference map) or a matrix (Canada Centre for Remote Sensing, 2010). Kappa coefficient can be calculated using the below formula:

$K = \frac{N\sum Xii - \sum(Xi*Xj}{(N*N) - \sum(Xi*Xj)}$ $\quad k = kappa\ coefficient, Total\ number\ of\ pixel\ points, xii = correctlyclassified\ points\ in\ column\ i\ andcolumn\ i, xi = sum\ of\ row\ points, xj = sum\ of column\ points.$

3.6.5 Model of land use land cover (land change modeler)

Land Use/Cover Change (LULCC) modeling is a rapidly growing scientific field because land-use change is one of the most important ways that humans influence the environment.

Knowing the changes that have occurred in the past may help predict future changes. Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler (LCM), Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (Eastman, 2006). For this research Land change Modeler was used and CA-MARKOV was used. Land change prediction in Land Change Modeler is an empirically driven process that moves in a stepwise fashion from Change Analysis to Transition Potential Modeling from Transition potential to Change Prediction.

3.6.5.1 Change analysis

Change is assessed between time 1 and time 2 between the two land cover maps. The changes that are identified are transitions from one land cover state to another. It is likely that with many land cover classes the potential combination of transitions can be very large. What is important is to identify the dominant transitions that can be grouped and modeled, termed sub-models. Each group or sub-model of transitions can be modeled separately, but ultimately each sub-model will be combined with all sub-models in the final change prediction.

The change analysis panel provides a rapid quantitative assessment of changes, allowing the researcher to generate evaluations of gains and losses, net change, persistence, and specific transitions graphical form. It also provides a means of generalizing the pattern of trend between two land cover map transitions (Eastman, 2006). Using change analysis of LCM, of the Ambo Town 1990, 2005, 2015and 2021 of LULCC in graphs of gains and losses, contributions to net change, transitions of land cover classes between different categories, and spatial trend were analyzed.

3.6.5.2 Markov Chain model analysis

Markov chains are stochastic processes and the matrices to show changes between land use categories (based on the basic core principle of continuation of historical development), and are often used in modeling and simulation changes and trends of LULC (Halmy et al., 2015; Mishra and Rai, 2016; Parsa et al., 2016). The homogeneous Markov model for prediction of land-use changes can be mathematically presented as follows (Subedi et al., 2013):

$$L(1+t) = Pij * L(t)$$

$$Pij = \begin{bmatrix} p11 & p12 \dots\dots\dots & p1n \\ p21 & p22 \dots\dots. & p2n \\ pn1 & pn2 \dots\dots\dots & pnn \end{bmatrix} \qquad Including \quad \sum_{J=1}^{n} Pij = 1$$

Where L (t) and L (t+1) represents land use status at time t and t + 1 respectively. (i, j= 1, 2… n) is the transition probability matrices that state i changes to state j and p = transition probability. The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix (Mousivand et al., 2007), stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012; Nugusa, 2019).

3.6.5.3 Transition potential modeling

The second step in the Change Prediction process is Transition Potential Modeling, where the potential of land to transition is identified (Eastman, 2012). The collection of transition potential maps is organized within an empirically evaluated transition sub-model that has the same underlying driver variables. A transition potential map for each transition is derived which is an expression of the time-specific potential for change. Variables can be added to the model either as static or dynamic components. Static variables express aspects of basic suitability for the transition under consideration and are unchanging over time. Dynamic variables are time-dependent drivers such as proximity to existing development or infrastructure and are recalculated overtime during the course of a prediction. The Drivers/Factors considered are explained in detail under data analysis.

Transition Potential Modeling used to identify the potential of land to transition. A transition sub-model can consist of a single land cover transition or a group of transitions that are thought to have the same underlying driver variables. These driver variables are used to model the historical change process. Transitions Sub model is modeled using either a multi-layer perceptron (MLP) neural network, logistic regression, or similarity-weighted instance-based machine learning tool (SimWeight), but in this research, MLP was used.

3.6.5.4 Multilayer perceptron (MLP)

Artificial Neural Network is a mathematical model which is inspired by the human nervous system which interconnects the neurons for fulfills complicated tasks in a short time. This model is used for computers to solve nonlinear systems (Artificial Neural Networks, n.d.). There are many types of ANN like Single Layer Perceptron, Multi-Layer Perceptron, Recurrent Network, Hopfield Network, Spiking Neural Network, and many more (Neural Network, 2010).

Multilayer Perceptron feeds-forward ANN is a network of simple neurons called the perceptron (Multilayer Perceptron, n.d.). It is composed of an input layer, output layer, and hidden layers between input and output layer. It is a feed-forward method which means data flows in one direction from input to output. The main algorithm of this model is computing the linear output from nonlinear inputs according to the weights by using a nonlinear activation function (Multilayer Perceptron, n.d.). Feed-forward means that data flows in one direction from the input to the output layer (forward). This kind of three-layer network is also known as Back Propagation Network‖ (IDRISI Taiga Help System, 2009).

1. **Input Layer**

The nodes are the elements of a feature vector. This vector might be the wavebands of a data set or the texture of an image (Atkinson et al., 1997). This can also be ancillary data like slope, elevation, soil type, zoning, etc (Civco, 1993). For this Research 6 inputs, variable values for prediction in the network were used (distance from Road, distance from River, LULC 2015, distance from Built-up area, elevation (DEM), and slope map of study area).

2. **Hidden Layer**

The second layer is an internal or hidden layer. It does not contain output units. One hidden layer can represent any Boolean function (Atkinson et al., 1997). The activity of each hidden unit is determined by the activities of the input units and the weights of the connections between the input and the hidden units.

3. **Output Layer**

The output layer presents the output data. For image classification, the number of nodes in the output layer equals the classes in the classification. General Model Information (input files, Parameters and Performance, and Model Skill Breakdown by Transition & Persistence), Weights Information of Neurons across Layers (Weights between Input Layer Neurons and Hidden Layer Neurons and Weights between Hidden Layer Neurons and Output Layer Neurons), and Sensitivity of Model to Forcing Independent Variables to be Constant.

3.6.5.5 Number of training samples and iterations

The number of training samples also affects the training accuracy. Too few samples may not represent the pattern of each category while too many samples may cause overlap. Again too many iterations can cause overtraining that may cause poor generalization of the network (IDRISI Taiga Help System, 2009). Overtraining can be prevented by the early stopping of training (Karul, 2006). The acceptable error rate is evaluated based on the Root Mean Square (RMS) Error (Karul, C, 2006). Automatic mode monitors and modifies the start and end learning rate of a dynamic learning procedure. The dynamic learning procedure starts with an initial learning rate and reduces it progressively over the iterations until the end learning rate is reached when the maximum number of iterations is reached. If significant oscillations in the RMS error are detected after the first 100 iterations, the learning rates (start and end) are reduced by half and the process is started again.

$$\boldsymbol{RMS = \frac{\sum(ei)2}{N} = \frac{\sum(ti - tai)2}{N}}$$

Where, N = the number of elements, i = the index for elements ei = the error of the ith element, ti = the target value (measured) for ith element tai = the calculated value for the ith element.

3.6.5.6 Change prediction

Change Prediction provides the controls for a dynamic land cover change prediction process. After specifying the end date, the quantity of change in each transition can either be modeled through a Markov Chain analysis or by specifying the transition probability matrix from an external model. Two basic models of change are provided: a hard prediction model and a soft prediction model. The hard prediction model is based on a competitive land allocation model similar to a multi-objective decision process. The soft prediction yields a map of vulnerability to change for the selected set of transitions. For this study hard prediction was used.

3.6.5.7 Model validation

After prediction, the Model validation which refers to comparing the simulated and reference maps was conducted. Sometimes the simulated maps can give misleading results. In that case, it is necessary to validate the projected/simulated map with the base/reference map. Therefore, model validation is an important step in the case of predictive change modeling (Eastman, 2009). The Validation is an important to stage panel that allows determining the quality of the prediction of land use/land cover map in relation to a map of reality. Validate provides a method to measure agreement between two categorical (integer or byte) images, a "comparison" map, and a "reference" map. It calculates various Kappa Indices of Agreement and related statistics that indicate how well the comparison map agrees with the reference map and gives three types of results bar graph with table, trend line graph as a function of multiple resolutions, and text.

Map comparison is vital in evaluating the analytical techniques for spatial data. It produces numerical expressions to compare two maps (Vliet, 2009). The best way to validate a model is to compare the predicted map of time t2 with the reference map of time t2 (Pontius et al., 2006). In this case for validating the output of the simulated LULC map in 2021, two maps were compared, the reference LULC map of 2021 and the simulated LULC map of 2021. The validation was based on kappa statistics and multiple-resolution. Many variations of the Kappa statistic have been introduced by Pontius such as Kappa for no information (denoted as Kno) and Kappa for grid-cell level location (denoted as kLocation) (Pontius, 2000).

1. **Kappa**: Kappa is a statistical measure of overall agreement between two maps (e.g. output of classified/simulated map and ground truth/reference map) or a matrix (Canada Centre for Remote Sensing, 2010). Kappa value ranges from -1 to +1. The maximum value +1 indicated, perfect agreement and the minimum value -1, indicates maximum disagreement. Kappa value 0 indicates the observed agreement matches the agreement expected by random arranging of all cells (Hagen, 2002). Kappa can be negative. This is a sign that there is no effective agreement between the two rates (Simon, 2008)

$$\boldsymbol{k} = \frac{\boldsymbol{p(A) - p(e)RL}}{\boldsymbol{1 - p(e)RL}} \qquad \boldsymbol{p(A)} = \sum_{n=1}^{m} pnm \qquad \boldsymbol{p(e)RL} = \sum_{n=1}^{m} pn * Pm$$

Where P (A) = Percentage of cells in the map that are identical; P (e) RL = Random Location (RL) conditional to the observed distribution in both maps.

Table 3.4: Strength of Agreement for Kappa Statistic (Landis, J., 1977)

Kappa statistics	Strength of agreement
<0	poor
0.00 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect/perfect

2. **kno**: indicates the proportion classified correctly relative to the expected proportion classified correctly by a simulation with no ability to specify accurately quantity or location‖ (Pontius, R. G., 2000). It is a statistic similar to Kappa, but better capable of expressing similarity both in quantity and location (Hagen, 2002)

3. **klocation:** Klocation indicates the success due to the simulation‘s ability to specify location divided by the maximum possible success due to a simulation‘s ability to specify location perfectly‖ (Pontius, 2000). It depends strictly on the spatial distribution of the categories on the map. It indicates how well the grid cells are located on the landscape (Pontius, 2000).
4. **Khiston**: Khisto depends on the total number of cells taken in by each category (Hagen, A., 2002). It is a statistic that can be calculated directly from the histograms of two maps (Hagen, 2002).

In order to ensure that the model is reliable in predicting a LULC for a specific project year, it must be validated using existing datasets. Therefore, the used model was validated by using two maps: the first one is the real land use and land cover of the year 2021, and the second map is a predicted (simulated) 2021 map. The latter was simulated by using the model and the same procedure that was implemented in predicting 2030,2040 and 2050 land use and land cover map, but, in this case, the 2003 and 2015 maps were used for simulating 2021 maps. The validate module in IDRISI Taiga was used for validating the model by producing several parameters: Kno, Klocation, and Kstandard that are used to identify the accuracy of the model.

In this research Land, Change Modeler tool was used to predict the future Land use /Land cover maps and MLP neural network analysis was used to determine the weights of the transitions that would be included in the matrix of transition probabilities of the Markov Chain for future prediction.

3.7 Relationship Between Population Growth and Built-Up Area Expansion

To relate population growth with the urban expansion of the town, it is necessary to project (interpolate) population growth as usual scenario like LULC prediction (Anderson et al., 1971). The projection of population growth was required in research to get specific data to fulfill the purpose of the study in the study time frame (1990_2050). So that it is possible to project population growth based on existing census data 1994, 2007, and 2009 to determine the correlation between built-up land area expansion and population growth in Ambo town. This can be done using regression analysis.

3.7.1 Regression analysis

In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome variable') and one or more independent variables (often called 'predictors, covariates', or 'features'). The most common form of regression analysis is linear regression. According to David, (2009) regression analysis can be used to infer causal relationships between the independent and dependent variables. Importantly, regressions by themselves only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset ***Correlation:*** is a statistical measure that determines the relationship or association of two variables. Correlation can be positive, negative, or no correlation. Positive correlation: when the value of one variable increases concerning another. Negative correlation: when the value of one variable decreases concerning another. No correlation: when there is no linear dependence or no relation between two variables. Correlation is utilized to assess the strength of the relationship between variables and for modeling the future relationship between them.

3.7.1.1 Simple linear regression modeling

Simple linear regression is a model that assesses the relationship between a dependent variable and an independent variable. The simple linear model is expressed using the following equation and estimates the values of the variables using the least square method.

$$\boldsymbol{Y = Ax + B + e}$$

Where: Y = Dependent variable, X = Independent (explanatory) variable, B = Intercept, A = Slope and e = Residual (error).

The degree of correlation is perfect if the value is near ±1, then it is said to be a perfect correlation, as one variable increases, the other variable tends to also increase (if positive) or decrease (if negative). High degree if the coefficient value lies between ±0.5 and ±1, then it is said to be a strong correlation. Figure 4 Correlation analysis between population growth and buildup area

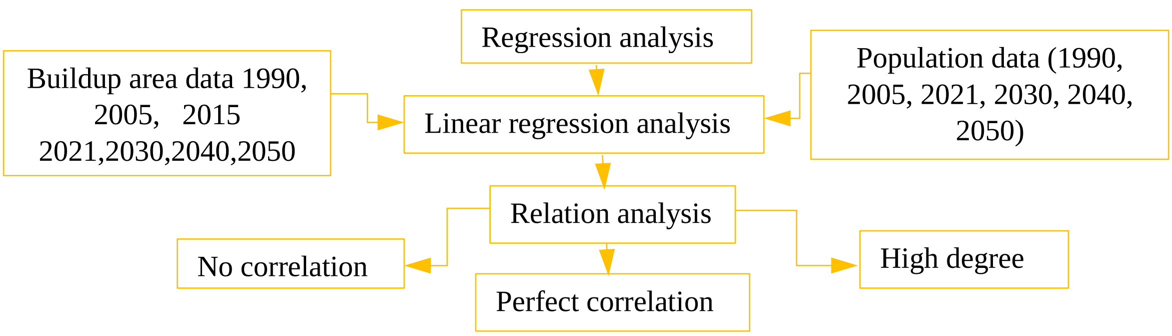


Figure 3.1: Correlation analysis between population growth and urban buildup area

CHAPTER FOUR: RESULTS AND DISCUSSION

In this section, based on the data gathered data analysis performed output images of LULC images developed for the years 1990, 2005, 2015, and 2021 presented in the following Figure 4.1, 4.2,4.3, and Table 4.4 shows the statistical change analysis of LULC between the years 1990 and 2021. An overall change in LULC in all four years is shown in Figure 4.4. Additionally, the future Land use land cover predicted for the years 2030, 2040, and 2050 were presented in the following Figures 4.20 and 4.21.

4.1. Land Use Land Cover Classification

Each image was classified into a set of spectral classes using the Support Vector Machine (SVM) algorithm in ENVI software. SVM is a non-parametric classifier. Unlike parametric classifiers such as maximum likelihood which assumes that the data is normally distributed, non-parametric classifiers do not base classification on a normality assumption or statistical parameters (Bulti., 2019). Training samples for each class were collected from each image. Because highly heterogeneous land covers data (e.g., urban areas) are unlikely normally distributed; the distribution of land cover surfaces is associated with various uncertainties which prevent their description based on data distribution (Lu & Weng, 2007). In this respect, non-parametric classifiers provide better results as compared to parametric classifiers in complex landscapes. Accordingly the classified image of landsat and sentinel image classified to six major classes (agricultural land, barren land, built-up area, forest area, grassland, and water bodies) based on the major class land of Ambo town. The accuracy assessment for each image were calculated and the result of all LULC are in acceptable range. The selection of the entire year was based on the avalabiliy and quality of data as the study area result in very shortage of spatial data.

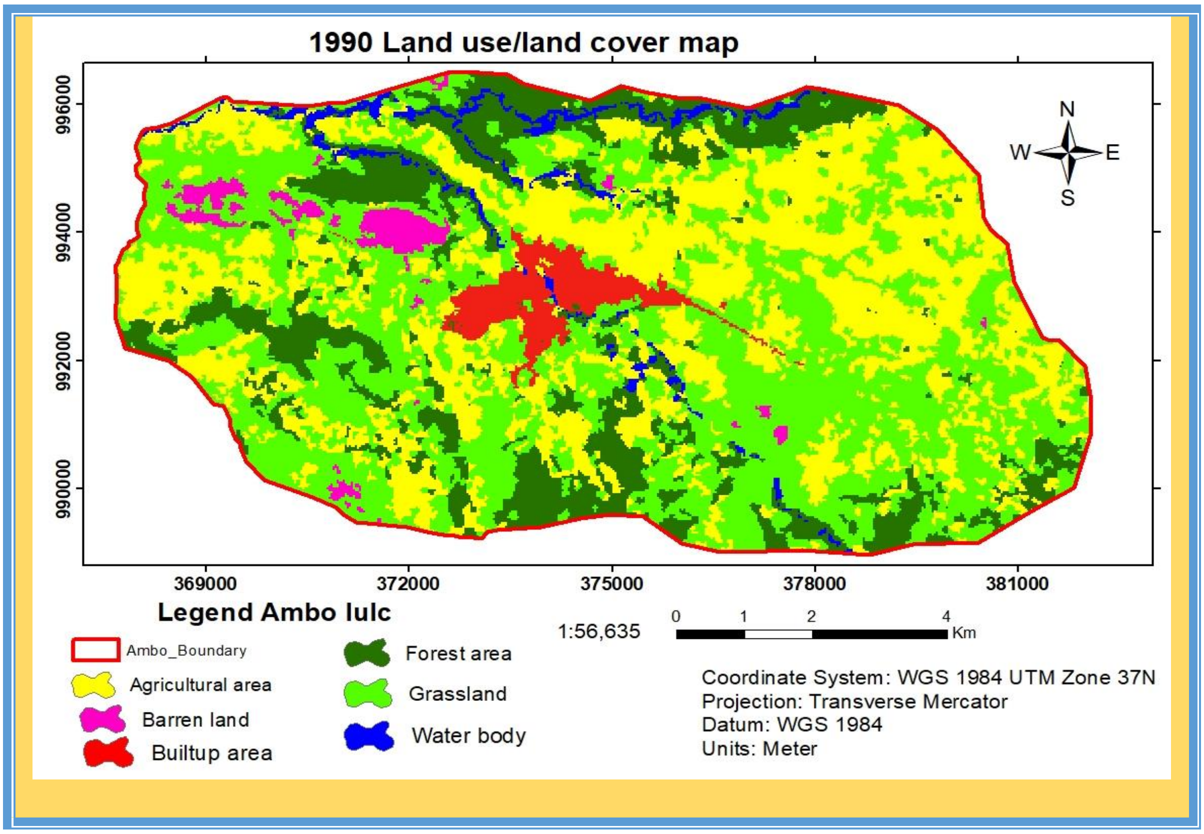


Figure 4.1: Land use/land cover 1990

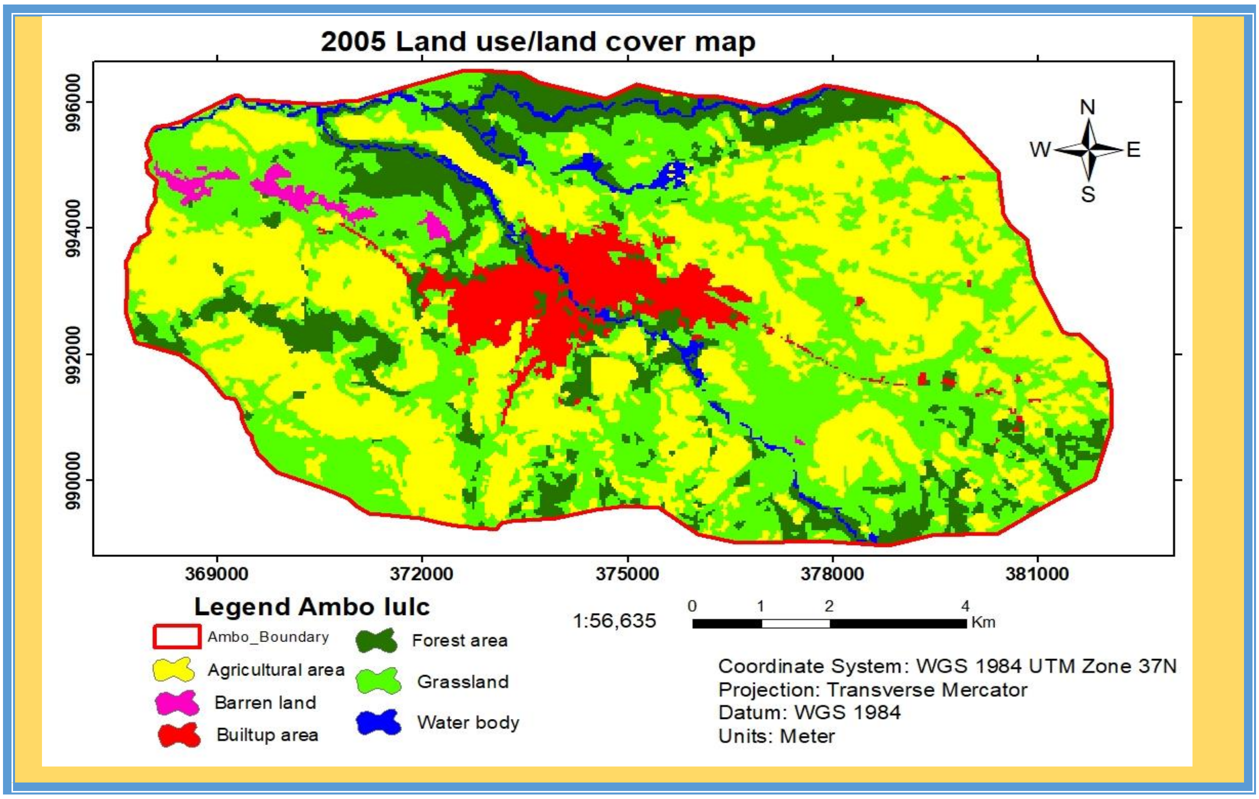


Figure 4.2: Land use/land cover 2005

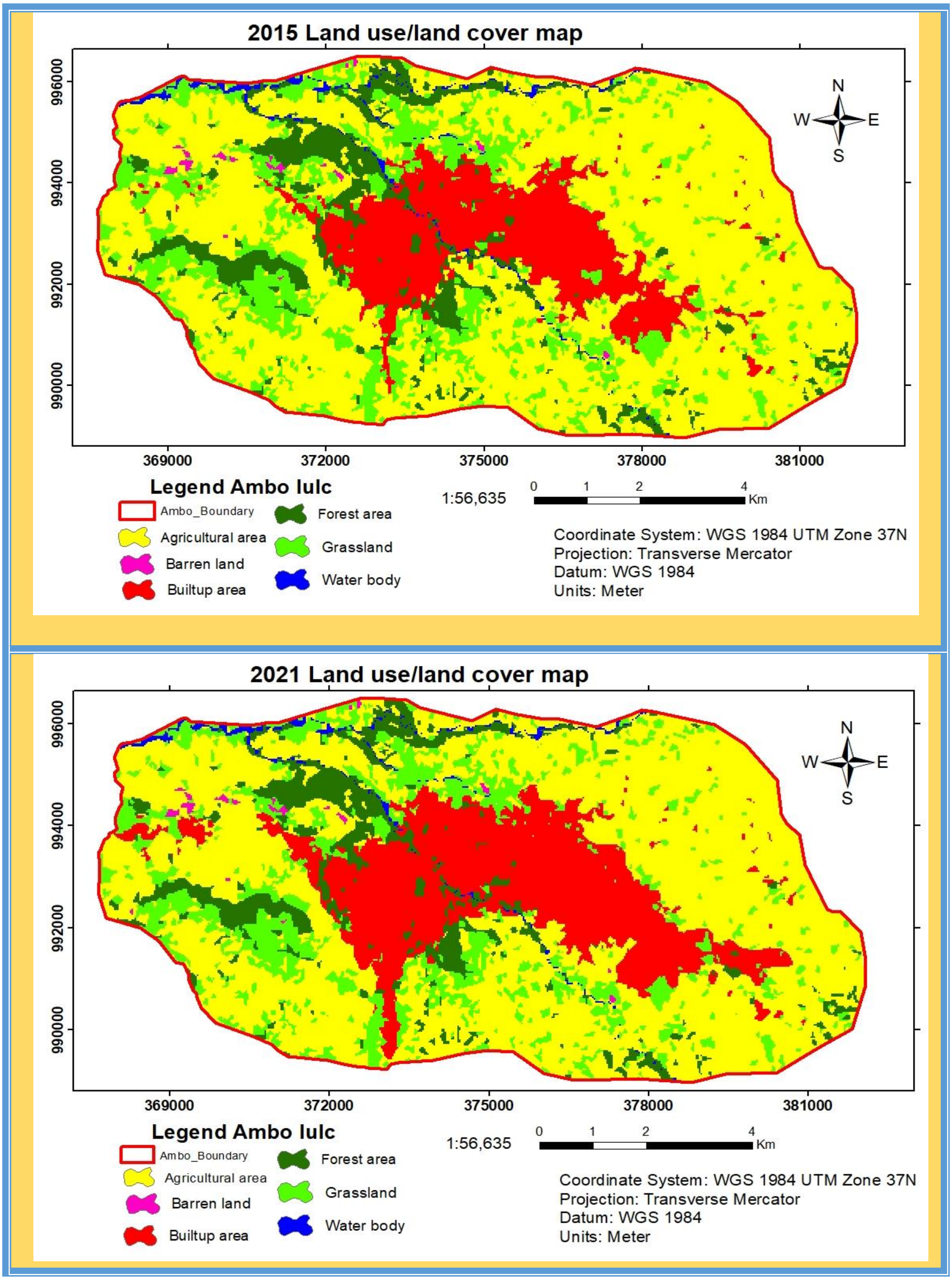


Figure 4.3: Land use/land cover 2015 and 2021

4.2 Accuracy Assessment for Land Use / Land Cover Image

LULC classification accuracy was assessed quantitatively using an error matrix which is the commonly used method in LULC classification accuracy assessment (Built, 2019). Accuracy assessment in this study revealed the overall accuracies of 88%, 90%, 92%, and 93% were calculated for 1990, 2005, 2015, and 2021, respectively. This implies that all classifications are in the acceptable range because the overall accuracy of each year is greater than 85% and the kappa coefficient greater than 0.80 represents strong (almost perfect) agreement (Rwanga and Ndambuki, 2017) is an indicator for a strong accuracy. The details of the error matrix table results are shown in Tables 4.1 and 4.2

Table 4.1: Landsat 5 classification accuracy for 1990

		Reference map							
	LULC Type	Agricult	Barren land	Buildup area	Forest area	Grassland	Water	Row total	Users accuracy
Classified LULC 1990	Agriculture	54	0	1	2	2	1	60	90
	Barren land	0	17	0	1	2	0	20	85
	Buildup area	0	1	23	1	0	0	25	92
	Forest area	2	0	0	45	3	0	50	90
	Grass land	4	0	0	3	51	0	60	87
	Water/River	0	0	0	0	0	25	25	100
	Column total	56	18	24	52	64	26	240	
	Producers accuracy	90	94.44	95.83	86.54	89.06	96.15		
	Overall accuracy	**89%**			**Overall kappa statistics**				**0.86**

$$\boldsymbol{Over\ all\ accuracy} = \frac{\sum Xii}{n} = \frac{54+17+23+45+51+25}{240} = \mathbf{0.89}$$

$$\boldsymbol{Kappa\ coefficient\ (k)} = \frac{n\sum Xii - \sum(Xi * Xj)}{(n*n) - \sum(Xi * Xj)}$$

$$= \frac{240\sum(54+17+23+45+51+25 - \sum\left(\frac{60*56+20*18+25*24+50*52+60}{64+25*26}\right)}{(240*240) - \sum(60*56+20*18+25*24+50*52+60*64+25*26)}$$

= **0.86** (Others calculated accordingly and displayed in Table 4.2)

Table 4.2: Landsat 7 (2005)and sentinel images(2015 and2021) classification accuracy assessment

Classified LULC 2015	LULC Type	Agricul	Barren land	Buildup area	Forest area	Grass land	Water	Row total	Users accuracy
		Reference map							
	Agriculture	65	0	0	2	3	0	70	92.86
	Barren land	0	17	2	0	1	0	20	85.00
	Buildup area	1	0	47	0	2	0	50	93.33
	Forest area	2	0	0	45	2	1	50	90.00
	Grass land	3	0	0	1	41	0	45	91.11
	Water/River	0	0	0	0	0	25	25	100.00
	Column total	71	17	49	48	49	26	255	
	Producers accuracy	91.55	100.00	95.92	93.75	83.67	96.15		
	Over all accuracy		**0.92**		Kappa coefficient (k)			**0.90**	

Classified LULC 2021	LULC Type	Agri	Barren land	Buildup area	Forest area	Grass land	Water	Row total	Users accuracy
		Reference map							
	Agriculture	61	0	0	1	3	0	65	93.85
	Barren land	0	19	0	0	1	0	20	95.00
	Buildup	1	0	57	0	2	0	60	95.00
	Forest area	2	0	1	39	2	1	45	86.67
	Grass land	2	0	1	1	41	0	45	91.11
	Water/River	0	0	0	0	0	25	25	100.00
	Column total	66	19	59	41	49	26	260	
	Producers accuracy	92.42	100.00	96.61	95.12	83.67	96.15		
	Over all accuracy	**0.93**			Kappa coefficient (k)			**0.91**	

Classified LULC 2005	LULC Type	Agricu	Barren land	Buildup area	Forest area	Grass land	Water	Row total	Users accuracy
		Reference map							
	Agriculture	54	2	0	0	3	1	60	90
	Barren land	0	19	1	0	0	0	20	95
	Buildup	1	0	37	0	2	0	40	92.5
	Forest area	2	0	0	45	2	1	50	90
	Grass land	4	0	0	1	55	0	60	91.67
	Water/River	0	0	0	0	0	25	25	100
	Column total	61	21	38	46	62	27	255	
	Producers accuracy	88.52	90.48	97.37	97.83	88.71	92.59		
	Over all accuracy		**90%**		Kappa coefficient (k)			**0.87**	

4.3 Change Analysis

After the preparation of land use land cover maps, the changes that occurred during the studied periods in each land cover were detected. Over the past decades, land covers in study areas such as forest area, Grassland, water body, and barren land were in continuous decline, while agricultural land showed a varying pattern. In general, out of the six LULC types identified in the study area, only one, namely built-up area, showed continuous increment over the past 31 years. The extent of change within the study area of the individual land cover categories in hectare and the percentage they occupied for 1990, 2005, 2015, and 2021 are presented in Table 4.3.

Table 4.3: Area statistics and percentage of land use land cover percentages units from 1990 - 2021

LU/LC	**1990**		**2005**		**2015**		**2021**	
Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	2895.85	33.94	3388.28	39.71	5023.94	58.89	4734.22	55.49
Barren land	168.79	1.98	89.24	1.05	35.42	0.42	35.38	0.41
Buildup area	283.52	3.32	533.28	6.25	1265.38	14.83	1703.69	19.97
Forest area	1473.09	17.27	1171.11	13.73	746.62	8.75	736.02	8.63
Grass land	3536.11	41.45	3164.75	37.09	1380.11	16.18	1244.13	14.58
Water/River	174.16	2.04	184.88	2.17	80.06	0.94	78.10	0.92
Total	**8531.53**	**100.00**	**8531.53**	**100.00**	**8531.53**	**100.00**	**8531.53**	**100.00**

In 1990 the study area was dominated by grassland covering 41.45% followed by agricultural land covering 33.94% of the study area. Forest area, buildup area, waterbody, and barren land shared 17.27%, 3.32%, 2.04%, and 1.98% of the total area respectively. Those areas, which are close to the built-up areas and urban centers, were subjected to a significant loss in the last three decades.

Table 4.4: Over all amounts and percentage of land use land cover change (1990 - 2021)

	1990 - 2005		2005 - 2015		2015 - 2021		1990 – 2021	
LU/LC Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	492.43	5.77	1635.66	19.17	-289.72	-3.40	1838.36	21.55
Barren land	-79.55	-0.93	-53.81	-0.63	-0.04	0.00	-133.40	-1.56
Buildup area	249.76	2.93	732.10	8.58	438.31	5.14	1420.17	16.65
Forest area	-301.99	-3.54	-424.49	-4.98	-10.60	-0.12	-737.08	-8.64
Grass land	-371.36	-4.35	-1784.64	-20.92	-135.98	-1.59	-2291.99	-26.86
Water/River	10.72	0.13	-104.82	-1.23	-1.96	-0.02	-96.06	-1.13
Total	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

During the investigation Periods, distinct changes have occurred on the major land use/land cover types. From 1990 to 2005, the built-up environment increased approximately 249.76Ha (88.09%) while forest area decreased 301.99Ha (20.50%), water body increased 10.72Ha (6.15%), and grassland and barren land decreased 371.36 Ha (10.50%), 79.55Ha (47.13%) respectively. During the second period between 2005 to 2015, the built-up environment increased drastically by 732.10 Ha (137.28%) while forest area decreased 424.49 Ha (36.25%), grassland continuously converted and decreased by 1784.64 Ha (56.39%), water body and barren land decreased 104.82Ha (56.70%), 53.81Ha (60.30%) respectively. During the third period, 2015 to 2021 all LULC decreased except the buildup area. Buildup area increased 438.31 Ha (34.64%), while agriculture land, barren land, forest area, grassland, and water body decreased by 5.77%, 0.11%, 1.42%, 9.85, and 2.45% respectively.

Table 4.5: Overall amount, extent, and rate of land cover change (1990 - 2021)

LU/LC Type	1990 - 2005			2005 - 2015			2015 – 2021		
	Change (Ha)	Extent (%)	Rate (%)	Change (Ha)	Extent (%)	Rate (%)	Change (Ha)	Extent (%)	Rate (%)
Agriculture	492.43	17.00	1.13	1635.66	48.27	4.83	-289.72	-5.77	-0.96
Barrenland	-79.55	-47.13	-3.14	-53.81	-60.30	-6.03	-0.04	-0.11	-0.02
Buildup	249.76	88.09	5.87	732.10	137.28	13.7	438.31	34.64	5.77
Forest area	-301.99	-20.50	-1.37	-424.49	-36.25	-3.62	-10.60	-1.42	-0.24
Grass land	-371.36	-10.50	-0.70	-1784.64	-56.39	-5.64	-135.98	-9.85	-1.64
Water/Riv	10.72	6.15	0.41	-104.82	-56.70	-5.67	-1.96	-2.45	-0.41

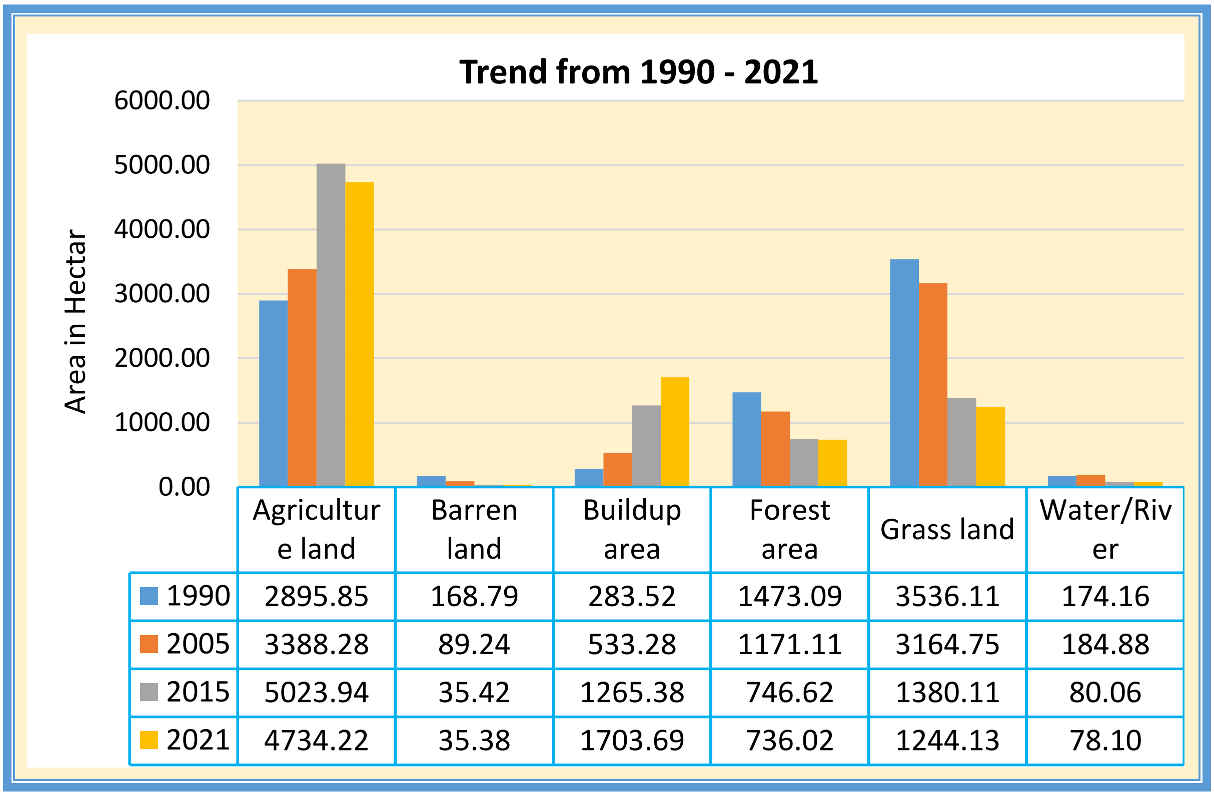


Figure 4.4: Historical change trends of LULC from 1990 – 2021 for all classes

From the above figure agricultural area reveal increament from 1990 to 2015; then decreases from 2015 to 2021. Built-up increases throughout the entire study period. Forest area and grassland continuously decreases from 1990 to 2021. Barren land and water body also decrease throughout the all study period.

4.3.1 Land use/land cover change during 1990 – 2005

Table 4.6: Post classification matrix, losses, gains, persistence and net change 1990 - 2005

	LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grass land	Water	Total
		Land class – 2005						
Land class - 1990	Agriculture	1995.93	1.28	118.87	73.12	673.31	31.85	2894.36
	Barren land	1.73	31.10	1.46	3.22	131.13	0.00	168.63
	Buildup	2.46	0.00	266.70	7.14	4.40	2.82	283.52
	Forest area	151.18	0.01	6.33	830.97	431.41	50.38	1470.29
	Grass land	1230.39	51.85	137.64	183.81	1898.98	27.66	3530.33
	Water/River	5.24	0.00	2.28	71.75	22.77	71.87	173.90
	Total	3386.93	84.24	533.28	1170.01	3162.00	184.58	8531.53

	1990 – 2005							
	Losses		Gains		Persistence		Net change	
LU/LC Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	900.51	26.24	1395.65	40.66	1990.70	68.74	495.15	14.43
Barren land	138.79	4.04	52.52	1.53	31.58	18.71	-86.27	-2.51
Buildup area	17.24	0.50	268.28	7.82	264.95	93.45	251.05	7.31
Forest area	639.08	18.62	340.84	9.93	833.91	56.61	-298.24	-8.69
Grassland	1633.98	47.61	1264.54	36.84	1900.37	53.74	-369.44	-10.76
Water/ River	102.60	2.99	110.36	3.22	75.17	43.16	7.76	0.23
Total	3432.19	100.00	3432.19	100.00	5096.67	59.74	0.00	0.00

The study observed that during the first period various LULC types were changed into other land cover types. For instance, grassland has lost its predominant position to agricultural land, forest area, and buildup area, barren land and maintained its position as the second-largest LULC classes with 37.09% area cover Land use and land cover trend in the study area. Figure 4.4 and Table 4.6 revealed that forest area has been on the decrease recording a reduction of 1633.98Ha in the first period. During the same period, agricultural land showed a net positive charge of 14.43% with substantial gains from grassland. Likewise, notable expansion in 268Ha gain buildup area from total LULC types was observed.

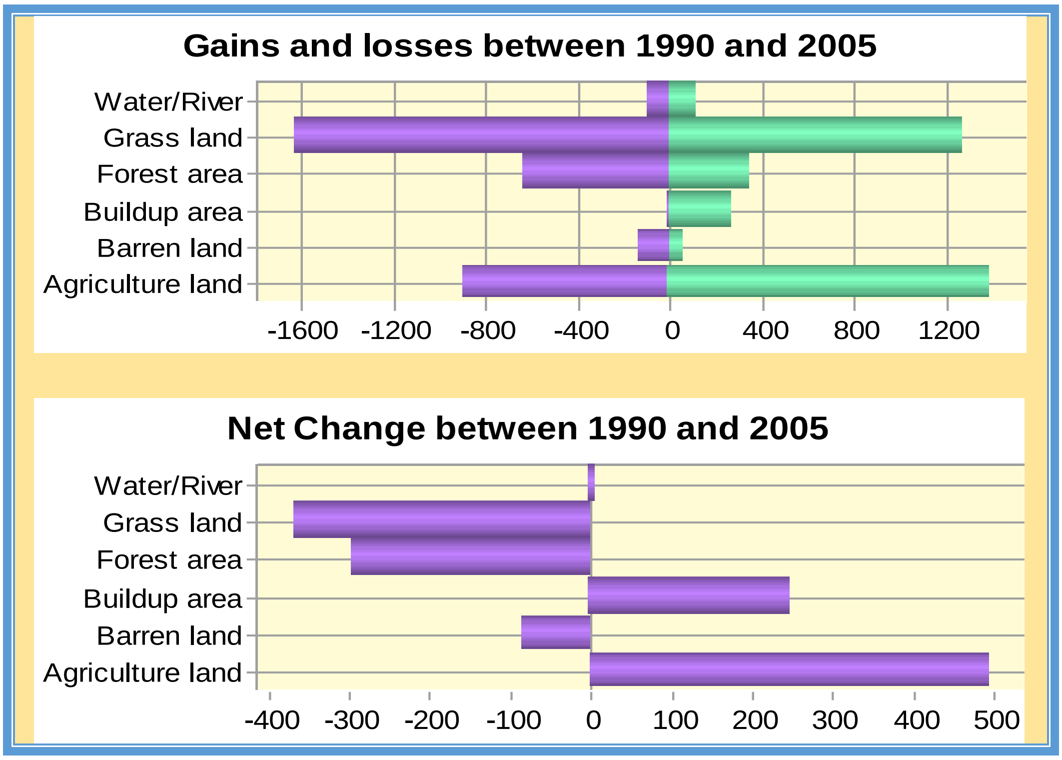


Figure 4.5: Gains, losses and net change between 1990 and 2005

4.3.2 Land use/land cover change during 2005 – 2015

The second period witnessed the conversion of LULC types to different land covers. The area of grassland declined continuously to 2215Ha in the second period. Likewise, forest area, water body, and barren land declined by 697.466Ha, 135.36Ha, and 78.148Ha, respectively. On the other hand, like the first-period cropland showed an increment of positive net change 1627.66Ha. The most striking change in this period is an increase in the built-up area that revealed net change positive 709.56. The trend of changes in the second period land use revealed a general trend of destruction that was considered except the buildup area and agriculture land cover which showed changes extensively, and Table 4.7 shows the comparison of the net change of land cover during the second period (2005–2015). Generally the land enchrochment between 2005 and 2015 indicate built-up area gain from agriculture land 347Ha, and 376Ha from grassland.

Table 4.7: Post classification matrix, losses, gains, persistence and net change 2005 - 2015

	2005 – 2015							
	Losses		Gains		Persistence		Net change	
LU/LC Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	970.623	21.82	2598.3	58.41	2415.7	71.30	1627.66	36.59
Barren land	78.148	1.76	20.214	0.45	5.9559	6.67	-57.93	-1.30
Buildup area	50.8954	1.14	760.45	17.09	482.33	90.45	709.56	15.95
Forest area	697.466	15.68	277.04	6.23	477.28	40.75	-420.43	-9.45
Grassland	2515.99	56.56	755.49	16.98	648.92	20.50	-1760.50	-39.58
Water/ River	135.36	3.04	36.998	0.83	50.174	27.14	-98.36	-2.21
Total	4448.48	100.00	4448.48	100.00	4080.39	256.81	0.00	0.00

		Land class 2015					
	LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/River
Land class 2005	Agriculture	2413.55	0.54	347.17	41.12	582.64	1.03
	Barren land	61.70	5.47	0.00	3.56	13.45	0.00
	Buildup area	20.74	0.00	489.34	18.15	4.83	0.23
	Forest area	521.78	0.07	41.73	490.35	100.80	13.90
	Grassland	1947.21	18.37	376.50	159.57	640.59	14.84
	Water/River	53.95	0.01	10.64	33.35	36.61	49.86

From table 4.7 losses, gains, persistence, net change and land enchrochment between 2005 and 2015 clearly presented. Accordingly the land echrochment result indicate all land class converted to built-up area from 2005 to 2015 agriculture contribute 347.17Ha, forest area 41.73Ha, grassland 376.50 Ha and water body contribute 10.64Ha.

The losse, gains and persistence result indicate agricultural positive net change 1627.66Ha, barren land negative netchange 57.93Ha, built-up area positive netchange 709.56Ha, forest area negative netchange 420.43Ha, grassland negative netchange 1760.50Ha, and water bodies negative netchange 98.36Ha.

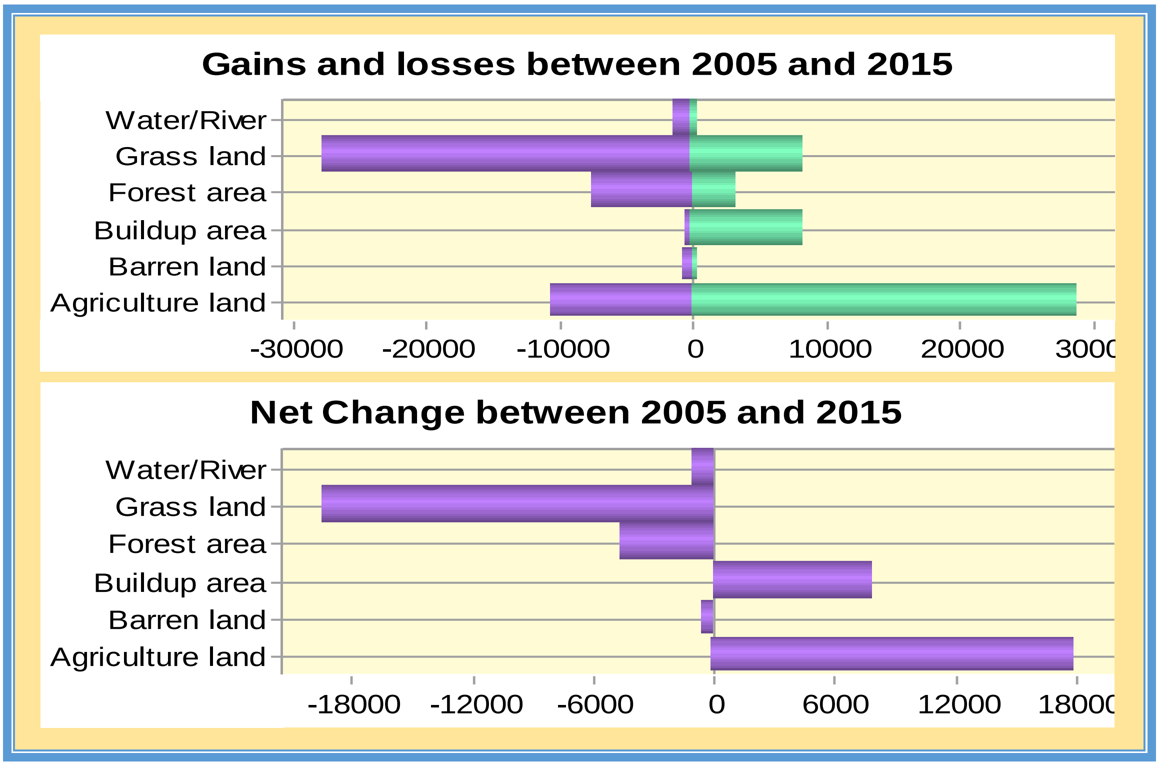


Figure 4.6: Gains, losses and net change between 2005- 2015

4.3.3 Land use/land cover change during 2015 – 2021

Table 4.8: Post classification matrix, losses, gains, persistence and net change 2015- 2021

	2015 – 2021							
LU/LC	Losses		Gains		Persistence		Net change	
Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	323.51	66.88	36.64	7.57	4677.51	93.10	-286.87	-59.31
Barren land	0.00	0.00	0.00	0.00	25.45	71.85	0.00	0.00
Buildup	6.68	1.38	442.81	91.55	1256.05	99.26	436.13	90.17
Forest area	10.11	2.09	0.00	0.00	742.50	99.45	-10.11	-2.09
Grassland	141.14	29.18	4.24	0.88	1255.69	90.98	-136.89	-28.30
Water/ Riv	2.26	0.47	0.00	0.00	81.40	101.67	-2.26	-0.47
Total	483.69	100.00	483.69	100	8038.59	94.22	0.00	0.00

		Land class 2021					
LULC Type		Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/River
Land class2015	Agriculture	4690.97	0.13	323.03	1.58	8.16	0.07
	Barren land	0.34	24.21	0.00	0.00	0.00	0.00
	Buildup	5.28	0.00	1255.36	2.01	2.70	0.03
	Forest area	4.21	0.00	10.40	731.76	0.25	0.00
	Grassland	33.36	0.03	113.13	0.50	1232.85	0.18
	Water/River	0.05	0.00	1.77	0.16	0.17	77.82

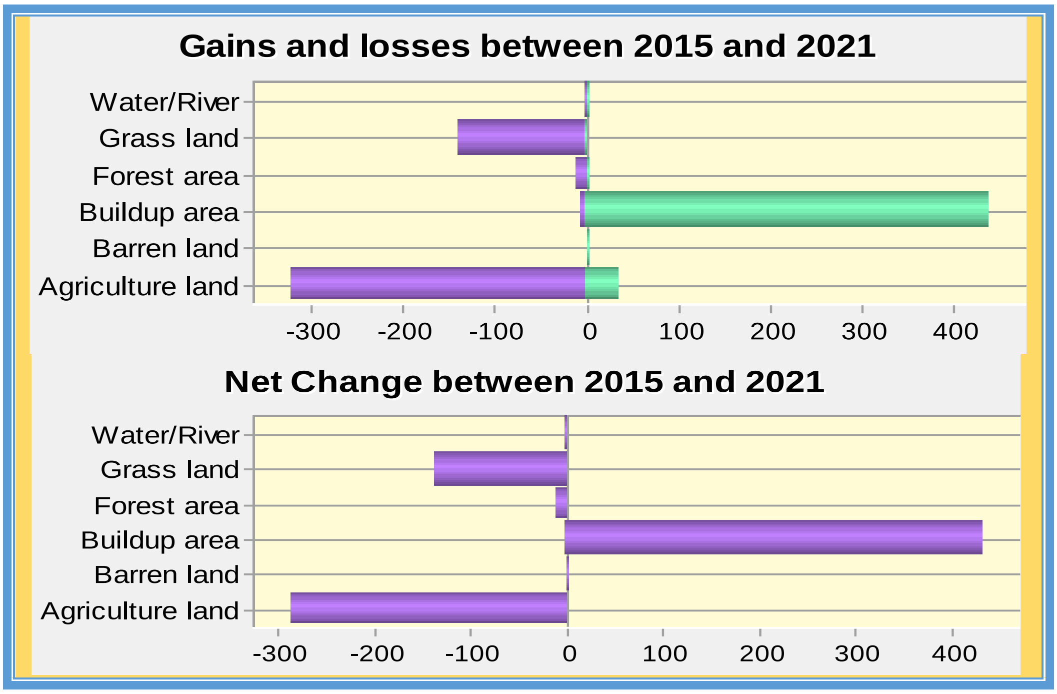


Figure 4.7: Gains, losses and net change 2015 to 2021

The third period was characterized by advanced LULC dynamics where previously intensifying land cover classes such as agriculture land, forest area and grassland declined their net change by - 59.31% and -2.09% and -28.30% respectively. The built-up area reveals rapid change with a net positive increase of 436.13Ha (90.17%). Hence, the expansion of built-up areas had resulted in a negative change of forest, grassland, and agricultural land.

4.3.4 Land use/land cover change during 1990– 2021

Table 4.9: Land use land cover change matrix during 1990 - 2021

		Land Class – 2021					
LU/LC Type		Agriculture land	Barren land	Buildup area	Forest area	Grass land	Water
Land class - 1990	Agriculture	1876.04	0.00	612.69	71.18	323.89	10.33
	Barren land	101.53	12.66	8.85	14.18	31.51	0.00
	Buildup area	0.06	0.00	272.91	10.54	0.00	0.01
	Forest area	814.02	0.40	33.85	432.36	173.70	14.04
	Grass land	1898.49	11.30	769.42	146.31	690.86	9.55
	Water/River	39.73	0.00	5.97	61.11	23.28	43.77

Agriculture land: In the 30 years, between 1990 and 2021, almost 612.69Ha of buildup area was obtained from agricultural land. During the entire study period (1990-2021), the conversion of forest area into agricultural land accounted for 814.02Ha. In the same period, grassland, water, barren land; accounted for 1898.49Ha, 39.73Ha, and 101.53Ha respectively.

Barren land: Within the 30 years, 1990 - 2021, almost 101Ha of barren land was obtained from agricultural land mainly. During the overall period (1990-2021), the conversion of forest area, grassland into barren land accounted for 0.4ha; 11.3ha respectively.

Buildup area: During the entire study period (1990 - 2021) the conversion of grassland into buildup area accounted for 769.42Ha. In the same period forest area, agricultural land, barren land, water body; accounted for 33.85Ha, 612.69Ha, 8.85Ha, and 5.97Ha respectively.

Forest area: During the entire study period (1990 - 2021) the conversion of grassland into forest area accounted for 146.31Ha. In the same period forest area, buildup area, barren land, water body; accounted for 10.54Ha, 71.18Ha, 14.18Ha, and 61.11Ha respectively.

Grassland: During the entire study period (1990 - 2021) the conversion of agricultural land into grassland accounted for 323Ha. In the same period forest area, buildup area, barren land, water body; accounted for 173Ha, 0Ha, 31.51Ha, and 23.28Ha respectively.

Waterbody: During the entire study period (1990 - 2021) the conversion of forest area into water body accounted for 14.04Ha. In the same period agricultural land, buildup area, barren land, grassland; accounted for 10.33Ha, 0.01Ha, 31.51Ha, and 9.55Ha respectively.

Table 4.10: Losses, gains, persistence, and net change of study area from 1990 - 2021

	1990 -2021							
	Losses		Gains		Persistence		Net change	
LU/LC Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	1025.76	19.75	2849.06	54.86	1865.08	64.41	1823.30	35.11
Barren land	157.20	3.03	12.27	0.24	13.18	7.81	-144.93	-2.79
Buildup area	10.47	0.20	1427.15	27.48	271.71	95.84	1416.68	27.28
Forest area	1038.66	20.00	310.07	5.97	432.43	29.36	-728.60	-14.03
Grassland	2830.56	54.51	560.39	10.79	699.54	19.78	-2270.1	-43.71
Water/ River	130.49	2.51	34.20	0.66	47.20	27.10	-96.29	-1.85
Total	5193.14	100.00	5193.14	100.00	3329.14	244.28	0.00	0.00

Over 31 years (1990–2021), the magnitude and directions of LULC change had become more dynamic. The net change for forest and grassland is negative with varying levels of deforestation and removal of grassland during the first and second distinct study periods.

This shows a heightened level of deforestation during these periods due to the expansion of built-up areas and agricultural land. Due to its small size, the water body did not show significant change but the second and third periods was marked a decline compared to the first period. A 1416 68Ha (27.28%) net change of built-up and 1823.30Ha (35.11%) were possibly triggering factors causing LULC change in the study area, mostly gaining areas from forest land, grassland, and barren land since the 1990s.

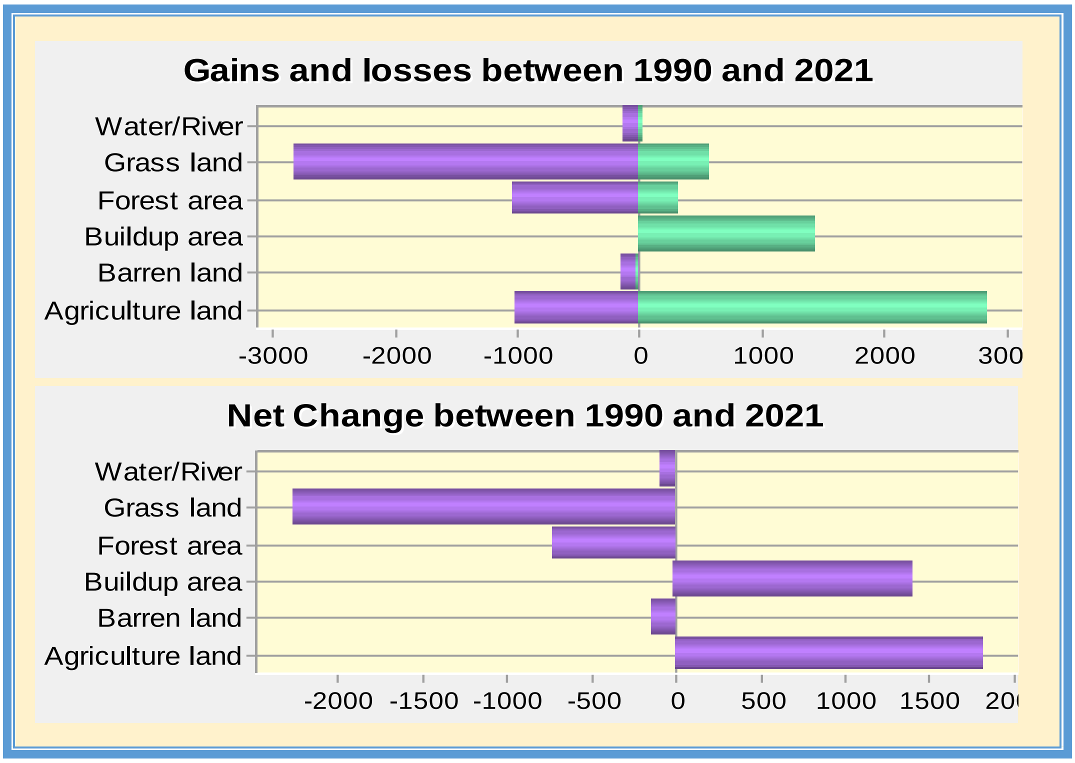


Figure 4.8: Gains, losses, and net change between 1990 and 2021

Figure 4.8 shows the continuous distruction of grass land and forest area. Also it indicates the decrease of water bodies and barren land aswell. Built-up area and agriculture land reveal increment with positive netchange 27.28%, and 35.11% respectively. The negative net change of grassland -2270.10Ha, and forest area -728.60Ha.

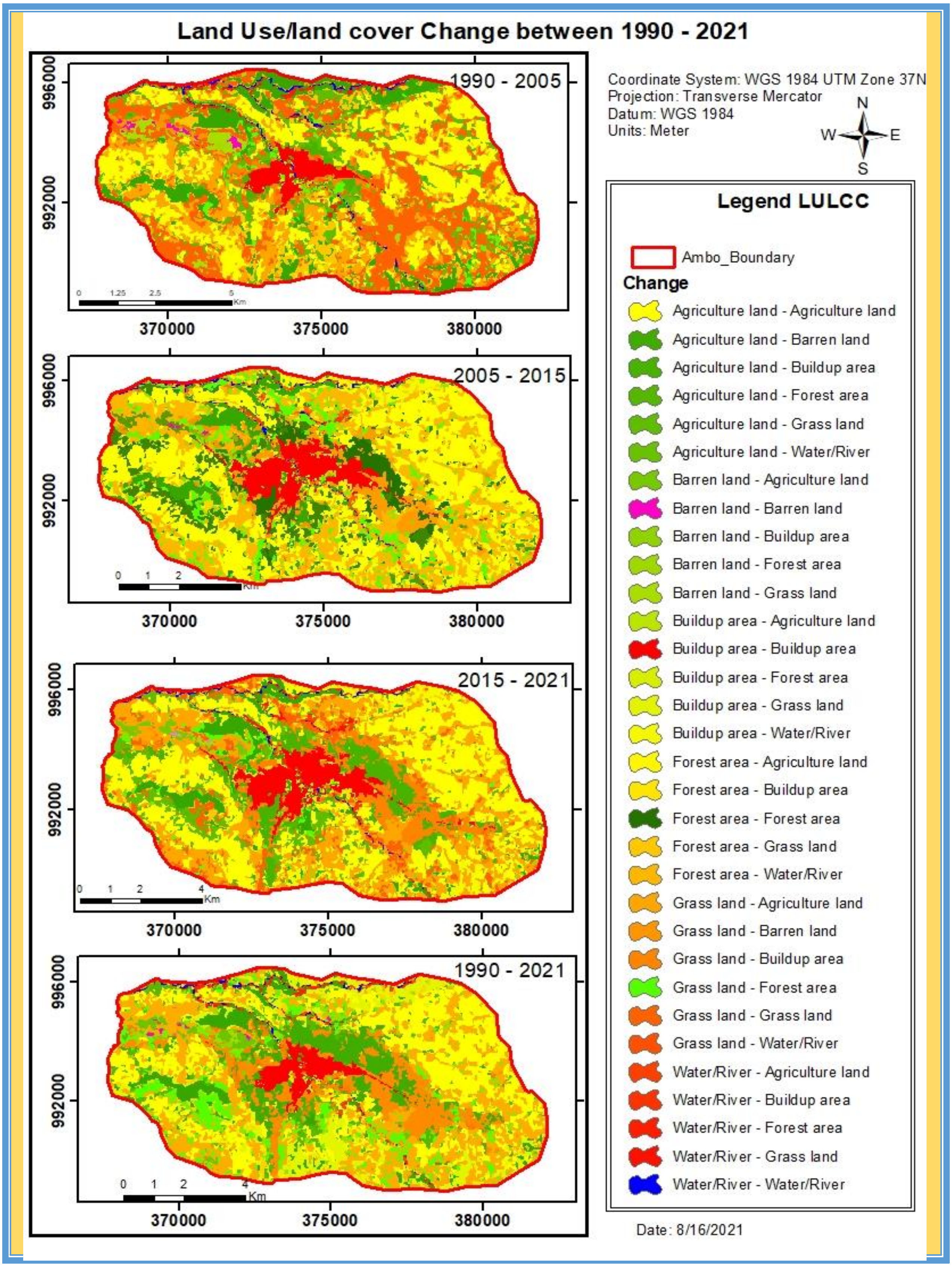


Figure 4.9: Land use/land cover change map 1990 - 2021

4.4 Urban Extent of the Study Area

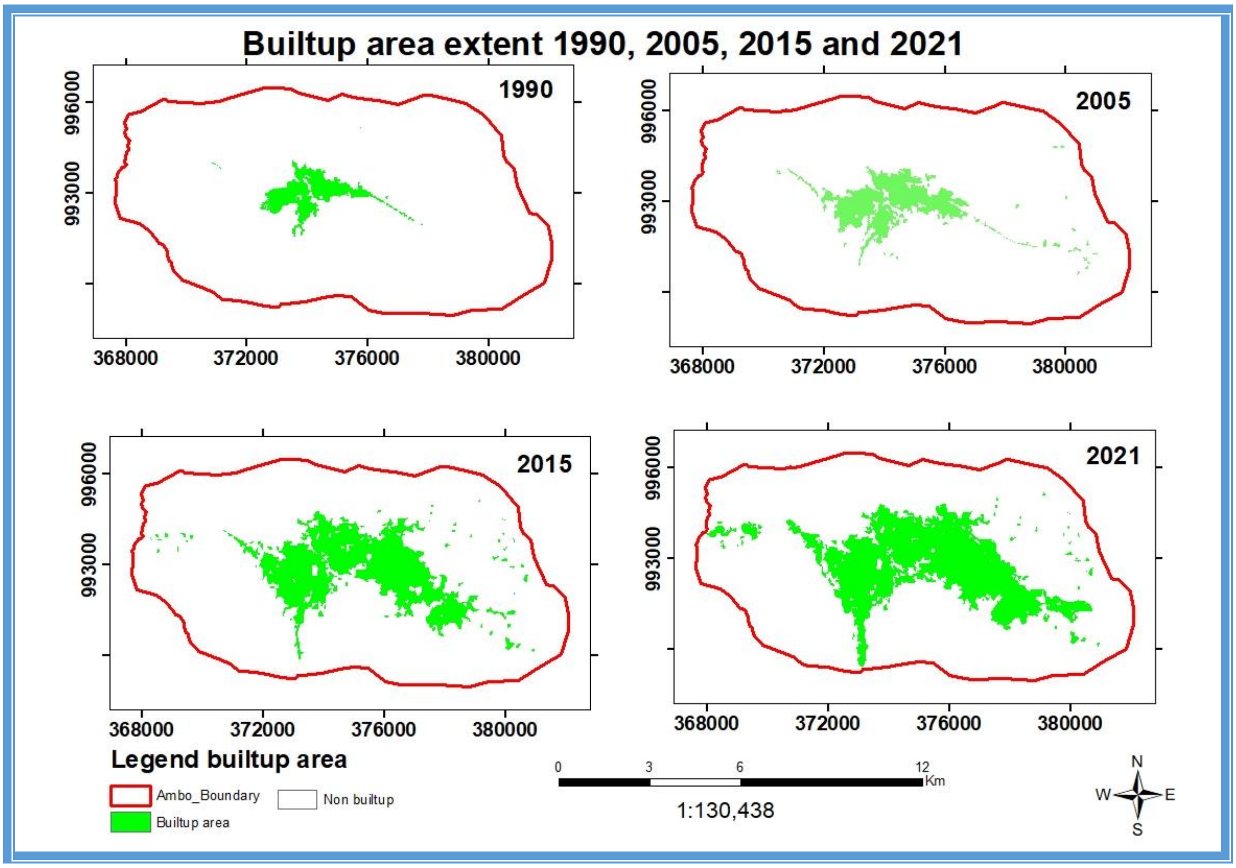


Figure 4.10: Classified image to the built-up area and non-buildup area

Table 4.11: Buildup area and non- built-up area 1990 - 2021

	1990		2005		2015		2021	
LU/LC Type	Ha	%	Ha	%	Ha	%	Ha	%
Buildup area	283.52	3.32	533.28	6.25	1265.38	14.83	1703.69	19.97
Non Build up	8248.01	96.68	7998.25	93.75	7266.15	85.17	6827.84	80.03
Total	8531.53	100	8531.53	100	8531.54	100	8531.53	100

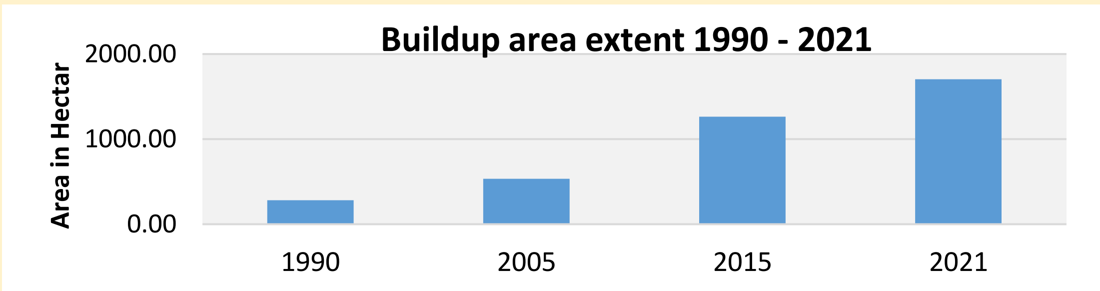


Figure 4.11: urban expansion 1990 -2021

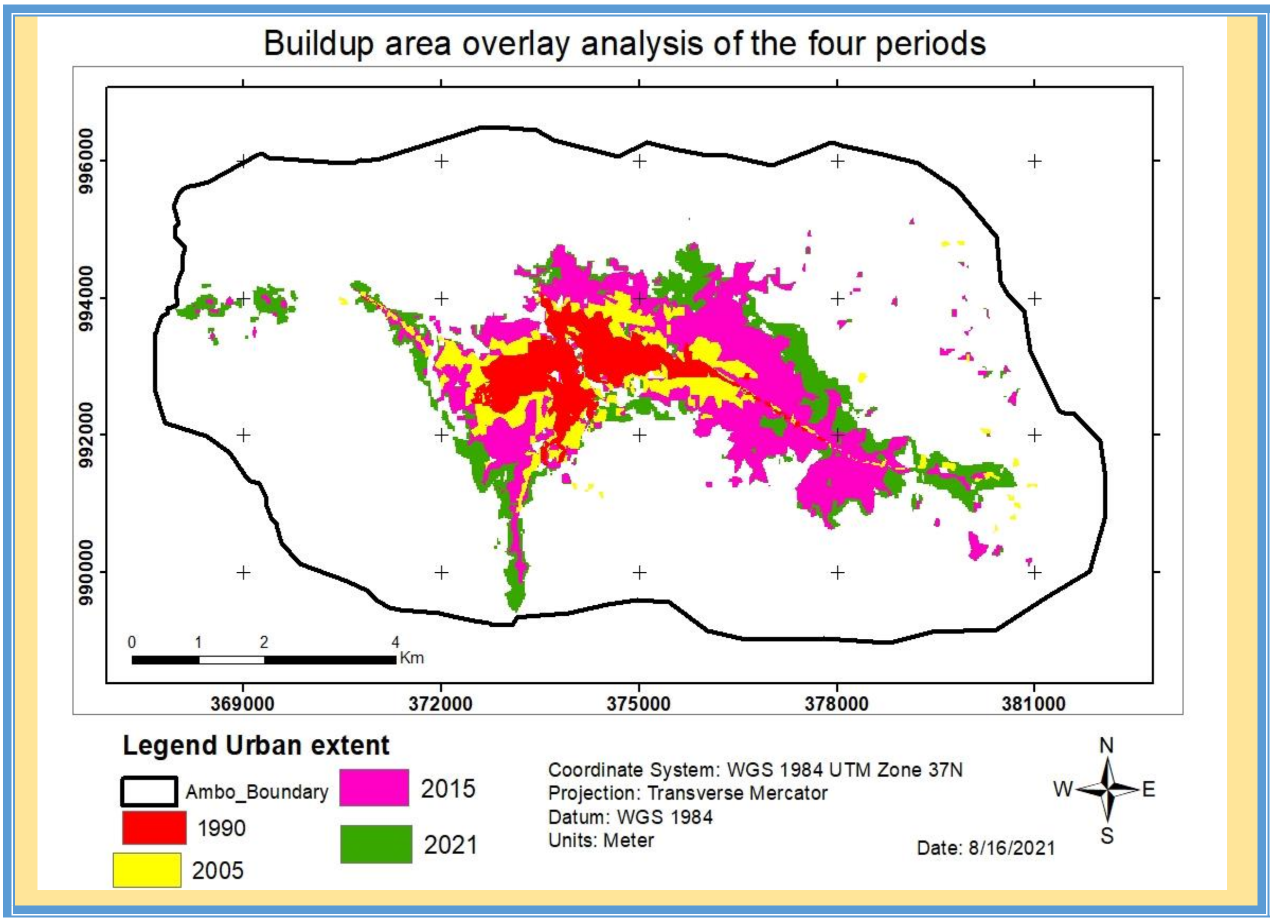


Figure 4.12: Buildup area overlay analysis 1990, 2005, 2015 and 2021

Table 4.12: All land classes changed to build up area 1990 - 2021

	1990 - 2005		2005 - 2015		2015 - 2021		1990 - 2021	
LULC Type	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	119.84	1.40	336.51	3.94	321.53	3.77	612.01	7.17
Barren land	1.53	0.02	0.00	0.00	0.00	0.00	9.11	0.11
Buildup area	264.95	3.11	482.33	5.65	1256.05	14.72	271.71	3.19
Forest area	6.68	0.08	41.87	0.49	6.59	0.08	34.29	0.40
Grass land	137.80	1.62	370.89	4.35	112.53	1.32	765.33	8.97
Water/River	2.44	0.03	11.19	0.13	2.17	0.03	6.41	0.08
Total	533.23	6.25	1242.79	14.57	1698.86	19.91	1698.86	19.91

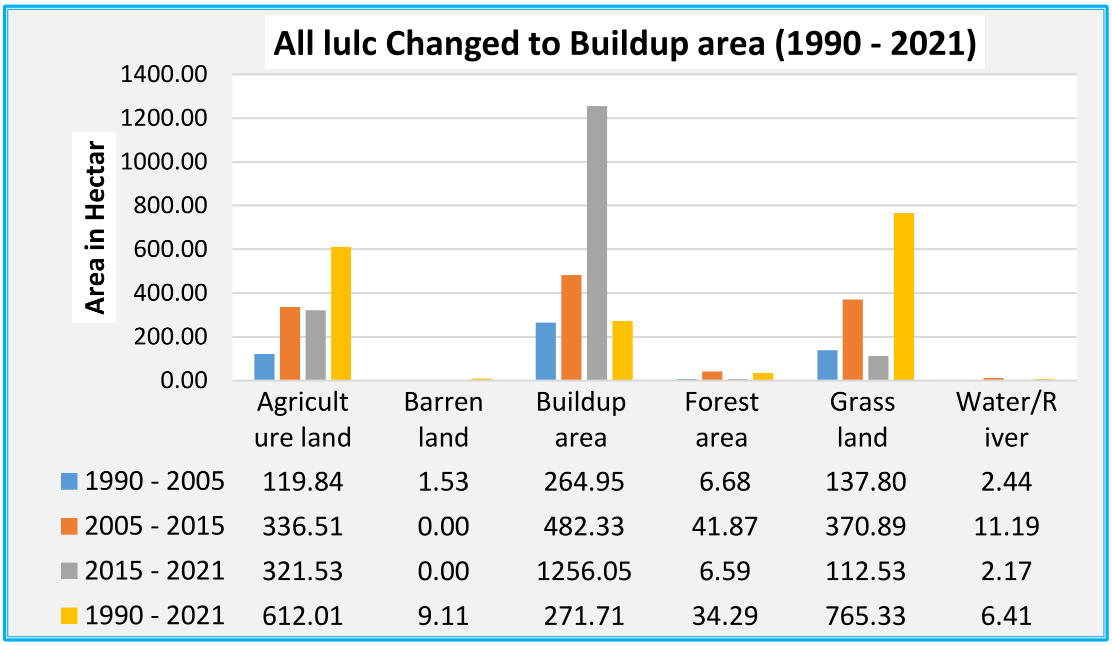


Figure 4.13: All land classes changed to the built-up area

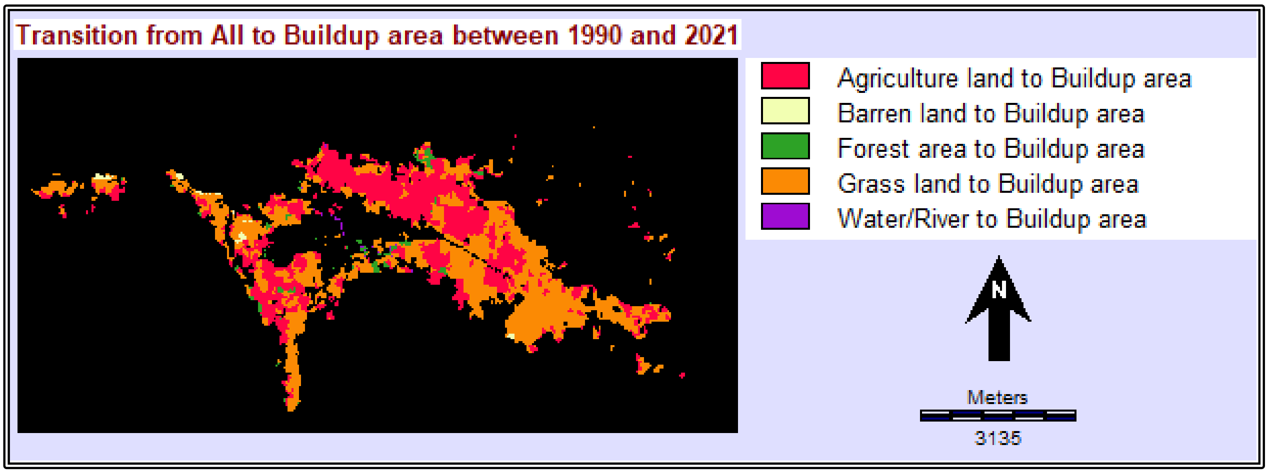


Figure 4.14: All LULC changed to buildup area 1990 - 2021

Generally, Ambo Town LULC Classes that contribute more Net change in a built-up area for three decades (1990-2021) is grassland that contributes (765Ha), agriculture land (612Ha), forest area (34 Ha), barren land (9Ha) and water body contribute (6.4Ha).

4.5 Future Prediction and Modeling Land Use/Land Cover

The LULC modeling is incomplete without validating the model with actual data. So, the results of LULC simulated areas need to be compared with the actual area. Therefore, the simulated LULC areas of 2021 were compared with the actual areas interpreted from the 2021 sentinel image, and the result was tested with kappa,klocation, klocation strata, and khiston in order to ensure the relevancy of the selected variable with LULC change in the model.

4.5.1 Markov chain

This model firstly has been used by socioeconomic researchers in the 1950s but after the 1960s it started to be used in urban studies too, and for LULC modeling it had been used in the late 1970s (Iacono and Levinson et al., 2012). The first usage of this model was on parcel level, later by Bell in 1974 it has been used for remote sensing sources as well (pixel-based) (Bell, 1974).

4.5.1.1 Implementation of Markov chain

Cramer's coefficient, which shows the relationship between variables and LULC classes, was calculated and the value for reclassified LULC 2015, distance from buildup, distance from the main road, distance from the river, elevation, and slop are all in an acceptable range greater than 0.15. For the prediction of 2021; LULC2005 and 2015 were used for this study. According to the MARKOV model, the relation between 2005and 2015 has been modeled to be used in the 2021 simulation. The results of the MARKOV model are; *A transition matrix:* This contains the probability of each land use/cover category which can change to every other category (Eastman, 2012). See table 4.13

Table 4.13: Markov conditional probability of changing among LULC type.

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/ River
Agriculture land	*0.7534*	*0*	*0.0636*	*0.0048*	*0.1782*	*0*
Barren land	*0.7094*	*0.107*	*0*	*0.0425*	*0.1411*	*0*
Buildup area	*0.0208*	*0*	*0.9469*	*0.0268*	*0.0054*	*0.0001*
Forest area	*0.3698*	*0*	*0.0087*	*0.552*	*0.0569*	*0.0126*
Grassland	*0.6135*	*0.0089*	*0.0829*	*0.0546*	*0.2346*	*0.0056*
Water/ River	*0.1603*	*0*	*0.0263*	*0.19*	*0.211*	*0.4125*

A transition areas matrix: This contains the number of pixels that are expected to change from each land use/cover type to other land use/cover type over the specified period (Eastman, 2012). The number of cells expected to be transformed to other classes can be observed in table 4.14.

Table 4.14: Cells expected to be transformed to other classes.

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grass land	Water/ River
Agriculture land	*51895*	*0*	*3525*	*0*	*0*	*0*
Barren land	*0*	*282*	*0*	*0*	*0*	*0*
Buildup area	*0*	*0*	*13993*	*0*	*0*	*0*
Forest area	*0*	*0*	*73*	*268*	*0*	*0*
Grass land	*0*	*0*	*1283*	*0*	*197*	*0*
Water/ River	*0*	*0*	*24*	*0*	*0*	*904*

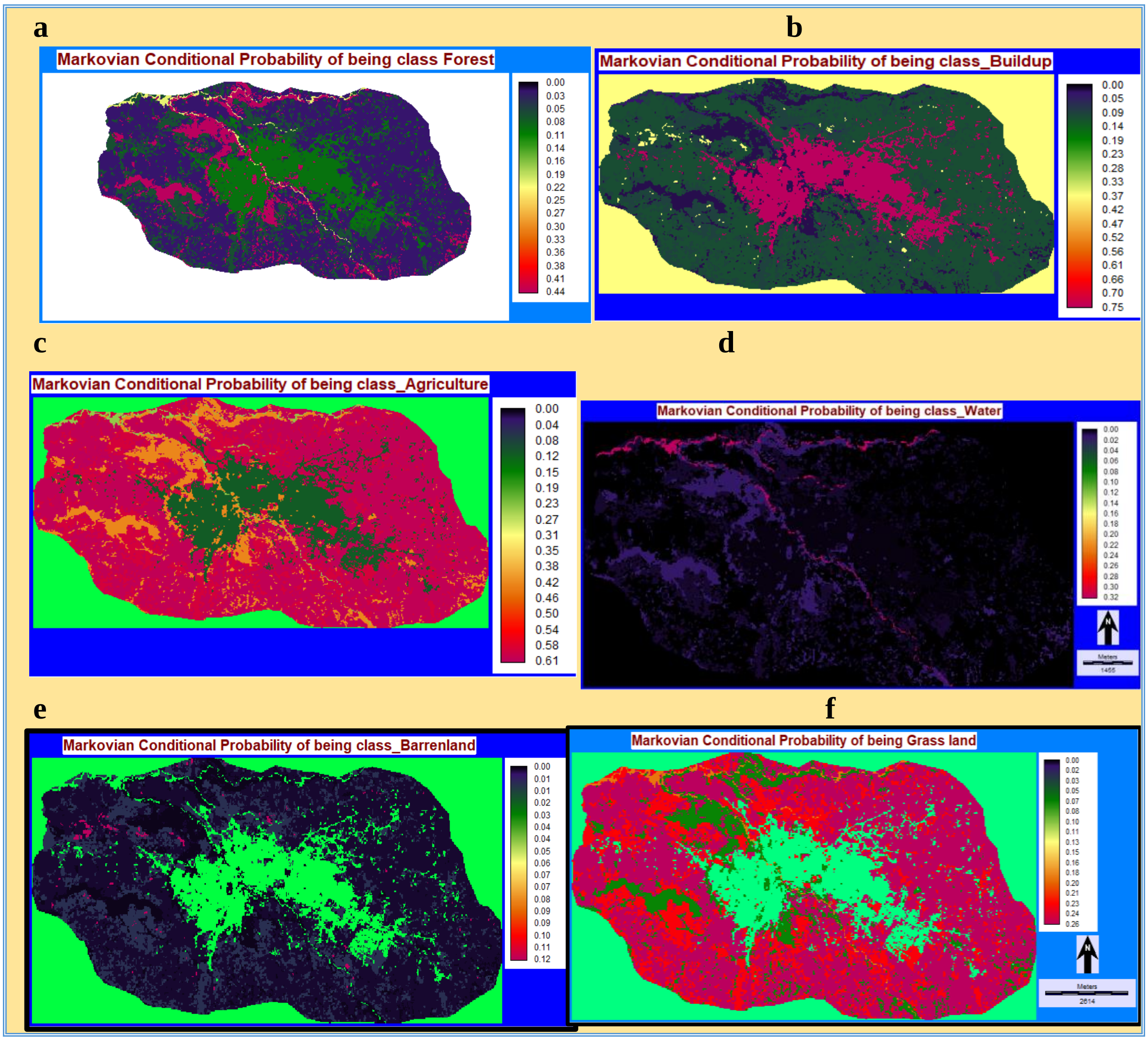


Figure 4.15: Transition land cover classes to a) forest area, b) buildup area, c) agriculture land, d) water body, e) barren land and f) grassland respectively.

4.5.1.2 Multilayer perceptron and Markov chain

The model which was used for modeling the future LULC of the study area was the combination of Markov Chain and Artificial Neural Network-based methods. In this model, ANN is used for defining the spatial allocation of simulated LULC categories, in other works for transition potential development, and Markov Chain used for prediction based on transition potentials. In this case, the first stage of the method is detecting the changes; this has been explained in detail in the methodology section of change detection. The second step of the method is transition modeling which helps to create the transition maps from each LULC category to urban areas, which can be done by using the MLP method. The third step was the change modeling and the validation of the model with the accuracy assessment. Before the implementation of the model the theory of the ANN and MLP needs to be understood so, it was described in the methodology part.

4.5.1.3 Combination of multilayer perceptron and Markov chain methods

The first stage of this combined method is transition potential development with the MLP method. This stage is composed of three sub-stages which are; sub-model development, testing the variables, and transition potential development. The second stage of the model is a simulation with the MARKOV method by using transition potentials and model validation.

4.5.1.4 Transition sub-model development and standardization of variables

For this research, the effect of the urban buildup area was the main indicator, for this reason, the changes from other categories to buildup area were used as a transition sub-model. To model the changes, the main variables which affect the changes need to be detected. These variables are reclassified LULC map of 2015, distance to urban centers, distance from the road, distance from the river, digital elevation model (DEM), and slope.

Factors are criterion that enhances or detracts from the suitability of a specific alternative for the activity under consideration. They are not reduced to simple Boolean constraints. It is therefore most commonly measured on a continuous scale (Eastman, 2012). Because of the different scales upon which criteria are measured, it is important to standardize the factors to a continuous scale of suitability. In IDRISI, the FUZZY module is provided for the standardization of factors using a whole range of fuzzy set membership functions. Because the Multi-Criteria Evaluation (MCE) module has been optimized for speed using a 0-255 byte level of standardization, it is recommended to standardize the factors in this scale (Eastman, 2012).

Based on the potential behavior of the local population towards land-use development six factors were selected in this study; distance from major rivers, distance from major roads, distance from existing built-up areas, LULC 2015, DEM, and slop calculated based on the physical distance.

Araya and Cabral (2010) described three fuzzy standardization functions to design criteria for factors to be used in a decision rule. These were sigmoid, J-shaped, and linear functions with adjustable settings. Based on this principle, factors in this study were standardized and categorized. For existing built-up areas a linear monotonically decreasing function has been applied. Since areas close to currently developed land are more suitable than areas farther from developed land which means that suitability decreases with distance. Thus, the control points considered were 0 and 4500m using the fuzzy membership function and In the case of roads, a linear symmetric function was considered as the area within 30 m is not suitable for urban growth.

However, between 30m and 4968m is decreasing with the highest suitability being near to 30m. Rivers were standardized based on their suitability to urban growth so that areas within 40m were restricted as a buffer zone and considered as unsuitable. A linear monotonically increasing function, therefore, has been applied since suitability increases with distance and control points 30m and 2433m. For slope considerations a sigmoidal monotonically decreasing function was applied as regions with slopes > 20% were considered as unsuitable for urban development. Areas with more red color indicate the highest suitability of 255 whereas the dark green color represents a lower suitability value of 0.

4.5.1.5 Transition Potential Development: To calculate and map these potentials MLP, which is a successful method in solving complex systems, has been used. As it has been illustrated in the figures below the result of the simulation is more or less similar to the existing situation but this needs to be tested by accuracy assessment.

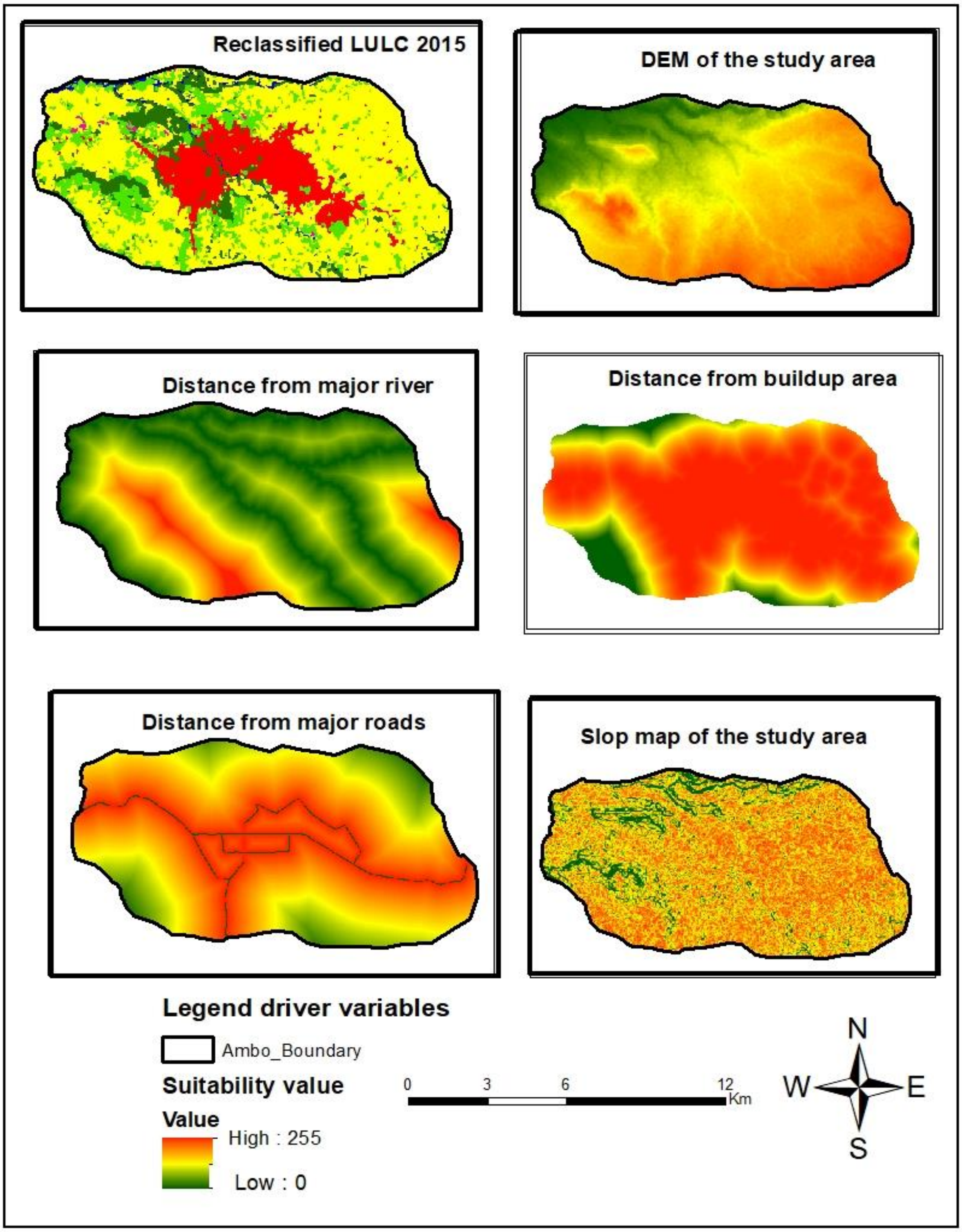


Figure 4.16: Driver variables used for future prediction

4.5.2 Influence of driver variable on urban growth

The sensitivity analysis revealed that LULC 2015 was the most influential driver variable. The second most influential driver variable was Distance from buildup area, distance from the road, distance from the river, DEM and slop score 3rd, 4th, 5th, and 6th respectively. According to the analysis, the slope was the driver variable with the least influence on the model.

Table 4.15: Relative significance of driver variables generated by forcing independent variables to be constant.

Model	Accuracy (%)	Skill measure	Influence order
With all variables	100	1	N/A
Dist.from buildup	63.64	0.27	2
LULC_2015	54.55	0.09	1 (most influential)
Distance from Road	100	1	3
Distance from River	100	1	4
DEM	100	1	5
Slop	100	1	6 (least influential)

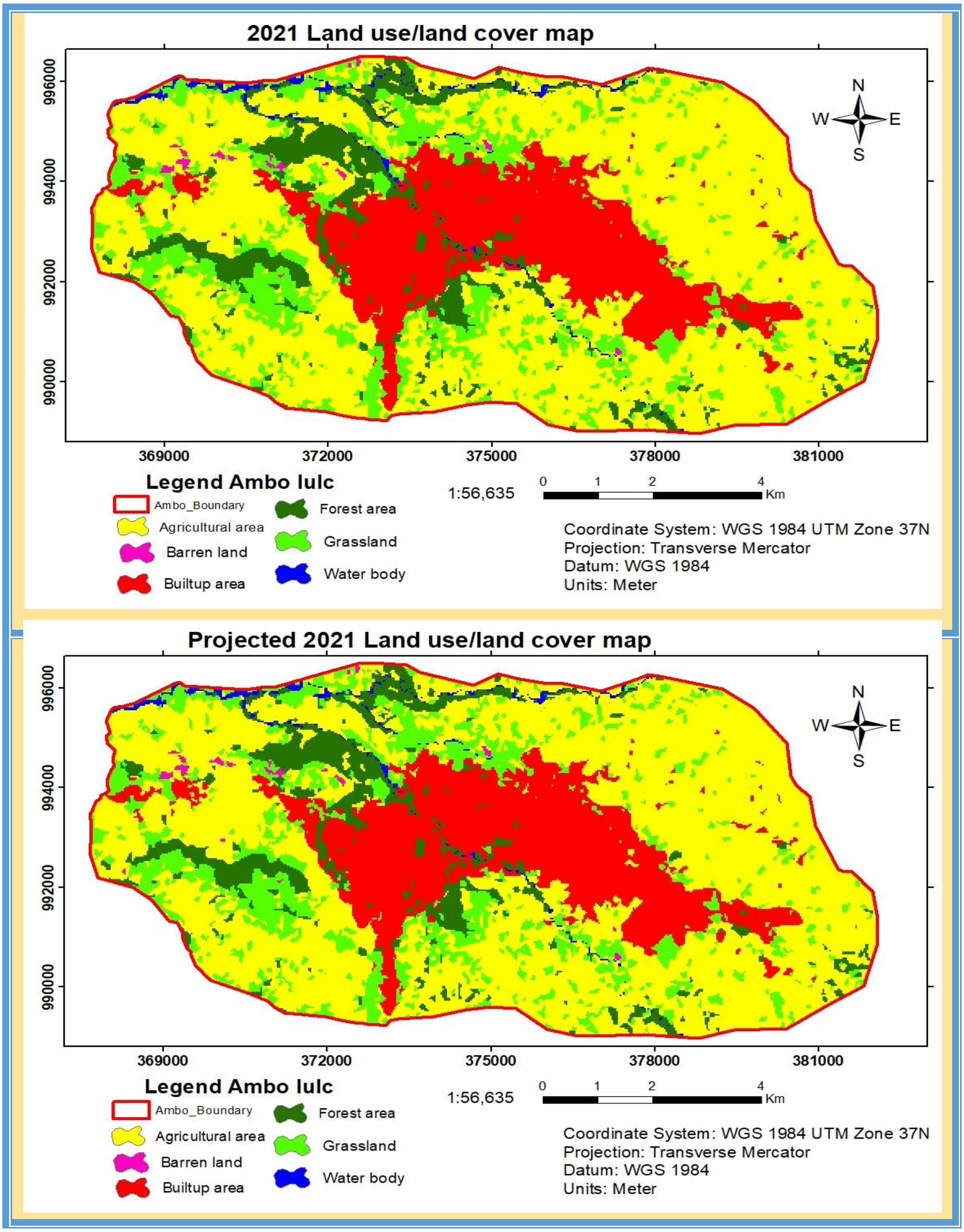


Figure 4.17: Actual land use land cover and projected 2021 (MLP and MARKOV)

4.6 Accuracy Assessment (Model Validation)

The accuracy assessment of image classification and simulation results is slightly different because in the latter case the accuracy is assessed by using the maps, not the specific points which are indicating the real category information (Rossiter, 2004). In many studies, kappa statistical measurements have been used for the accuracy assessment Pontius & Millones (2011). The aim was to observe the main changes between 2019 classified and then comparing the results with the predicted map, to understand if the overall changes have been predicted correctly or not. The method used for the accuracy assessment, calculating kappa values related to the location and the quantity to observe the accuracy in each class. These are Klocation and Khisto which demonstrate the source of error, whether it is location or quantity. Klocation shows the similarity in the spatial distribution of classes but does not differentiate between classes that are close or distant and it is independent of the total number of cells per class (Serna, 2011); (Pontius, 2000). Khisto measures quantitative similarity between two maps, in other words, it checks the similarity in the amount of the cells in the testing map and reference map (Serna, 2011).

Table 4.16: Kappa index, information allocation of simulated and actual LC map of 2021

k indicators	
K_{no}	0.95
$K_{location}$	0.94
$k_{location\ strata}$	0.94
$k_{standard}$	0.93
Overall accuracy	0.94

As a result of accuracy assessment, since the overall kappa is 94%, Strength of Agreement for Kappa Statistic is almost perfect (Landis, 1977), and the crammers value was tested for each driver or factor and it reveals greater than 0.15 and above 0.2 crammers value, so the model is acceptable and it can be used for the future simulation 2030, 2040 and 2050.

Table 4.17: Comparison change amount of actual and projected LULC 2021

LU/LC Type	2021		2021 - projected		Actual vs proj	
	Ha	%	Ha	%	Change	%
Agriculture land	4734.22	55.49	4703.80	55.13	30.42	0.36
Barren land	35.38	0.41	33.80	0.40	1.58	0.02
Buildup area	1703.69	19.97	1710.47	20.05	-6.78	-0.08
Forest area	736.02	8.63	739.74	8.67	-3.72	-0.04
Grass land	1244.13	14.58	1265.46	14.83	-21.33	-0.25
Water/River	78.10	0.92	78.27	0.92	-0.17	-0.01
Total	8531.53	100.00	8531.53	100.00	0.00	0.00

Table 4.18: Comparison of actual and projected land use/land cover

LU/LC Type	Actual	Projected
	Ha	Ha
Agriculture	4734.22	4703.8
Barren land	35.38	33.8
Buildup	1703.69	1710.47
Forest area	736.02	739.74
Grassland	1244.13	1265.46
Water/River	78.1	78.27

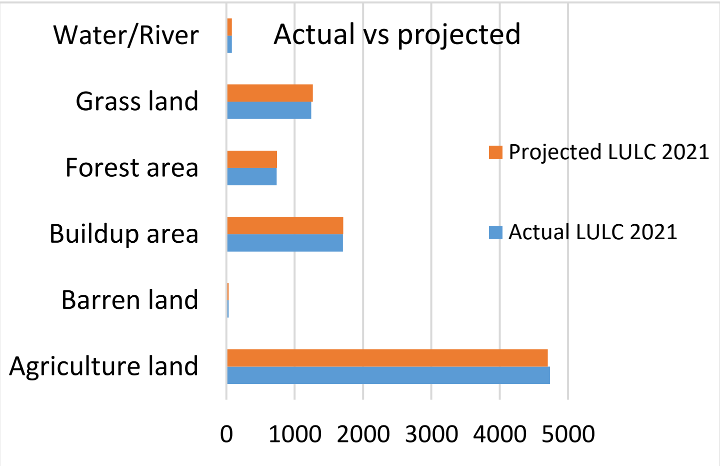


Table 4.19: Cells expected to be transformed to other classes (2030)

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grasslan d	Water/ River
Agriculture land	*47156*	*0*	*8264*	*0*	*0*	*0*
Barren land	*0*	*282*	*0*	*0*	*0*	*0*
Buildup area	*0*	*0*	*13992*	*0*	*0*	*0*
Forest area	*0*	*0*	*542*	*798*	*0*	*0*
Grass land	*0*	*0*	*2498*	*0*	*981*	*0*
Water/ River	*0*	*0*	*81*	*0*	*0*	*847*

Table 4.20: Markov conditional probability of changing among LULC type (2030)

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/ River
Agriculture land	*0.6561*	*0.0012*	*0.1491*	*0.0216*	*0.1711*	*0.001*
Barren land	*0.7218*	*0.0089*	*0.0476*	*0.0386*	*0.182*	*0.0011*
Buildup area	*0.0636*	*0*	*0.877*	*0.0435*	*0.0153*	*0.0006*
Forest area	*0.5428*	*0.0004*	*0.065*	*0.2567*	*0.1242*	*0.0109*
Grassland	*0.6203*	*0.0022*	*0.1614*	*0.0474*	*0.1651*	*0.0037*
Water/ River	*0.4343*	*0.0013*	*0.0874*	*0.1743*	*0.1695*	*0.1332*

Table 4.21: Cells expected to be transformed to other classes (2040)

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/ River
Agriculture	*42949*	*0*	*12470*	*0*	*0*	*0*
Barren land	*0*	*283*	*0*	*0*	*0*	*0*
Buildup area	*0*	*0*	*13993*	*0*	*0*	*0*
Forest area	*0*	*0*	*1164*	*175*	*0*	*0*
Grass land	*0*	*0*	*3605*	*0*	*873*	*0*
Water/ River	*0*	*0*	*147*	*0*	*0*	*782*

Table 4.22: Markov conditional probability of changing among LULC type (2040)

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/ River
Agriculture	*0.5874*	*0.0012*	*0.225*	*0.0313*	*0.1534*	*0.0016*
Barren land	*0.6499*	*0.0018*	*0.1408*	*0.0367*	*0.1689*	*0.0019*
Buildup area	*0.1097*	*0.0001*	*0.8122*	*0.05*	*0.0269*	*0.0011*
Forest area	*0.5819*	*0.0009*	*0.1396*	*0.1253*	*0.1453*	*0.0069*
Grass land	*0.5719*	*0.0013*	*0.2329*	*0.0423*	*0.149*	*0.0027*
Water/ River	*0.532*	*0.0012*	*0.1581*	*0.1143*	*0.1526*	*0.0418*

Table 4.23: Cells expected to be transformed to other classes (2050)

LULC Type	Agriculture land	Barren land	Buildup area	Forest area	Grassland	Water/ River
Agriculture	*39588*	*0*	*15832*	*0*	*0*	*0*
Barren land	*0*	*282*	*0*	*0*	*0*	*0*
Buildup area	*0*	*0*	*13994*	*0*	*0*	*0*
Forest area	*0*	*0*	*1748*	*593*	*0*	*0*
Grass land	*0*	*0*	*4507*	*0*	*971*	*0*
Water/ River	*0*	*0*	*208*	*0*	*0*	*720*

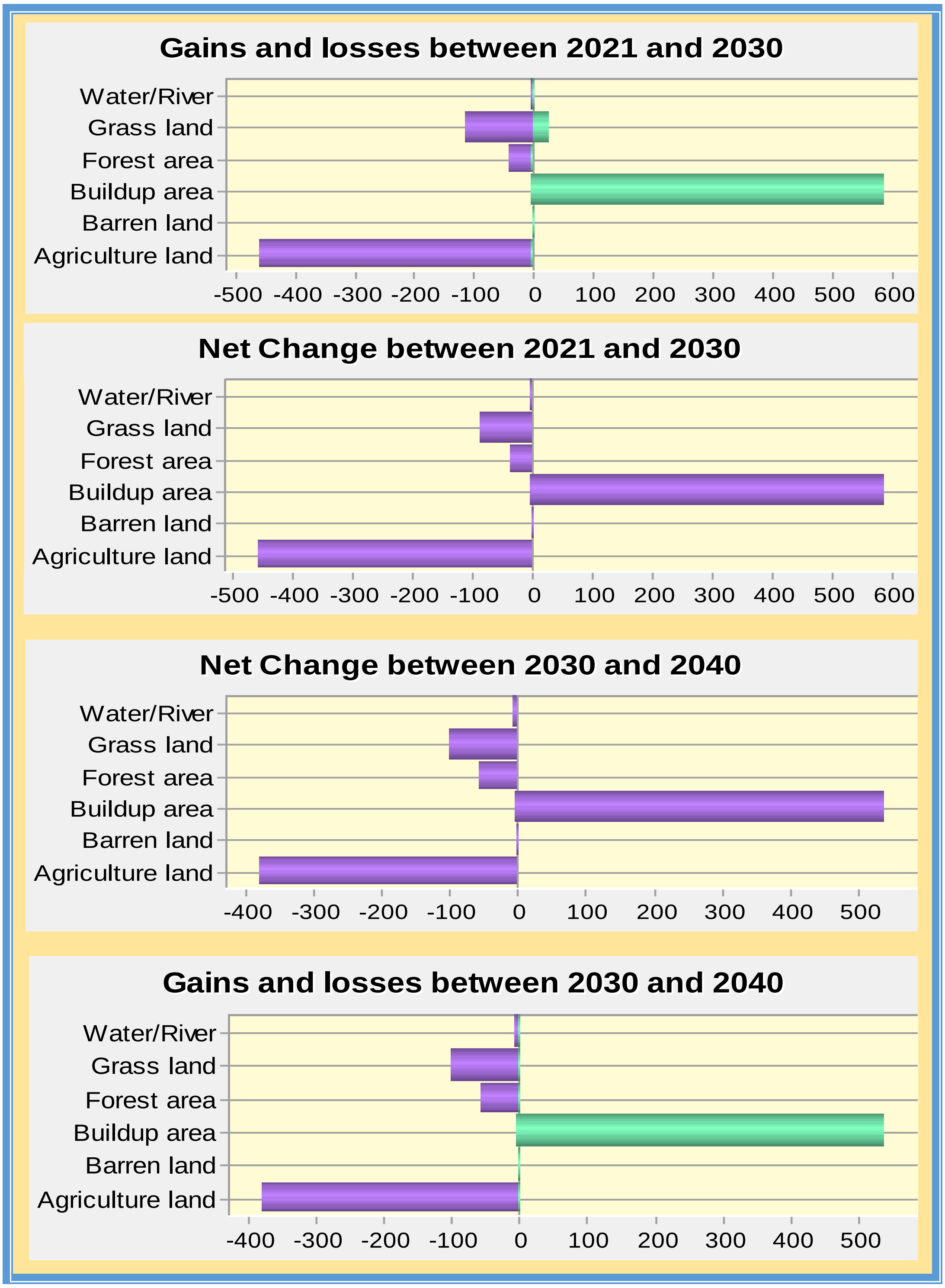


Figure 4.18: Gains, net change, and losses between 2030 and 2040

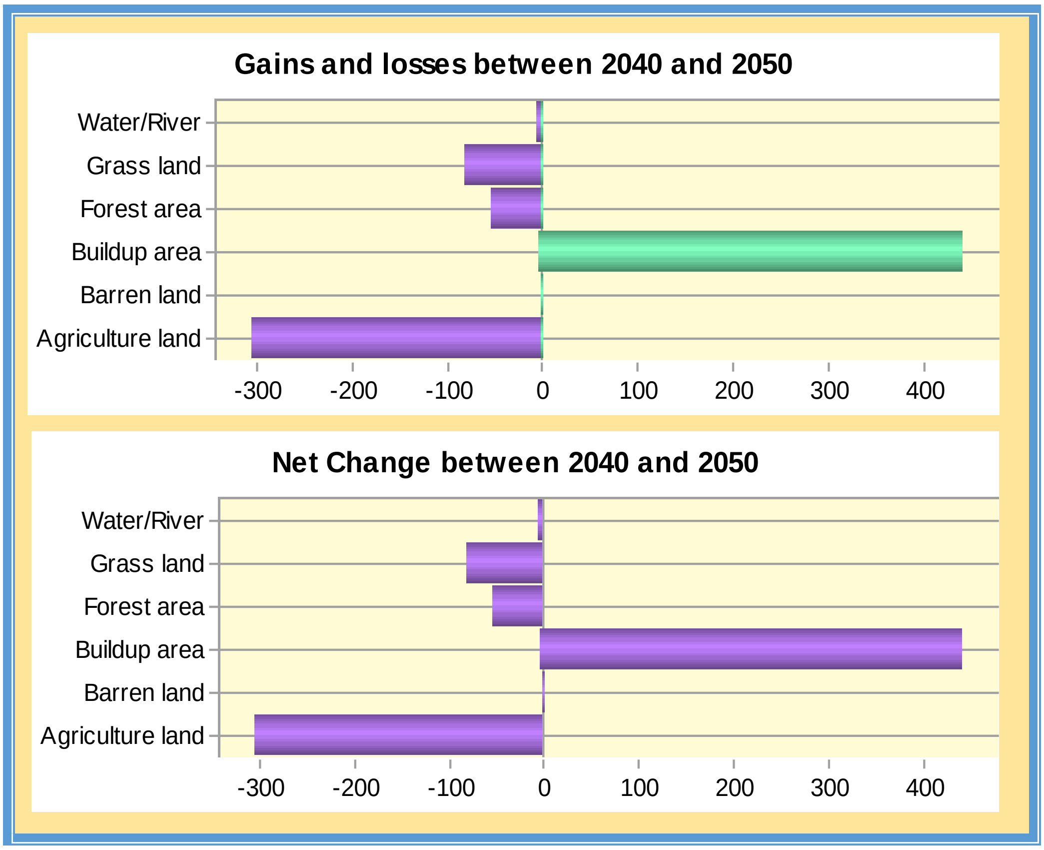


Figure 4.19: Gains, losses, and net change between 2040 and 2050

From the above figures 4.18 and 4.19 the continuous destruction of agriculture due to the urban expansion, and also the decline of grassland, forest area, and water body that contribute to the built-up area from 2030 to 2050. As a result built-up area increase 982.55Ha from 2030 to 2050.

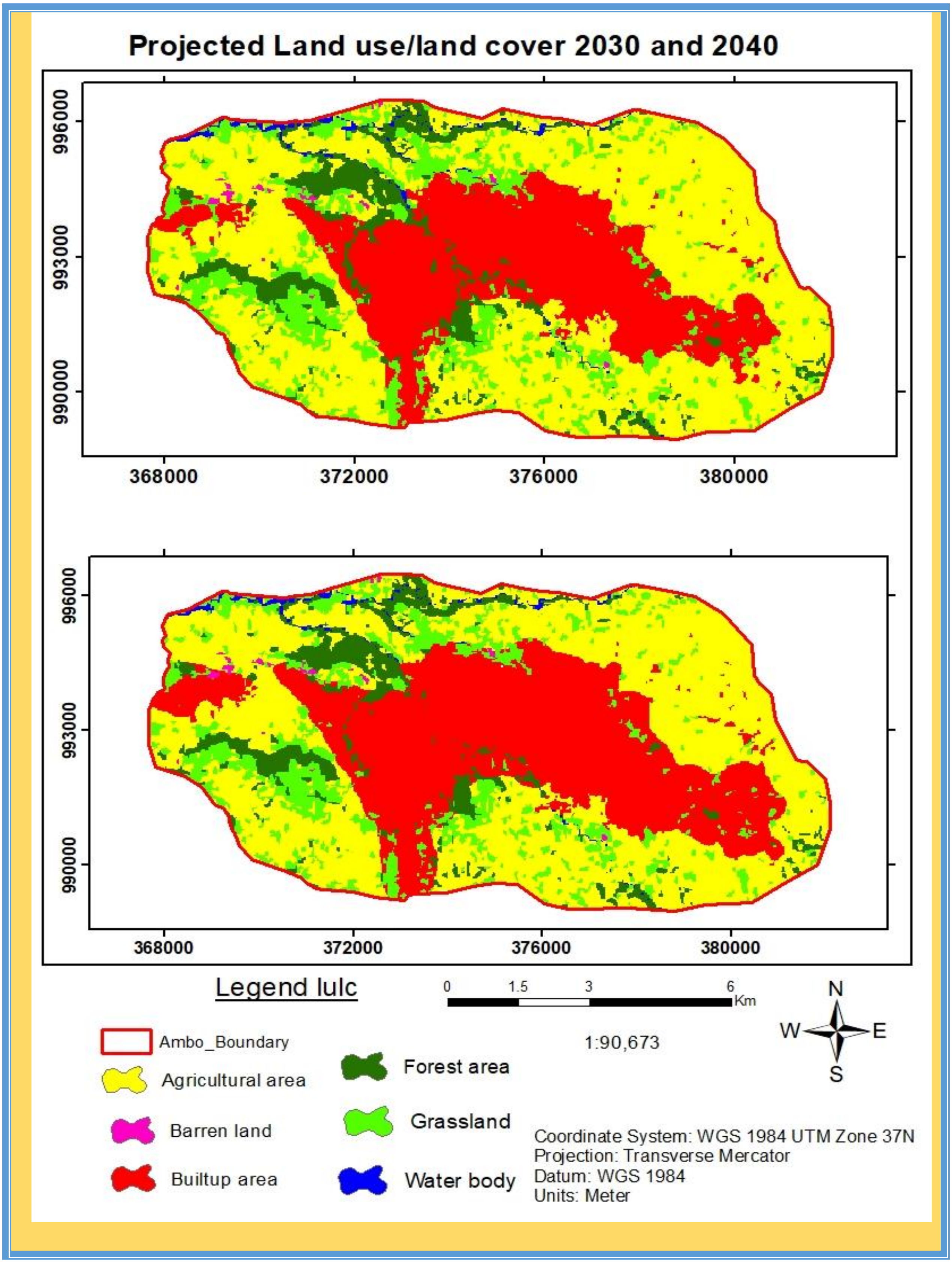


Figure 4.20: Projected land use land cover 2030 and 2040

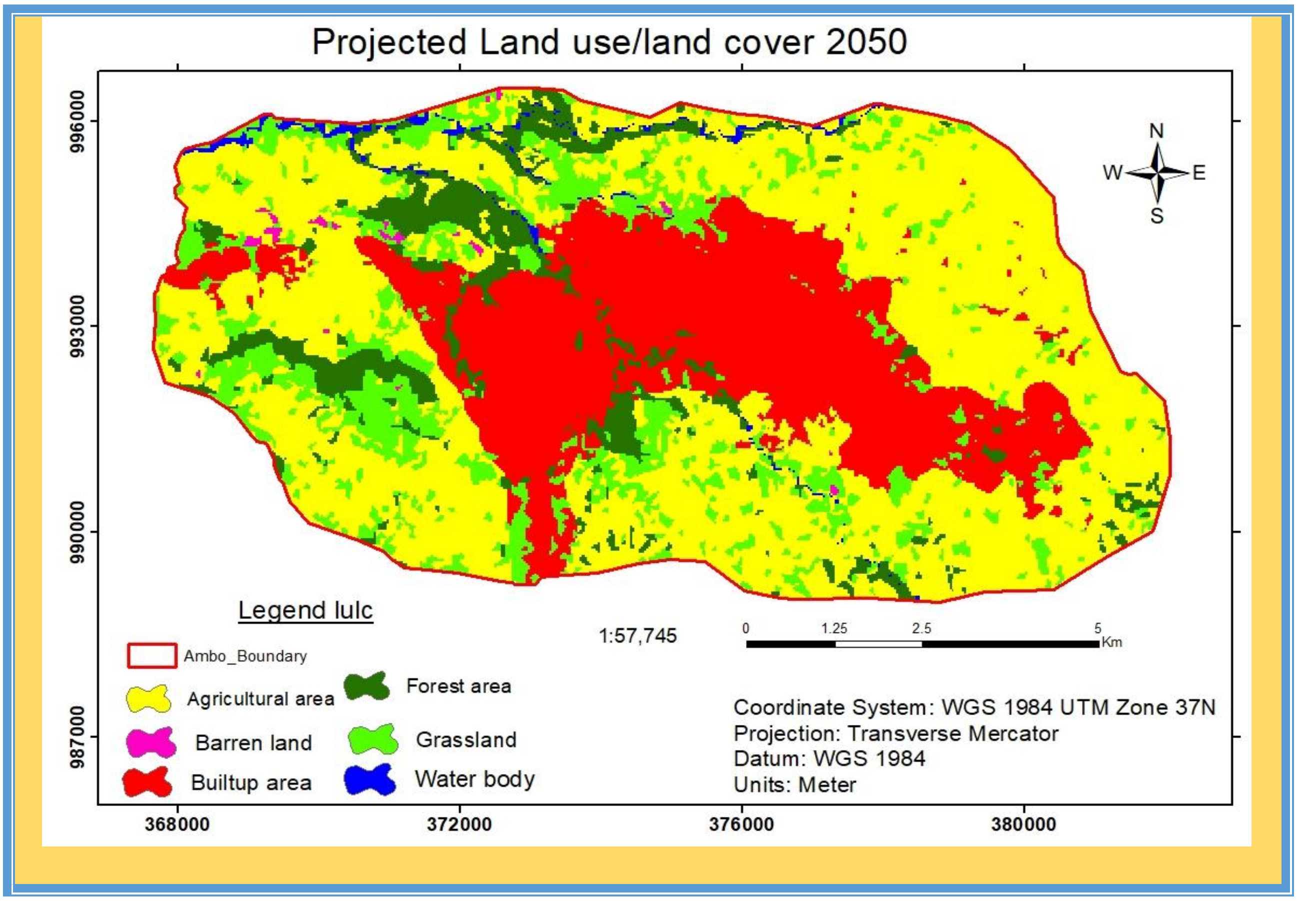


Figure 4.21: Project land use/land cover 2050

Table 4.24: projected buildup area and non-buildup area 2030 - 2050

Lu/LC type	2030		2040		2050	
	Ha	%	Ha	%	Ha	%
Built-up area	2294.99	26.90	2838.20	33.27	3277.54	38.42
Non Built- up	6236.54	73.10	5693.34	66.73	5253.99	61.58

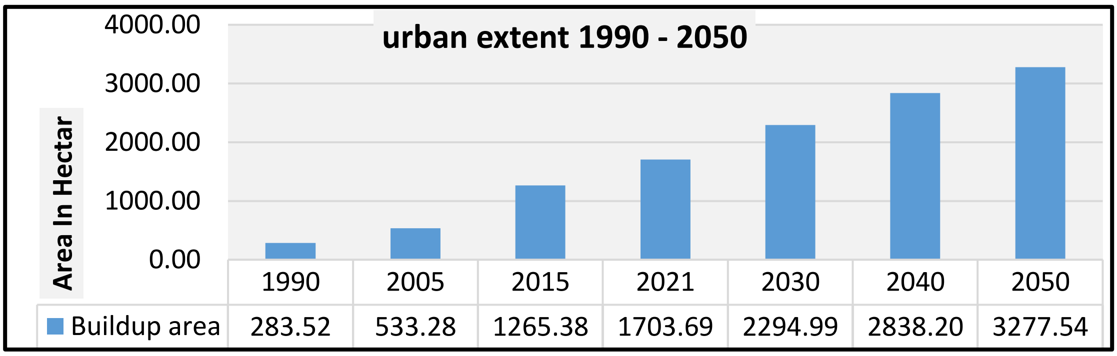


Figure 4.22: Existing and Future expected trend of buildup area expansion 1990 - 2050

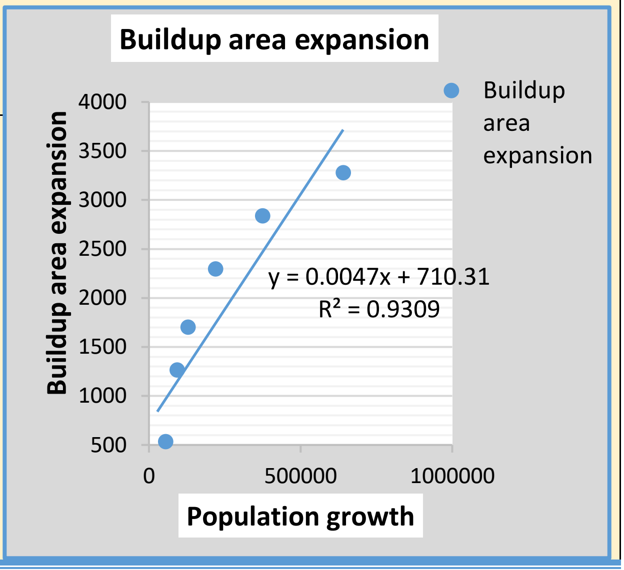
4.7 Relationship Between Buildup Area and Population Growth

The analysis between population growth and buildup area was carried out using simple linear regression modeling which assesses the relationship between dependent and independent variables. Population growth projected from the existing census population data 1994, 2007, and 2009. Urban buildup area is also predicted as described in detail in the result and summarized in figure 4.22.

$$\textit{Land consumption rate} = \frac{\textit{Total buildup area}}{\textit{Total population}}$$

Table 4.25: Correlation between population growth and buildup area

Year	Population growth	Buildup area expansion	Consumption rate
1990	27525	283.52	103
2005	54778	533.28	97.35
2015	93133	1265.38	135.86
2021	128501	1703.69	132.58
2030	219498	2294.99	104.55
2040	374934	2838.2	75.69
2050	640441	3277.54	51.18



Land consumption rate refers to the density of buildup area and distribution of spatial pattern which determines the direction of urban expansion either horizontal or vertical From the above table it is observed that from 1990_2030 trends of urban expansion is low density and dispersed spatial pattern exist which indicates horizontal urban expansion. However, from 2030_2050, there will be high density and undispersed spatial pattern which refers to urban development is vertical.

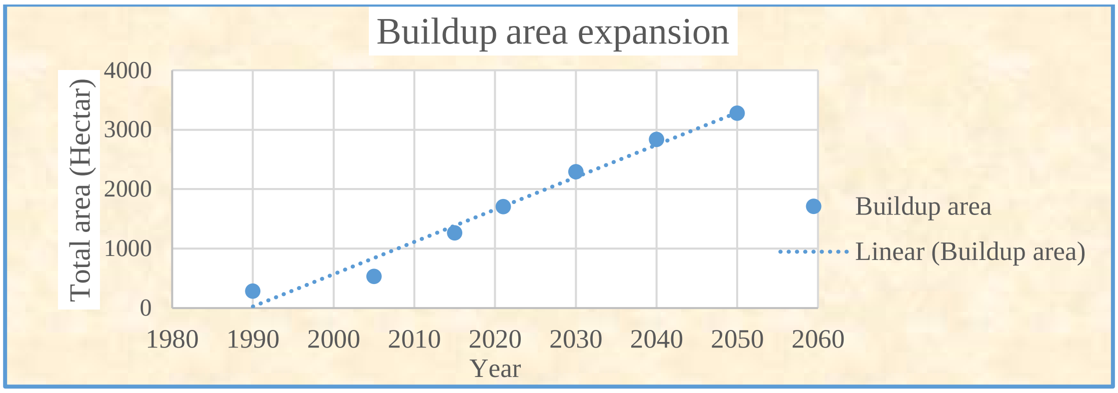


Figure 4.23: Trend of the buildup area expansion in the study period (1990 – 2050)

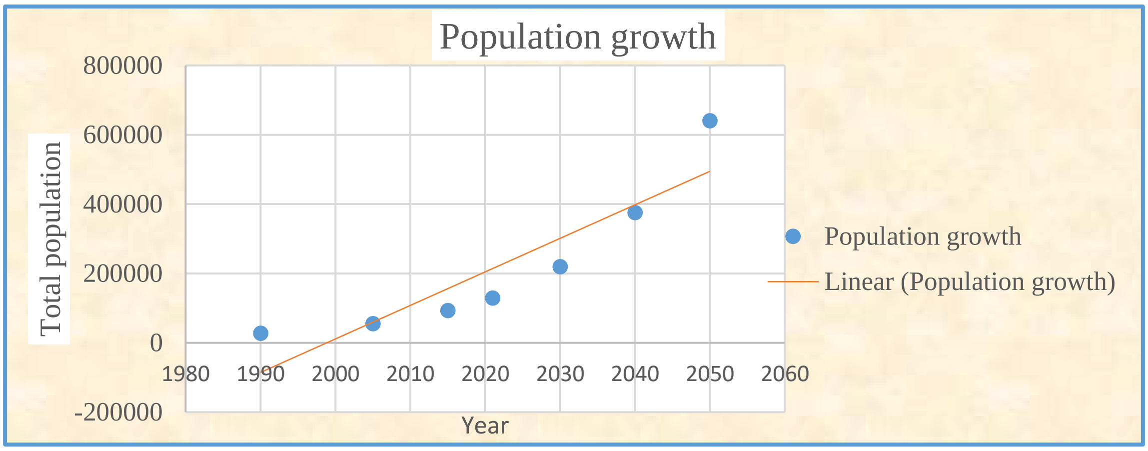


Figure 4.24: Trend of population growth in the study period (1990 – 2050)

$$B = 0.0047P + 710.31$$

Where B= total buildup area, P= population growth. The degree of correlation is high because the value of the coefficient lies between ±0.5 to ±1. So they have a positive correlation due to the slope is positive and one variable increases with respect to another variable and the two variables have a linear relationship. Built-up area increases by 0.4% for each 1 increment in population growth and the other parameters obtained was, R^2 = 0.9309, which indicates the accuracy of the regression model.

4.8 Discussion

The classified image demonstrates Overall classification accuracies 89%, 90%, 92%, and 93%, for the year 1990, 2005, 2015 and 2021, respectively. The values of Kappa statistics for classified images are greater than 0.8, indicating strong agreement between the classified LULC classes and ground truth, hence the maps satisfied accuracy criteria for LULC change detection analysis. The information summarized in Table 4.5 shows the spatial extents; percentage changes over time as well as the annual average growth of the six land use/land cover classes (agriculture land, barren land, buildup area, forest area, and grassland and water body) in Ambo town between 1990 and2021. Overall, the results show the extensive LULC changes in Ambo town over the study period. During the investigation periods, distinct changes have occurred on the major land use/land cover types. From 1990 to 2005, the built-up environment increased approximately 249.76Ha (88.09%) while forest area decreased 301.99Ha (20.50%), water body increased 10.72Ha (6.15%), and grassland and barren land decreased 371.36 Ha (10.50%), 79.55Ha (47.13%) respectively.

During the second period between 2005 to 2015, the built-up environment increased drastically by 732.10 Ha (137.28%) while forest area decreased 424.49 Ha (36.25%), grassland continuously converted and decreased by 1784.64 Ha (56.39%), water body and barren land decreased 104.82Ha (56.70%), 53.81Ha (60.30%) respectively. During the third period, 2015 to 2021 all LULC decreased except the buildup area. Buildup area increased 438.31 Ha (34.64%), while agricultural land, barren land, forest area, grassland, and water body decreased by 5.77%, 0.11%, 1.42%, 9.85, and 2.45% respectively.

The third period was characterized by advanced LULC dynamics where previously intensifying land cover classes such as agriculture land, forest area, and grassland declined their net change by – 59.31%, -2.09%, and -28.30% respectively. The built-up area reveals rapid change with a net positive increase of 436.13Ha (90.17%). Hence, the expansion of built-up areas had resulted in a negative change of forest, grassland, and agricultural land. Lastly based on LCM model urban growth was projected based on the past trends for 2030, 2040, and 2050, it reveals that the built-up area will be 2294.99ha, 2838.20ha, and 3277.54ha respectively. The regression analysis was also performed for built-up area expansion and population growth to determine the strength of the relationship between them and to define what urbanization is in the study area, so linear regression was selected to analyze the relationship between the two variables since we have one dependent and one independent variable and so, analyze reveals that they have a positive linear relationship and degree of correlation was high degree.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Urban growth and the concentration of people in urban areas are growing steadily especially in developing countries. Urban Land use and land cover changes have a wide range of consequences at all spatial and temporal scales. Because of these effects and influences, it has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and their drivers over space and time is important to predict future developments, set decision-making mechanisms, and construct alternative scenarios.

This study was conducted to analyze the impacts of urbanization on LULC change, the existing patterns and to predict the future LULC maps to lead the planning authorities for sustainable development using a land change modeler (LCM). The built-up area had an increasingly positive trend of change in its areal extent while forest area and grassland decreased continuously in the four periods. There has been also an observable increasing and decreasing trend of change in the other land cover classes of agricultural land, water bodies, and barren land. The average annual rate of change in built-up area as determined from the Landsat and ESA's sentinel image change statistics was 5.87 % (249.76ha) from 1990 to 2005, 13.7 % (732.10ha) from 2005 to 2015, and 5.77 % (438.28 ha) from 2015 to 2021, 16.19 % (1420.17ha) for the entire period of 1990 to 2021. Generally, Ambo Town LULC classes that contribute more net change in a built-up area for three decades (1990-2021) is grassland that contributes (765Ha), agriculture land (612Ha), forest area (34 Ha), barren land (9Ha), and water body contributes (6.4Ha).

The resulting 2030, 2040, and 2050 projected land-use maps revealed that the urban areas will continue to massively expand, encapsulating several parts of the study area. According to the projection, it is expected that by 2030, 2040, and 2050, about 2294.99ha, 2838.20ha, and 3277.54ha of land in the town will be covered by buildup area respectively, which covers roughly 26.90%, 33.27%, and 38.42% of the town. This means that, between 2021 - 2030, 2030 - 2040, and 2040 - 2050, the total areas that are covered by buildup area will increase by 6.93% (591.30ha), 6.36 % (543.21ha), and 8.67% (739.34ha) respectively.

The study concludes that there is a significant increase in the urban areas that have reached from 283.52hectare in 1990 to 1703.69hectare in 2021. This happened due to the rapid increase in population which reached from 27525 in 1990 to 128501 in 2021.

At the moment, the town is expanding in almost all directions at a significantly faster rate than ever before. The population is increasing and developments are taking place within and outside the town limits in the form of roads (constructing and widening), residential built up, commercial rise, and mixed land use expansion. Urban expansion is taking place in almost all directions particularly along the roads. New residential structures are increasing and de-shaping the morphological pattern of the town. This reflects the saturation of town in terms of built-up area and currently, it has reached the stage of urban sprawl as newly emerged urban areas. Resultantly, the services provided by local government and municipal authorities are now facing many challenges.

Road network problem, Incompatibility, Urban deterioration, and poor urban quality, Lack of services for the center, Lack of market hierarchy, Inefficient and uncoordinated utilization of potential site and resources, Inadequacy of pedestrian walkways, Inefficient traffic management, Sanitation emergency associated with lack of waste collection system and disposal site for both solid and liquid waste, Growing pollution and land erosion, Illegal settlement, Unplanned fencing and' kiosks' on streets, Unplanned quarrying and deforestation, Lack of focus to urban redevelopment renewal and upgrading in the built-up areas, especially original settlements and inner-city are Problems under serious stress. This reflects an alarming situation for local government and urban planners. Effective planning and proper management of the city systems is an essential need of the time otherwise urban problems may aggravate further in near future.

5.2 Recommendation

The results of this specific study have shown that GIS, remote sensing, and land change modeler are important tools in land use and land cover change studies. Therefore, based on the findings of this study, the following are recommended as future research directions:

- ♥ The use of high-resolution imageries such as IKONOS and Quick Bird is important in generating good-quality land cover maps. Because urban areas have complex and heterogonous features, high-resolution imagery provides better information by mapping these areas. Moreover, the use of ancillary data as ground truth helps for better accuracy of image classification.
- ♥ Consistent multi-temporal Landsat satellite data for each year provides a detailed comparison of images, change analysis, and modeling. Especially for the Markov chain model, it is a requirement of an equal interval of images acquisition although there has been uneven temporal availability of data.
- ♥ Incorporating socio-economic data, land policy, biophysical and human factors (population density, technology, political) could improve the performance of land-use models for future predictions. Hence, it is important to the planners, decision-makers, and stakeholders for efficient utilization of land.
- ♥ Any city planners and responsible persons who want to manage their urban expansion and forecast trends of urban expansion in the future scenarios will be able to share this material.

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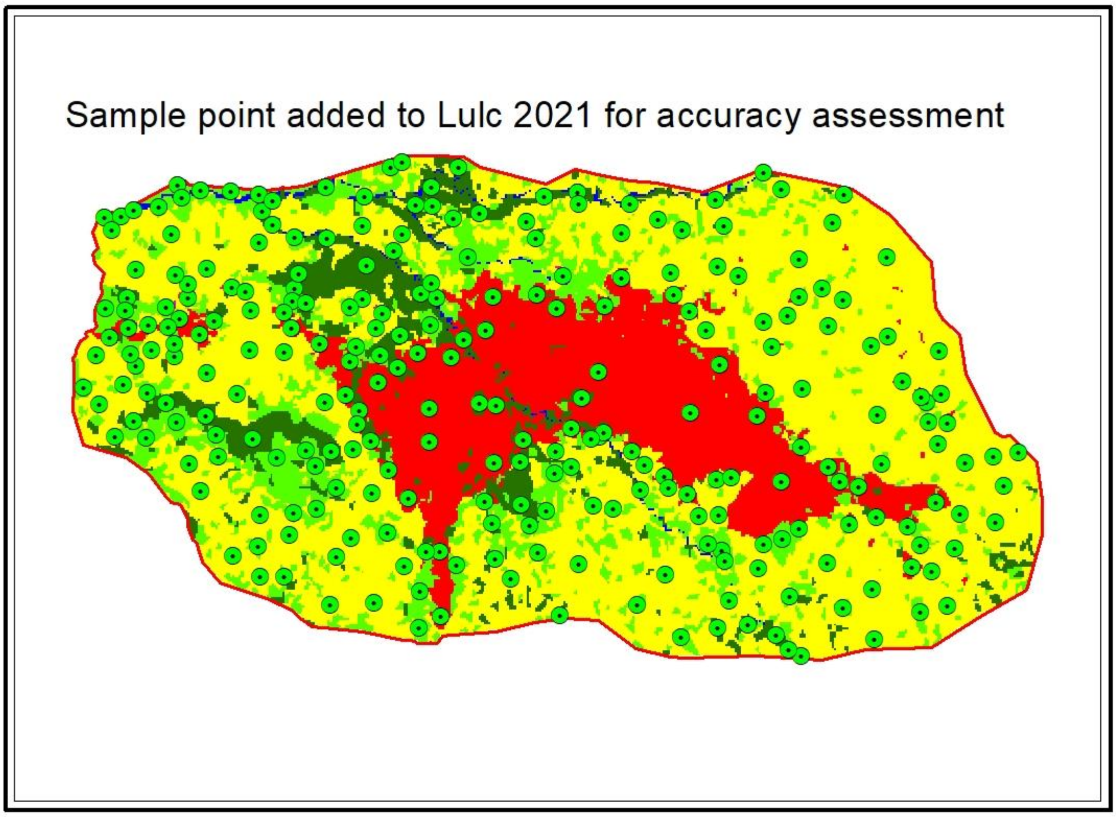
APPENDICES

Appendix I: Sample GCP collected for accuracy assessment and classification from field and Google earth.



Randomly Selected Point data added for accuracy assessment on ARCGIS ENVIRONMENT for classified sentinel image 2021

id	point_x	point_y	description	id	point_x	point_y	description
171	379624	992629	Agricultural area	185	372433	995069	Grassland
172	378504	993018	Agricultural area	186	372989	994589	Grassland
173	377933	994018	Agricultural area	187	372973	993970	Grassland
174	377076	993891	Agricultural area	188	371877	993633	Grassland
175	379116	994343	Agricultural area	189	371778	994232	Grassland
176	379536	993653	Agricultural area	190	368241	995383	Agricultural area
177	379766	994978	Agricultural area	191	368598	994780	Agricultural area
178	380536	993573	Agricultural area	192	370297	994177	Agricultural area
179	378465	994947	Agricultural area	193	370424	995185	Agricultural area
180	378957	995478	Agricultural area	194	369646	994804	Agricultural area
181	377242	994835	Agricultural area	195	369122	995320	Agricultural area
182	376552	994740	Agricultural area	196	370797	993565	Agricultural area
183	376369	995526	Agricultural area	197	370281	993597	Agricultural area
184	375814	995335	Agricultural area	198	369654	993256	Agricultural area

id	point_x	point_y	description	id	point_x	point_y	description
1	369374	994363	Barren land	41	378111	989349	Water
2	369368	994568	Barren land	42	377355	990445	Water
4	369190	994708	Barren land	43	376103	991510	Water
5	369048	994229	Barren land	44	375487	992304	Water
6	370026	994525	Barren land	45	368469	994367	Forest area
7	370223	994462	Barren land	46	368561	992539	Forest area
8	370951	994502	Barren land	47	369051	992793	Forest area
9	370926	994324	Barren land	48	369633	992618	Forest area
10	371133	994293	Barren land	49	371505	992085	Forest area
11	372267	994131	Barren land	50	371915	992694	Forest area
12	371972	994346	Barren land	51	370337	992267	Forest area
13	374943	994698	Barren land	52	372490	993322	Forest area
14	372392	996306	Barren land	53	372517	993812	Forest area
15	372554	996383	Barren land	54	373476	993752	Forest area
16	368283	992304	Barren land	55	372834	994430	Forest area
17	370095	992933	Barren land	56	372024	994850	Forest area
18	371119	992106	Barren land	57	371022	994718	Forest area
19	377314	990604	Barren land	58	370622	995816	Forest area
20	377257	991140	Barren land	59	372758	995750	Forest area
21	368384	995575	Water	60	372996	996015	Forest area
22	368563	995670	Water	61	373701	995631	Forest area
23	368930	995725	Water	62	373390	996312	Forest area
24	369215	996051	Water	63	375173	995935	Forest area
25	369564	995974	Water	64	377335	995439	Forest area
26	370012	995952	Water	65	378298	989129	Forest area
27	370427	995906	Water	66	377703	989512	Forest area
28	371419	996009	Water	67	377240	989456	Forest area
29	371997	995870	Water	68	374323	991292	Forest area
30	374665	995882	Water	69	374306	991927	Forest area
31	375942	995772	Water	70	375077	991854	Forest area
32	377209	995825	Water	71	373702	992803	Forest area
33	368135	995566	Water	72	375230	992869	Forest area
34	377934	996231	Water	73	375551	992370	Forest area
35	373069	994363	Water	74	374557	994415	Forest area
36	371436	995252	Water	75	374856	994219	Forest area
37	370962	995275	Water	76	373796	993888	Forest area
38	370621	995450	Water	77	375473	993259	Forest area
38	370468	995663	Water	78	380356	992817	Forest area
39	378492	989033	Water	79	379605	991106	Forest area
40	377425	989868	Water	80	368209	993782	Builtup area

Id	point_x	point_y	description	id	point_x	point_y	description
80	368209	993782	Builtup area	121	380130	990357	Builtup area
81	368592	993362	Builtup area	122	380427	990301	Builtup area
82	368517	993535	Builtup area	123	379207	991002	Builtup area
83	368487	993922	Builtup area	124	380070	990962	Builtup area
84	368436	994176	Builtup area	125	380490	991319	Builtup area
85	368788	993956	Builtup area	126	379349	991554	Builtup area
86	369177	993503	Builtup area	127	378886	991845	Builtup area
87	369176	993684	Builtup area	128	380672	992506	Builtup area
88	369762	994025	Builtup area	129	380269	992899	Builtup area
90	369542	993817	Builtup area	140	380570	992942	Builtup area
91	369248	994052	Builtup area	141	379991	993127	Builtup area
92	370797	994157	Builtup area	142	379786	993785	Builtup area
93	370913	993921	Builtup area	143	378288	994110	Builtup area
94	371321	993686	Builtup area	144	378890	993944	Builtup area
95	371776	993416	Builtup area	145	378059	993637	Builtup area
96	371712	992921	Builtup area	146	377557	994695	Builtup area
97	372234	993518	Builtup area	147	376594	994407	Builtup area
98	372083	992241	Builtup area	148	375824	994659	Builtup area
99	371883	992484	Builtup area	149	375562	994245	Builtup area
100	373127	989637	Builtup area	150	376823	994163	Builtup area
101	373120	990590	Builtup area	151	373903	994377	Builtup area
102	372655	991387	Builtup area	152	378189	991639	Builtup area
103	372350	991808	Builtup area	153	377840	992607	Builtup area
104	372191	993106	Builtup area	154	377285	993369	Builtup area
105	372953	992229	Builtup area	155	376840	992663	Builtup area
106	373929	991919	Builtup area	156	372959	992718	Builtup area
107	374354	992252	Builtup area	157	367822	993035	Builtup area
108	373957	992768	Builtup area	158	368746	992289	Builtup area
109	372786	993538	Builtup area	159	369199	992515	Builtup area
110	373282	993475	Builtup area	160	369284	995861	Grassland
111	375068	992431	Builtup area	161	369818	992011	Grassland
112	375374	992264	Builtup area	162	368141	994210	Grassland
113	375969	992080	Builtup area	163	368762	992955	Grassland
114	376455	991712	Builtup area	164	369072	993940	Grassland
115	376515	991545	Builtup area	165	369786	992336	Grassland
116	376801	991442	Builtup area	166	370945	991162	Grassland
117	377452	991691	Builtup area	167	371282	991233	Grassland
118	377236	991663	Builtup area	168	371576	991539	Grassland
119	377930	990694	Builtup area	169	370695	991995	Grassland
120	378463	990939	Builtup area	170	371263	991864	Grassland

Appendix II: Transition potential mapping