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DEPARTMENT OF GEODESY AND GEOMATICS

(SPECIALIZATION IN GEOMATICS ENGINEERING)

MODELING LAND-USE/ LAND-COVER DYNAMICS USING REMOTE SENSING AND GIS TECHNIQUES: THE CASE OF AMBO TOWN

Thesis Submitted to the School of Civil and Environmental Engineering Graduate Studies of Addis Ababa Institute of Technology in Partial Fulfillment of the Requirement For the Degree of Master of Science in Geodesy and Geomatics Engineering (Specialization in Geomatics Engineering).

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This is to certify that a thesis prepared by Tedela Mosisa Amena entitled: Modeling Land-Use Land-Cover Dynamics Using Remote Sensing And GIS Techniques: The Case Of Ambo Town, and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Geodesy and Geomatics with specialization in Geomatics engineering.

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Chair of Department of Graduate program coordinator

DECLARATION OF ORIGINALITY

I declare that the work which is being presented in the thesis entitled “modeling land-use land-cover dynamics using remote sensing and GIS techniques: the case of ambo town” submitted to Addis Ababa institute of technology, school of civil and environmental engineering in partial fulfillment of the requirements for the award of the degree of master of science in Geomatics engineering is entirely my work carried out from May to October 2020 under supervision of Dr. Worku Zewdie (advisor) from Ethiopia space science and technology institute. all references, including citations of published and unpublished sources, have been appropriately acknowledged in the work. I additional announce to the work has not been submitted for academic assessment, either in its unique or alike form, wherever also.

Tedela Mosisa ------------------------- ------------- Name of Candidate Signature Date as Master research advisors, we hereby certify that we have read and evaluated this MSc Research prepared under our guidance by me, entitled.

Dr. Worku Zewdie ---------------------- ---------------

Advisor Signature Date

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LIST OF ACRONYMS

BUS	Business -As -Usual Scenarios
CA	Markov-Cellular Automata Markov Model
CSA	Central Statistical Agency
CRGE	Resilient Green Economy Strategy
DEM	Digital Elevation Model
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper /Plus
ETM	Earth Trends Modeler
FAO	Food and Agriculture Organization
GCP	Ground Control Points
GIS	Geographical Information System
GPS	Geographic Positioning System
KIA	Kappa Index Agreement
LCM	Land Change Modeler
LPG	Level Product System
LULCC	Land-Use and Land-Cover Change
LULCD	Land-Use and Land-Cover Dynamic
MCE	Multi-Criteria Evaluation
MODIS	Moderate Resolution Imaging Spectrometer
MOSAIC	Multimodality Operational Site Analysis and Intelligent Change-Detection
MSS	Multi-Spectral Scanner
ONRS	Oromiya National Regional State
OLI	Operational Land Imager
RMSE	Root Mean Square Error
ROC	Relative Operating Characteristic
RPS	Reform Policy Scenarios
TM	Thematic Mapper
TIRS	Thermal Infrared Sensor
UTM	Universal Transverse Mercator
WLC	weighted Linear Combination
WGS	World Geodetic System

ABSTRACT

Land use and land cover change are complex and tremendously dynamic. Many scholars have analyzed the pattern over some time. Few scholars have tried to integrate spatially and cellular automata (CA) as dynamic discrete space and time systems. The purpose of this study was to monitor the land use and land cover dynamics of Ambo town and to model its future development under different scenarios using GIS & RS techniques. This research used GIS and remote sensing in mapping land use and land cover dynamics in Ambo Town between 1990 and 2020 to detect and analyze the dynamics that have taken in the Town between these portions of time. The data sets used were Landsat TM of 1990, Landsat ETM 2000, 2010, and Landsat 8 OLI 2020. The modeling used in the present study comes under having particular shared characteristics of 'scenario models'. The maximum likelihood algorism of supervised image classifications is used *to generate land-use land-cover maps and assessment of their dynamics. The cellular Automata Markov (CA-Markov) modeling approach was used to forecast land-use change for 2030. Analysis of Landsat image data of Ambo Town from 1990 – 2020 showed there are significant land use and land cover changes in the town. In 1990 forest, agricultural land, and built-up area covered 21.8 %, 60.19 %, and 13.73 % of the total area, respectively. Bare land constituted less than 5% of the area. However, in 2000, after a decade, the agricultural land area was declined to–16.0 8% while built-up area, forest, and bare land were increased to 8.84 %, 3.69%, and 3.62% respectively. In 2010, after three decades, bare land and built-up area constituted 2.94 % and 22.55% of the area, respectively. On the other hand, agricultural and bare land areas were decreased by 14.71% and 10.83% from 33.33 % to 22.5 % and 26.47% to 11.7% respectively. With existing conditions, the simulated LULC map of the year 2030 indicates the same trends that forestland and built-up areas will increase by 2.99 %, and 4.04 %, respectively whereas agricultural land and bare land areas will be decreased by 3.76%, and 2.82. Therefore, the government has to provide different innovative policy reform strategies/scenarios to overcome the business as usual scenario. As urban land use expanding to agricultural land and forest, alternative land use is disproportionality affected, due to this it has an impact on productivity and environmental service. Thus, the town administration has to devise a mechanism that reduces urban expansion.*

Key words: CA-Markov, GIS, Land cover, Land dynamic, Land use, Modeling, Remote sensing

CHAPTER ONE

1. INTRODUCTION

1.1. Background

The land is a complex and dynamic system that consists of geology, topography, hydrology, soil and microclimate, and a community of plants and animals that are continually interacting under the influence of climate and people activities (Lu and Weng, 2007). Land-use is subject matter to the natural environment and involvement of human activities, thus considerate the driving factors at the back the land-use change (LUC) is crucial for the land-use planning and management of key land surface of the earth’s ecosystems services and functions (Leemhuis *et.al*., 2017). Leads further performance of agricultural sectors in particular and the whole economy in general. However, continued agricultural growth remains a necessity not an option for most developing countries like Ethiopia and the growth must be achieved on a sustainable basis not jeopardizing the underplaying natural resource base or imposing costly externalities on others (Lepers, 2014).

Land-use and land -cover change and human natural modification have largely resulted in global warming, biodiversity loss, deforestation, and an increase in natural flooding. The land-use and land-cover prototype of a region is a result of natural and socio-economic feature and their operation by man in point in time and breathing space. Because of anthropogenic activities, the earth's surface is being significantly distorted in several ways and man’s attendance on the earth and his uses of ground have had a thoughtful effect upon the natural environment.

To understand how land -use and land- cover affect and interact with the earth systems (e.g. atmosphere, biosphere, and hydrosphere), accurate information is needed on what types of changes occur, where information is needed, what information is needed, and when they occur, and rates of at which changes occur (Mahmoud and Divigalpitiya, 2017).

Land- cover refers to the direction of the physical individuality of Earth's surface, captured in the distribution of soil, water, vegetation, every applied on an undulation of the ground surface of the earth’s and other physical facial appearance (Li *et.al*.,2016). Land use refers to how the ground has been used by humans and their environment (such as agriculture, settlements, industry, farms, grazing land, etc.). Land-use and land-cover (LULC) change has been regarded as an important factor influencing climate change and environmental conditions (Pickett *et.al.*, 2017), and has a close relationship to population migration and economic conditions (Koranteng*et.al.*,2016).

The land-use change proximate factor land-use is definite by the purpose for which humans obtain the benefit of the land-cover. There is far above the ground changeability in time and space in biophysical environments, socioeconomic activities, and cultural context that are connected using the land-use revolution. Identifying the reason for land-use and land- cover consideration of how people make land-use decisions and how a variety of factors interact in specific contexts to power decision-making on land use. Decision-making is influence by factors at the global, regional, or local, scale. Proximate (or direct) causes of land-use change make up human activities or instant events that create from future land use and in a straight line affect land- cover (Lepers, 2014). They engage a physical achievement on land- cover. Underlying (or indirect or root) causes are fundamental forces that strengthen the additional proximate causes of land-cover change. They function more diffusely (i.e., from a distance), often by altering one or more proximate causes (Araya, 2009). Underlying causes are shaped by a complex of, political, social, economic, technological, cultural, demographic, and biophysical variables that comprise preliminary conditions in the human-environment relations and are structural (or systemic) in nature (Leemhuis et al., 2017). Proximate causes in general work next to the restricted height (households, individual farms, or communities).

Remote sensing plays a pivotal role in making and documenting the actual change in the land-use and land -cover global, local, and regional scales The compilation of remotely sensed data makes easy the synoptic analyses of Earth system patterning, function, and change at global, regional, and local scales over time; such data also provide a significant connection between concentrated, limited to a small area environmental research and regional, national, and international conservation and management of biological diversity (Green *et.al.*, 2000). Remote sensing has become a major data source for mapping and monitoring LULC dynamics over time (Hansen and Loveland, 2012) because it can capture land surface information at the time when satellites pass through.

Agricultural growth remains a necessity not an option for most developing countries like Ethiopia and the growth must accomplish by effort on a sustainable basis, not a failure of the underplaying natural resource base (Ayele, 2017). According to (Behailu *et.al* 2010)the anthropogenic influences on shifting land-use change are a primary component of many current environmental concerns as the land-use and land-cover dynamic is gaining recognition as a key driver of environmental dynamic. Tizora,(2018) demonstrated that land- use denotes the human employment of land which includes settlement, cultivation, pasture, rangeland, recreation, and so on, whereas land cover indicates the bodily condition of the land.

Models of land-use and cover dynamics are powerful devices that can be used to understand and analyze the crucial linkage between socio-economic series of actions associated with agricultural activities, land development, and natural resource management strategies and the ways that these changes affect the structure and function of ecosystems. For that reason, satellite images can often be used to detect land-use dynamics through the ability to notice significant details of the biophysical characteristics of the land. Spatial models are needed for understanding reality and comprise a temporal dimension as well as the particular on the earth's surface.

They have implemented and user land-cover dynamic models that can simulate multiple land-use and land-cover dynamics types. As a result, Cellular Automata are collected of five fundamentals as described underneath: Cell Space: The cell breathing space is collected of an individual cell. The community within a Town: every cell has two very close to an additional in one-dimensional cellular automata, while in two- dimensional cellular automata model there are two conducts to describe it. This current research aimed at an option the spatial evolution concept embedded in CA (Cellular Automata) and applies it to land-use and land-coverage dynamic in West Shoa Zone. A time series of multi-scale and multi-temporal (including historical) satellite imagery will be used to describe characteristics of land-use and land-cover dynamic trends over the period from 1990 to 2020. Socio-economic and biophysical driving forces of experiential dynamics are enduring foundation through a system of employment in cooperation on activity associates and agencies willing to share resources and powerfully wanting to do to make use of developed techniques and model results. This research examines the use of GIS and Remote Sensing in Mapping Land-use and land-cover maps and monitoring changes at regular intervals of time is limited in respect to its extent of coverage and expensive; which means, it is also a major contributing factor to the observed classification of each class of that area. Furthermore, applications of various spatial models for proposing future land-use changes are slight in this study area. Hence, it is vital to simulate the procedure concerned with the spatial pattern of land use which ultimately assists in the executive of land-use planning and organization (Deng *et.al*., 2010). In the study, present here, the aim is to explore the dynamic and future spatial patterns of land-use changes from 2020 to 2030 using the Dynamics of Land System (DLS) model under two scenarios: The BAU (Business-as-Usual) scenario was set for future land transitions based on historical and recent socioeconomic trends, e.g. Economic and population growth without any new sustainable environmental no change everything. The business as usual (BAU) scenario was intended mostly based on the supposition of a continuance of land-use and land- cover change rates of the history 30 years in the deliberate landscape (Kindu *et.al*., 2018). Generally, this research aimed to analyze and model the long term land-use and land-cover dynamic (from 1990 to 2020) in West Showa Zone and Ambo town by integrating remote sensing, geographical information system (GIS), and Modeling tools and provided quantitative analysis of land-use and-cover dynamic information in the area.

This study is prepared to Quantify and Modeling Ambo Town Land-use and land-cover changes and predicts the future LULC maps to lead the planning authorities for sustainable development using geospatial tools and techniques.

1.2. Statement of the Problem

According to Foody (2001) land-use and land-cover (LULC), change is a global change that is induced by natural and anthropogenic factors, and recently the issue has implications for many of the worldwide policy issues. These changes in LULC reflect the population growth, land consumption rate, and climate change. Within the immature state, land-use activities are not healthy prepared. It was noticed in the study area that unplanned built-up expansion, mining activities, and shifting agricultural activities are the forerunner to land degradation as also supported by (Ehsan and Kazem, 2013). The LULC change assessment in Ghana for the period 1991–2016 also established a continuous increase in the settlement at the expense of open forest and closed forest lands (Ackom *et.al.*, 2020).

Researchers have studied land-use and land-cover change at the local level, mostly on undulation of the ground scale (Kindu, 2013) indicating a significant reduction of natural forest cover and grasslands particularly in Ethiopian highlands. The study conducted on Hawassa town (Ayele, 2017) indicated that the uncontrolled growth of urban has adversely affected the towns' ecosystem which indirectly influences the weather parameters and eventually leads to local climate modification. This has initiated the researcher to conduct this research to estimate the effects of LULC on Ambo town. So far, to the best knowledge of the researcher, no one has conducted the effects of LULC dynamic analysis on Ambo town using GIS and RS technologies to estimate the change on the town. It would be worth mentioning that the researcher is familiar with the study area and observed that there has been a high rate of urbanization in the town. Ambo Town has also experienced human-induced problems including informal house expansion, logging, and road expansion that have contributed to land-cover changes (Mienmany, 2018). A diverse array of land-use and land-cover dynamic models have been developed and implemented globally as important tools in making land-use decisions, yet the implementation of such models is limited in West Shoa in general and Ambo Town in particular.

One key problem of developing a town like Ambo town is the random urban development mostly without proper planning strategies. Urban growth affects the ecology of the town by modifying local climate conditions, eliminating and fragmenting native habitats, and generating anthropogenic pollutants. From these points of view, the major part of Ambo town is unplanned and less designed. The most important reasons for this situation are short of appropriate land distribution by the land administrative office of the town for the residents at a time. Moreover, the emergence of informal settlements, population growth, rural-urban migration, lack of affordable housing, and weak governance (particularly in policy, planning, and urban management) have contributed to the improper occupation of lands. Informal expansion of Ambo town has also resulted in depletion of natural resources, human labor exploitation, financial extravagance, time consumption, an unplanned town with a lack of attractive fullness of town structure, and deterioration of the environment. Therefore, geographic information systems and remote sensing analysis facilitate sustainable management of LULC change planning, wise decision-making, monitoring of urban expansion, and development. Hence, in this work, the researcher used a 30 years cellular automata model, remote sensing, and GIS techniques to identify the factors affecting the LULC dynamics and simulate the future LULC scenarios of the town.

1.3. Research questions

The main research questions of this study were:

1. What is the land-use and land-cover dynamics in the past three decades?

2. How to model future land-use dynamics under two different scenarios?

3. What are the driving factors of LULC development and dynamics in Ambo town?

1.4. Objectives of the Study

1.4.1. General objective

The general objective of this study is to monitor the land-use and land-cover dynamics of Ambo town and to model the spatial pattern of land use under different scenarios.

1.4.2. Specific objectives

1. To investigate land-use and land-cover dynamics of Ambo town in the past three decades (1990-2020)
2. To model future land-use dynamics under two different scenarios
3. To identify major deriving forces of land-use and land-cover changes between 1990 and 2020.

1.5. Significance of the Study

The modeling of the land-use and land-cover dynamic within the study area has a scientific and improvement of importance for the future. Overall, such information is vital for comparing the past and present conditions and predicts the future trends of the LULC change and expanding such method of protecting the informal settlement expansion and expanding such techniques to Ambo town in the West Shoa people Oromia region and expanding such techniques to other Town. Thus, a community of Ambo town benefits primarily. Its surroundings and help as a source of data for another researcher who wants to carry out another study in this area. Ambo town municipality's investment will invest in Ambo town and other scholars who wish to do researches in this area. Furthermore, policymakers, development planners, local land managers, and concerned bodies benefit a lot from this research.

1.6. Scope of the study

This study was delimited to modeling land- use and land- cover change by using GIS and RS technique the case of Ambo town because of resource limitation, which is one of the Ambo Town in West Shoa of in Addis Ababa of the Oromia region and is restricted to develop GIS and remote sensing-based map changes in Ambo Town. Using GIS, remote sensing, focus group discussion, key informants, and GPS technology. The land-use and land-cover change, modeling, and environmental change, and the factors of these changes for the last 30 years were evaluated and analyzed from satellite images and ground surveys. Using focus group discussion and key informants interviews for enhancing the ability to capture more detailed and timely information for the ground truth about the boundaries of Ambo town land-cover class identification like; forest, bare land, agricultural land, built-up area. To understand the possible causes of Ambo town and environment of surrounding area changes and address the issues (the main factors of land use, slope, and proximity to the road) that enhance the change detection, land- use, and land- cover analysis in addition to socio-economic activities and natural factors of the area were assess through primary and secondary data collections. Change modeling and prediction of future LULC is the latest research, growing rapidly in a scientific field that is extremely large amount useful to urban planning and Urban Land resources.

1.7. Organization of the Thesis

This thesis was organized into five chapters and different sections in which the first chapter deals with the introduction to the research, statement of the problem, objective, research question, significance, scope, and organization. The second chapter concerns reviewing literature that is relevant to the topic. The third chapter deals with a description of the study area, research methods, and materials. The fourth chapter deals with the research output and discussion of the result whereas the fifth concludes the chapter and recommendation the whole thesis.

CHAPTER TWO

2. LITERATURE REVIEW

2. THEORETICAL BACKGROUND

This Chapter provides a literature review of LULC change modeling. The first section of the literature review will explain the concepts; land, land- use, and land- cover. LULC change and factors which influence or drive LULC change will be reviewed from both a local and international perspective. This will be followed by theory on LULC change models and concepts or issues, which are important in LULC change modeling. Thereafter a summary of the most popular land-use model classification techniques will be provided based on published literature. The last section of the literature review will present current African academic modeling projects.

2.1. LAND-USE AND LAND-COVER

2.1.1. Land

The United Nations Convention to Combat Desertification documentation defines land as, “the terrestrial bio-productive system that comprises soil, vegetation, another biota, and the ecological and hydrological processes that operate within the system” (Angessa et al., 2019). A more holistic definition of land is provided in the Food and Agriculture Organization (FAO) Land and Water Bulletin 2, where land is described as “a delineable area of the earth's terrestrial surface, encompassing all attributes of the biosphere immediately above or below this surface, including those of the near-surface climate, the soil and terrain forms, the surface hydrology (including shallow lakes, rivers, marshes, and swamps), the near-surface sedimentary layers and associated groundwater reserve, the plant and animal populations, the human settlement pattern and physical results of past and present human activity (terracing, water storage or drainage structures, roads, buildings, etc.)” (Akintola, 2018).

2.1.2. Land-Use

The terms land-use and land-cover are often used interchangeably, though they have different meanings. Land use is the purpose for which land is used whereas land cover refers to the physical characteristics of the surface of the land. A formal description by FAO states that land use is “the arrangements, activities, and inputs people undertake in a certain land-cover type to produce, change or maintain it” (Kutter and Neely, 1999).

The use of land is therefore uncertain, does not end at political boundaries, and can be both legal and illegal (Cooper, 2014) Land-use systems exist when different land uses are systematically linked through temporal interactions e.g. crop rotation or spatial relations.

2.1.3. Land-Cover

According to Turner et al. (1994), “Land-cover is the biophysical state of the earth’s surface and immediate subsurface.” Land-cover, therefore, includes quantity and types of all features over the earth such as vegetation, water, soil, artificial surfaces, etc. Turner et al. (1994) as illustrated in Table 1 demonstrate the difference between land-use and land-cover. Turner et al. (1994) further add that land use involves the intent or purpose for which land is utilized. A different aspect, “biophysical manipulation” is also described as how humans treat land to achieve intent e.g. the planting of grass for pasture.

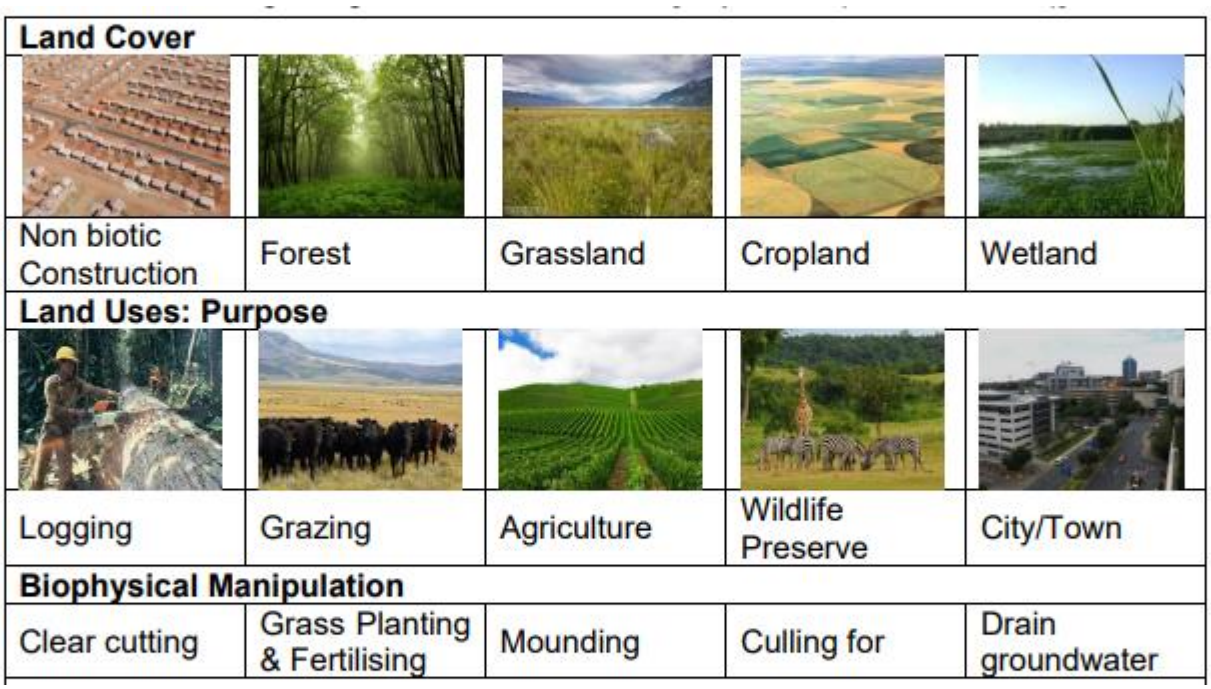


Figure 1: Distinguishing Land Cover and Land Use [adapted from (Turner et al., 1994)]

Land-use and land-cover are linked; however, it should be noted that a single land cover can support multiple lands-uses and vice versa. For instance, a land-cover e.g. grassland can support many lands-uses such as grazing and recreation, and single land-use may take place on various land-covers. Land-cover can be determined by analyzing remotely sensed images such as satellite images or aerial photos whilst land-use and land-use change will require additional socio-economic data and methods to determine the activities occurring on the landscape (Ellis and Pontius, 2007). Verburg et al. (2009) agree with this and state that, unlike the land-cover, land-use is not directly observable though it can be inferred from activities such as grazing or structural landscape elements e.g. logging roads. This study is conducted at a regional scale therefore the data that will be used in analysis and modeling will be a combination of data obtained from satellite imagery and socio-economic data. The term LULC will therefore be used to refer to land use and land cover in this study.

2.2. LULC CHANGE AND DRIVERS

2.2.1. International Review of Drivers of Land-Use Change

LULC change involves a conversion from one LULC to another or intensification of the present or current LULC (Turner et al., 1994). The changes in LULC are determined by how individual landowners, communities, businesses, and governments control land use and make decisions on how to use land. Such decisions are influenced by the interactions between socioeconomic factors such as population and environmental factors (e.g. topography and climate) which vary at different scales (Fekadu, 2017). (Green et al., 2000) confirms this and further clarifies that environmental drivers do not have a direct impact on land-use change but impacts land cover change which in turn influences land managers' decisions. LULC change can therefore be modeled as a function of socio-economic and environmental factors. These factors are often referred to as 'driving factors'. The driving factors of LULC change are also categorized as either proximate or underlying, where the former are direct modifications by individuals at a local scale such as individual farms and the latter are indirect changes that occur at a regional scale (Fasika et al., 2019). Proximate driving factors are usually caused by human activities such as infrastructure and agriculture expansion whereas underlying factors are caused by complex interactions between social, political, demographic, and environmental variables (Lepers, 2014).

2.2.2. Drivers of Land-use and land-cover

This section of the literature review covers drivers of LULC change in the global. The focus will be on underlying causes, which consist of political, demographic, economic, technological, cultural, and environmental variables. This is because, unlike proximate factors, underlying factors operate at regional levels, which coincide with the scale of this study.

2.2.2.1. 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 (Lepers, 2014).

2.2.3. 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 (Ha, 2011). Also the minor causes such as redevelopment and rebuilt up of inner cities again cause displacement of citizens (Li et al., 2016).

2.2.4. 3. Environmental factors

Population pressure just like human demand for construction material, policy and agricultural expansion, and occupancy insecurity fuel wood were the major driving forces behind the land use and cover change. Environment effects include those of climate, slope, mountain barriers, and the existence of drillable water aquifers (Li et al., 2016).

2.3. Urban land-use dynamics

From a broader point of view, urbanization is one of how human activities altering global land-cover. Although the urbanization trend is global, according to the reports of the United Nations Centre for Human Settlements (Palmer et al., 2009), it has shown most remarked changes in developing countries associated with the migration of rural people to cities for better opportunities. Following this, there had been estimated a rapid growth of population in urban areas at an average rate of 2.3% per year between 2000-2030 (Muzein, 2006).

2.3.1. Remote Sensing

Remote Sensing is the science and the expression of acquiring information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with an object, area, or phenomenon under investigation (Eastman, 2003). According to (Fasika et al., 2019), 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 cameras, multispectral scanners provide a large variety and amount of data about the earth's surface for detailed analysis and dynamic with the help of various ground-based, space borne and airborne sensors. It is occurring now with powerful capabilities to understand something and managing earth resources. Remote Sensing has been proven a very useful tool for Land-use land-cover dynamics.

2.3.2. Geographic Information System (GIS)

GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced information (Ackom et al., 2020). GIS also allows the integration of these data sets for driving 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 (Mienmany, 2018).

2.4. Types of Image Classification

Land-cover maps are commonly created from remotely sensed data through unsupervised or supervised classification techniques (Haque and Basak, 2017).

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 (Ayele, 2017). 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 include 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, and time constraints (Ha, 2011). These factors highly determine the type of classification algorithm used for image classification. Various image classification methods are applied to extract land-cover information from remotely sensed images. There are several classification methods and each method is specific to the data and the locations because in each location land categories are varies and have different values in the image. For instance, the image value (Berhanu, 2017) of agricultural land is dependent on the type of crop that grows on that land (Behailu, 2010). Even the same crop in different climates can have different colors, which changes the color of the image. Moreover, the seasons also affect the color of land-covers. There are different approaches to classification. According to Araya (2009). Image classification can be done based on three objectives which are: Type of learning (Supervised and Unsupervised), Assumptions on data distribution (Parametric, Non-Parametric), and Number of outputs for each spatial unit (Hard and Soft) Moreover, there are also objectives regarded levels of classification, which are; Pixel-based Classification and Object-oriented Image Segmentation and Classification.

2.4.1. Pixel-Based Classification

Pixel-based classification is the traditional method of image classification. This is mainly based on the pixel reflectance values of the image (Kousalya *et al*., 2012). According to the type of learning, there are mainly two kinds of pixel-based classification supervised and unsupervised (Al-Ahmadi and Hames, 2009). The supervised classification relies on the prior knowledge of the study area (Canada Centre for Remote Sensing, (Deng *et a*l., 2010). Supervised classification is a procedure for identifying spectrally similar areas on an image by identifying "training" sites of known targets and then extrapolating those spectral signatures to other areas of unknown targets (Wen *et al*., 2011). There are different algorithms for supervised classification; the classic classifiers are minimum distance, parallel pipelined, and maximum likelihood methods. The maximum likelihood algorithm uses a maximum likelihood procedure derived from Bayesian probability theory; it applies the probability theory to the classification process. This method is a supervised method that uses the training sites, from these sites it determines the class center and the variability in the raster values in each band for each class. This helps to determine the probability of the cell to be belonging to a particular class defined in training sites. The probability is depending on the distance from cell to class center, class size, and the shape of the class in spectral space. The maximum likelihood classifier computes the class probabilities and classifies the cell where the probability is higher (Fekadu, 2017).

2.4.2. Training Site Selection

The unsupervised classification was used in the image classification before fieldwork to understand the general land-cover classes of the study area. This is because unsupervised classification is automated and requires little knowledge of the study area. Classification of the Land sat images was carried out within ERDAS IMAGINE 2015. The maximum iterations were set to 10 and the number of classes set to five for each image to ensure consistency in the results.

According to their spectral signature using different band combinations, the classified images were assigned a class in the output raster. The LULC classes were confused when classified by the unsupervised scheme. Settlements and cultivated land were highly mixed because most of the settlements are intermingled within the agricultural field. However, the natural forest was easily separated from other classes in all images. Based on the unsupervised classification, sample training sites were selected for data collection during fieldwork. The class assignment was achieved through a comparison of the classified image with field observation.

2.4.3. Supervised Classification

Handing larger than incredible the image analyst supervises the pixel categorization process by specifying, to the computer algorithm, numerical descriptors of various land-cover change recognition current in the representation of land-use change clearly shows that area.

Training samples that express the typical spectral pattern of land-use and land-cover classes are defined. Pixels in the image are similar numerically to the training samples and are labeled to land-cover classes that have a similar integral part of a logarithm. All the classification techniques like the maximum likelihood classification (MLC), parallelepiped and minimum distance to mean classification may be applied to get the best classification technique (Behailu, 2010). The maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class (Roy *et.al*., 2015). Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). Maximum Likelihood is among commonly used supervised classification methods used with remote sensing image data. The Maximum Likelihood classification method is well known for the analysis of satellite images (Lu and Weng, 2007). So far, satellite image interpretation using the maximum likelihood approach was mostly applied for land-cover classification and monitoring of land-use changes (Shalaby and Tateishi, 2007) showing overall high accuracies (mostly over 80%). MLC classification is based on a parametric approach that involves the assumption of the selected classes of signature in the normal distribution (Al-Ahmadi and Hames, 2009). The disadvantage of maximum likelihood classification is training classes are generally based on field identification and not on spectral properties therefore spectral signatures are forced. Training data selected by the analyst may not be representative of the condition present throughout the image. Training data can be time-consuming and costly and unique categories are not represented in the training data.

The support vector machine (SVM) algorithm is not suitable for large data sets. SVM does not perform very well when the data set has more noise i.e. target classes are overlapping. In cases where several features for each data point exceed the number of a training data sample, the (SVM) will underperform. In supervised classification, the serving to establish the identity of the owner and location of certain representative patches of the land-cover types present in a landscape need to be identified before classification. Occurring at the beginning field input is normally required for acceptable map accuracy (Ehsan and Kazem, 2013).

2.5. Categorizing Land-Use Change Models

Many researchers provide an overview of land-use change models by categorizing or classifying models based on different factors. The most popular classifications are by (Fekadu, 2017) (Fasika et al., 2019); based on a three-dimensional framework of space, time, decision-making; Lambin et al. (2000); (Green et al., 2000) who categorized models according to the modeling traditions which they belong; and (Gorokhovich & Voustianiouk, 2006) who classified 18 models into geographic, economic and integrated categories. However, significant progress in land change models has occurred since the above reviews. Recent literature which updates and classifies land-use change models is by Silva and Wu (2012) who grouped models into six benchmarks of modeling approaches, levels of analysis, spatial scales, temporal scales, spatial dimensions, and planning tasks. Popular modeling approaches and categories mentioned above are briefly described below. Agarwal et al. (2002) reviewed models by searching databases for a comprehensive list of models then short-listed 19 models based on their spatial, temporal and human.

2.5.1 Empirical-statistical Models

Empirical-statistical models use multiple linear regression techniques to analyses changes in land use patterns and select important drivers of land-use change (Fasika et al., 2019). These models can predict land-use change intensity in the immediate past and are only valid in predicting land-use changes which are represented in the calibration dataset (Lepers, 2014).

2.5.2. Dynamic Simulation Models

Dynamic simulation models are also known as process models as they attempt to simulate processes, which induce land-use and land-cover change. They are based on the assumption that spatial and temporal patterns of land- use are influenced by the interaction of socio-economic and environmental processes (Lepers, 2014).

2.5.3. Integrated Models

Integrated models are made up of a combination of other modeling capabilities using an approach that is best at answering the research question (Lepers, 2014). These models are also known as hybrid models and are mostly large-scale models. (Malczewski, 2018) also categorized and described models based on underlying theories, purposes of the model, levels of analysis, and types of land- used being modeled. According to Malczewski (2018), the following are the main categories of models: statistical and econometric models, spatial interaction models, optimization models, integrated models, natural sciences-based models, GIS-based models, and Markov chain-based models.

2.6. Dynamic Methods

Digital dynamics surround and have the quantification of temporal phenomena from multi-date imagery that is most commonly come to possess by satellite-based multi-spectral sensors. In general, dynamic involves the application of multi-temporal datasets to be concerned with analyzing the temporal effects of the phenomena (Lu and Weng, 2007).

2.7. Post Classification Dynamic

This method compares two independently produced classified land-use cover maps of two different dates. Therefore, it minimizes the problem of normalizing atmospheric and sensor differences between two dates and can indicate the nature of change. It was found to be an accurate procedure for land-use and cover change detection provided that the two land-use cover maps have been accurately produced (Muzein, 2006).

2.8. Accuracy Assessment

According to (Foody, 2001) in thematic mapping from remotely sensed data, to express a concept correctly in all details is used typically to express the degree of ‘free from error’ of a map. A thematic map is supported by something on a change made with a classification that may be considered accurate if it supplies an impartial representation of the land cover of the region it portrays.

2.9. Modeling LULC Change

The term models have been used in different contexts and several application areas. It is large in an area defined as abstract qualities in art or approximation of reality achieved by simplification of complex real-world relations to the point that they are understandable and analytically Manage (Tizora, 2018), as cited in (Behailu, 2010).

2.9.1. Modeling LULC Dynamic with CA-Markov

Ulam and Von Neumann originally conceived Cellular Automata (CA) models in the 1940s to provide a formal framework for investigating the behavior of complex, extended systems (Tizora, 2018).CA is a change detection, discrete space, and time system. A cellular automaton system has as an essential feature consists of a regular grid of cells, each of which can be in one of a finite number of k possible states, updated synchronously in discrete time steps according to a local, identical interaction rule (Roy *et.al*., 2015).

The ability of most CA models to correlate socioeconomic factors with the development process is still weak (Karsidi, 2004).

CA usually maintains similar frameworks regarding assembly, testing, validation, and calibration. It is a combination of Markov chain; multi-criteria, and multi-objective land distribution with land-cover prediction procedures that add an element of spatial contiguity as well as knowledge of the likely relating to space distribution of transitions to Markov-chain analysis. By cellular automata (CA) must be done just some elements mention below.

Simulating the in attendance by a graph from the past using the image point in time succession. Examination of the simulations via the remotely sensed time series of past conditions and through the available collection of field monitoring.

Satisfactory of the model to iterate the year of option in the forecast. make a note of the resemblance model outputs to an autoregressive time-series come near for occurring just the once every year situation (Cervantes-Godoy *et.al*., 2014).

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Location

Ambo town is located in Western Ethiopia and Western Oromia region in West Shoa Zone. It is located west of Addis Abeba at a 114 km distance. This town has a latitude of 8°58′N-8° 59′N and longitude 37°50′E -37°52′E and an elevation of 2106 meters. This West Shoa zone is namely Ambo Town (Figure 2). The area of the town is 10.2 sq km^2 (ten-point two square kilometers**).** Ambo is known for its mineral water, which is bottled outside of town; it is reportedly the most popular brand in Ethiopia.

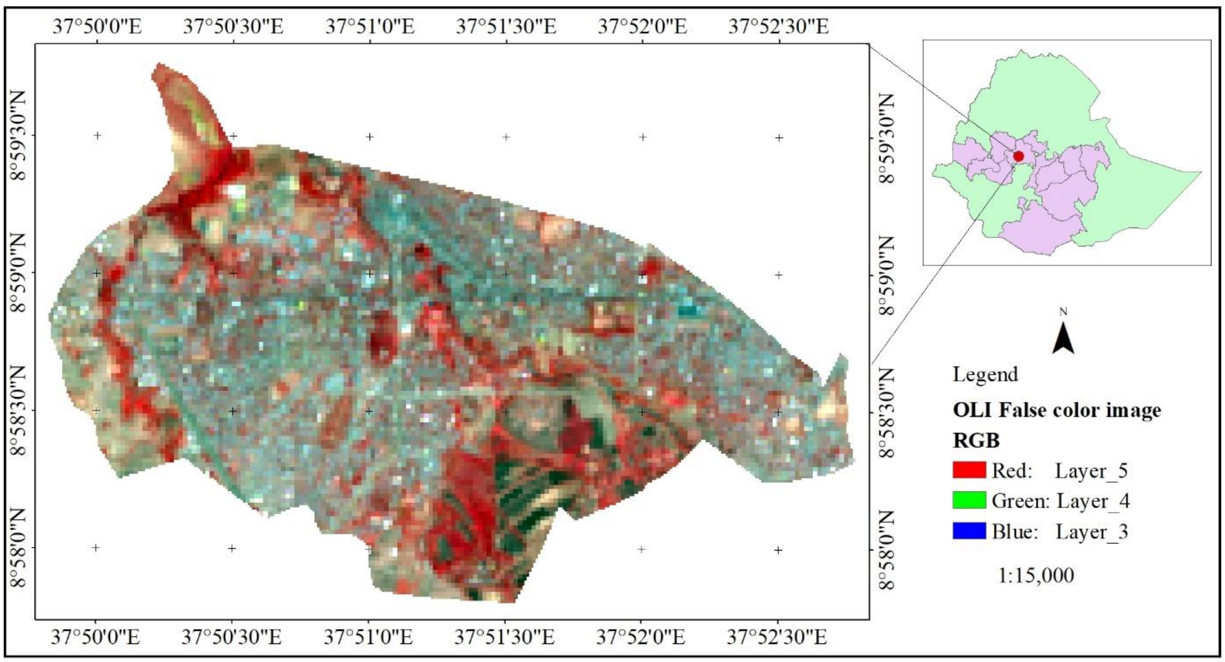


Figure 2: Location of the study area

3.1.2. Climate

Based on meteorological data from the Ambo research center, for the period 1995-2019, annual rainfall in the study area ranges from 775 mm to 1265.70mm yr^{-1} with a mean annual rainfall of 1044.6mm yr-1 (Figure 3). The rainy season in the area is from May to September and the wettest month is July (233.7 mm). It is dry season, with erratic rain of less than 65 mm per month between October and April. The mean annual minimum and maximum temperatures are 10.38 °C and 26.28 °C, respectively.

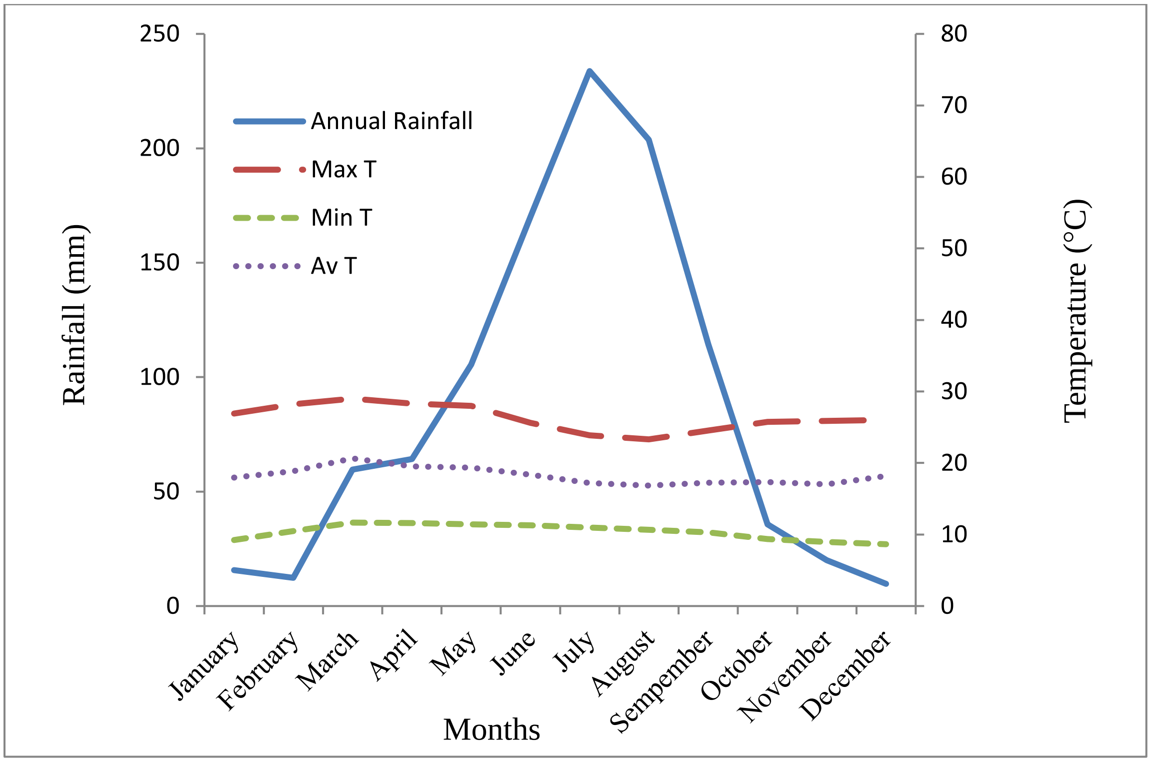


Figure 3: Monthly average rainfall and temperature of Ambo town

The around in Ambo Climate diagram of the study sites (Ambo town). The monthly average for the years 1995 – 2019 was obtained from the Ambo Agricultural Research center.

3.1.3. Population

The population size and their distribution vary from the history of early human settlements. High population pressure existed in the middle altitude where human beings were settled first and in low land areas, the distribution of the population was low and scattered (Ayele, 2017).

Urbanization is the most powerful and visible force that has fundamental changes in land use and land cover change around the globe. Ethiopia has one of the fastest-growing urban populations and least urbanized countries in the world. According to (Ayele, 2017) the Urbanization level of Ethiopia was 11.4 percent (4.3 million) in 1984, 13.7 percent (7.4 million) in 1994, and in 2007 it increased to 16.2 percent (11.9 million). According to the rank given by Oromiya National

Regional State to all urban centers of the region in 2011, Ambo town is one of the second grade and fastest growing towns in Oromiya National Regional State established in August 2008. The population of Ambo town was 47,261 in 1994; 67,604 in 2007 source from (CSA) and has grown to 94,049.9 in 2020 (estimated), showing that the population of the town has increased by around thirty doublings within the past 30 years (Ambo Town Communication office 2020). The issues of Urban land use and land cover changes of Ambo Town become the most main problems of societies in social, economic, and environmental such as cultural disturbance, health problems, deteriorating environmental quality, uncontrolled development, loss of prime agricultural lands, and protected Forest lands (Ambo Town Communications offices, 2020).

3.1.4 Vegetation

The study area is characterized by farmland, settlement land, bare land, forest land, and grazing land which are made up of shrubs or small trees and are usually fairly open; grasses and other small plants grow between the shrubs (personal observation). Vegetation is patchy and composed of small to medium-sized shrub species dominated by some scattered tree species. The vegetation description presented by Berhanu (2017) shows that the study area is characterized by dry evergreen montane forest on the basis that the dry evergreen montane forest covered the area between 1500 and 3000 m a.s.l. in the central and northern part of the Ambo. Dry Evergreen Montane Forest is a very complex vegetation type occurring in an altitudinal range of 1500-2700 m, with average annual temperature and rainfall of 14-25° C and 700-1100 mm, respectively. The Ethiopian highlands contribute more than 50 % of the land area of Ethiopia with Afromontane vegetation, of which dry montane forests form the largest part (Bekele, 1993).

The common wood plant species which are distributed around Ambo town and along Huluka and Tentale river include Oleaeuropaea subsp. cuspidata, Albiziaschimperiana, Acacia spp., Cordia Africana, Oliniarochetiana, Croton macrostachyus,Maytenusarbitifolia, Clausenaanisata, Maesalanceolata, Vernonia spp., Ficusspp, Phoenix reclinata, Bersamaabyssinica, and different shrubs and herb species.

3.1.5. Major Land-Use and Land-Cover Classes

In the study area, there are four major land-use and land-cover classes; those are built-up area, forest land, bare land, and agricultural land. The techniques and data used to identify the land use type were substitute with a top map, ground verification, expert opinion, supported by Google earth image, and key informants (Angessa *et.al*., 2019). In the study area of, four types of land use, but the one constraint of Ambo town unplanned and undersigned have two rivers that cross the town, those rivers are Tentale and Huluka Rivers. In addition, the river area is less than bare land in the ambo town, because of this identification by using many methods assigned four dominant obtained. The reason why these rivers were not included in the dominant land use type is that the depths of these rivers were high and hidden by the forest. Due to this, the reflectance shows more forest patterns. Furthermore, the river area cannot be covered by satellite swath due to its less reflectance during data recording. The classification was modified based on FAO Africover as shown in Table 1.

Table 1: Major land-use and land-cover class types of the study area

Land cover Class	Properties
Forest land	In a wider sense cover around Tentale and Huluka river in Ambo Town and include any kind of woody plant vegetation growing in and around human settlements
Built-up area	Urban areas with permanent residential, commercial land other facilities of varied patterns.
Bare land	Bare land represents areas with no dominant vegetation cover.
Agricultural land	Agricultural land is defined as the land area that is either arable, under permanent farms, or permanent pastures

3.2. Data types and sources

For this research, different types of software and materials were used to accomplish the desired objective. Ground control points (GCPs) have been taken during field observation by using GPS. In addition to this, a digitized and geo-referenced topographic map was used for geo-referencing satellite imageries and to identify some LULC types. Many researchers have also used satellite imagery for the classification of land-use and land-cover, mapping forest habitat, detecting forest disturbances, assessing landscape structural change, etc.

Recently, the techniques of remote sensing have been remarkably developed and analysis of the imageries has greatly contributed to identifying the phenomena on the earth's surface. In this research, by using imageries of Landsat TM, ETM+, and OLI data, different LULC classes of the study area were identified. The temporal extent of the collection, the characteristics and quantity of Landsat data, and the ability to collect new data directly comparable to that in the archive make Landsat data a unique resource, one used extensively to address a broad range of issues in earth science. The multi-temporal Landsat images used in this study are indicated in Table 2.

Table 2: Types of data used and their source

Data types	Sources of data	Path/Row	Spatial Resolution(m)	Acquisition date	Attributes
Image	Landsat TM 1990	168/054	30*30	26/11/1990	USGS land-use and land-cover dynamics classification
	Landsat ETM2 +000	168/054	30*30	14/11/2000	
	Landsat ETM +2010	168/054	30*30	31/11/2010	
	Landsat 8 OLI 2020	168/054	30*30	5/11/2020	
DEM	NASA/USGS	168/054	30*30	17/11/2020	Slope
EthioGIS	Ethiopian geospatial information agency	Administrative boundary			Ambo town delineation

The Landsat TM 1990 image was taken from International Livestock Research (ILRI), GIS Centre, (2000, 2010) ETM+, and (2020) OLI data were downloaded from GLCF and USGS website.

3.2.1. Ground truth data Collection approach

To accomplish the specified objectives of this research study both primary and secondary data were used. The primary sources of data include field data that was collected with the use of Global Positioning Systems (GPS), selected key informants (natural resource management experts, and other responsible bodies) by using structured interviews. Ground–truth data were gathered on the field to be used for image classification and verification of the satellite imagery. Focus group discussions (FGDs) and key informants' interviews (KII) were used to provide qualitative information. Key informants were selected purposively from different social groups, who have detailed knowledge about the LULC dynamics of the study area (Angessa et.al., 2019). These include elders (6), municipal natural resource experts (10), community leaders (5), and experts from the land administration of the municipality (6). In total 27 key informants were used. The purpose of key informant interviews is to collect information from a wide range of people including elders, community leaders, professionals, or residents who have first-hand knowledge about Ambo Town. The focus group discussions (FGD) were consisting of six to eight individuals. Three FGDs were conducted where two of them were represented with seven individuals, and eight individuals represented the third group.

The secondary data source involves related published and unpublished materials, for instance, Ethiopian Map Agency (EMA) contributed large-scale maps 1:50,000, Ethiopian central statistics agencies population data of study area, the temperature, and rainfall data were obtained from the Ethiopian meteorological agency.

3.3. Materials and Software

Based on the types of research, different materials and software were used to manipulate the collected data and give output results. For analysis of modeling of land-use and land-cover change in Ambo Town, the following materials and software used are shown in table 3.

Table 3: Materials and software used

No	Software/Material	Purpose
1	ArcGIS (10.5)	Data acquisition, editing, manipulation, analysis, modeling, visualization, publication, and storage
2	ERDAS imagine (2015)	Digital image preprocessing, image classification, map land-use/ land-cover
3	IDRISI (17)	Land change modeling and time series analysis, multi-criteria and simulation modeling, surface compare and predict for the future
4	Google Earth	Visualization,
5	Microsoft office (2016)	Writing, chart preparing, graphs, and statistical analysis
6	GPS	Collect Ground Controls Points (GCPs)

3.3.1. Methods of Data Analysis

Data collected from various sources were analyzed by applying multi-criteria evaluation (MCE) by integrating with ArcGIS 10.5, ERDAS Imagine 2015. Ground truth from the field and satellite images were used and analyzed by using ArcGIS version 10.5, and ERDAS imagine 2015 software. ArcGIS was used to reclassify and calculates the pixel values of all LULC classes and complement the display and preparation of maps. ERDAS imagine was utilized for layer stacking of bands, radiometric calibration particularly for atmospheric correction, haze, and noise reduction. All this preprocessing was performed before executing classification analysis. Besides Google Earth was used to check the land use and land cover of the area before field data collection. The overall processes allowed the investigator to better enhance and improve the images for classification and interpretation and the resulting sampling sizes for point data were 200 points with a maximum sample size of 50 samples per class and a total of 200 GPS data's were collected. From these 70 (35%) points were used for training and the rest 130 (65%) points to assess the accuracy of land use land cover classification.

Ground–truthing data were gathered on the field to be used for image classification and verification for the satellite imagery of 2020. Key informants, who have detailed knowledge and experience on the LULC dynamics of the town, verified 1990, 2000, and 2010 images. Based on the classified maps of the respective years, the informants were asked to provide the types of LULC of the specific years from their experience. In addition to this, Google earth images and Topo maps were used for the verification of LULC types (Angessa *et.al.* 2019). Identifying the complex interaction between changes and their drivers using Focus group discussions (FGDs), key informants interviews (KII) and field observation is important to predict future developments, set decision-making mechanisms, and construct alternative scenarios. Data (FGDs) and (KII) collected was described qualitatively to complement the ERDAS output.

3.4. Land-Use and Land-Cover Scenarios and Future Demands

Scenario analysis is important for projecting future land-use changes. Two scenarios were designed for this study, namely the Business-as-Usual (BAU) scenario, and the Policy reform scenario (PRS). Based on existing LULC-related policies in Ethiopia, local demographic information, and historical LULC dynamics of the study landscape, future scenarios have been defined to predict LULC demand for 2030. The BAU scenario was designed mainly based on the assumption of a continuation of LULC conversion results of the past 30 years in the current study area (Kindu *et.al*., 2018). Thus, before the demand calculations for 2030 in the BAU scenario, the rate of change between 1990 and 2020 for each LULC type was determined using the following formula (Kindu *et.al*., 2018):

$$\boldsymbol{r}=(\frac{\mathbf{1}}{\boldsymbol{t_{1-t_2}}})*1n\,(\frac{\boldsymbol{A_2}}{\boldsymbol{A_1}}) \qquad (1)$$

Where r = rate of changes for each LULC type, A1 and A2 = extent of each LULC type at time t1 and t2, respectively.

Afterward, the trends of each LULC type during the last three decades were extrapolated using the following formula:

$$A_n = A_O e^{rt} \qquad (2)$$

Where A_n = the area estimate for each LULC type in year n, A0 = area of the base year, t = period that is the difference between year n and year 0; and r = average annual rate of change.

Policy reform and innovation are key drivers of any town's remarkable economy, where this scenario is to mean the government can provide different innovative strategies to overcome the BAU. The policy reform scenario was designed for only strict implementation of spatial policies in which assumed that the area (natural forests, plantation, and woodlands) leading to the competition of the remaining LULC types to obtain the demands for LULC types in 2030.

3.5. Driver-Pressure-State-Impact-Response (DPSIR) Framework

The Dpsir is an analytical framework that can be used to organize, report, and illustrate the effects of human activities on the environment. This framework was developed by the European Environmental Agency in the 1990s and has since been applied in environmental research projects to support planning decisions (Yimesgen and Daba, 2019). The Dpsir framework was adapted in assessing LULC changes in the study area to present various aspects and issues which emerged from interviews and document readings.

3.6. Pre-processing Image

Pre-processing is the preliminary processing with the intention of deals with correcting radiometric distortions, atmospheric distortion, and geometric distortions there in the raw image data. Radiometric corrections include those that can be contributed through sight enlightenment, atmospheric factors, viewing geometry, and instrument response characteristics. Geometric corrections include those related to the variation of the flight altitude, attitude, earth curvature, velocity of the platform, and the like (Kousalya *et.al*., 2012). Preprocessing functions engage those procedures that exist usually required before the main data analysis and extraction of information and are generally grouped as radiometric corrections. Atmospheric belongings can cause imagery to contain a partial dynamic variety, appearing as haziness or reduced contrast. For this study, haze reduction was complete to sharpen the representation and a nonlinear contrast stretch (histogram equalization) that redistributes pixel values to make approximately the same number of pixels with each value within a range. Combining multiple (usually single band) images as bands/layers into a single output multi-band image (layer stacking), and reduce the size of the image file to include only the area of interest (sub-setting) was performed. Before sub-setting, the images of the digital map (shapefile of the study area) are re-projecting to UTM/WGS84 zone 37 to make similar with satellite images. Composite bands 2 (blue), band 3 (green), band 4 (red), and band 5 (Near Infrared) are stacked and subsetted by the boundary shapefile of the study area using ERDAS Imagine 2015.

3.6.1. LULC Classification

Images from different periods are used for the classification of land-use and land-cover dynamics of the study area. This multi-temporal raw satellite data were imported to Erdas Imagine 2015 image processing software. After this, land-use and-covers dynamic maps, and land-cover statistics were generated to compare the temporal dynamic of the study area for the past three decades using ERDAS 2015 software. The flow chart for the general methodology to classify LULC types is shown in Figure 4. Finally, land-cover maps of Ambo town were produced based on 1990 Landsat TM, Landsat (2000, 2010) ETM+, and (2020) OLI data using supervised. However, after supervised classification, some classes were combined and the final land-cover map of Ambo Town was sketched. The step-by-step approach (methodology) takes to achieve the stated objectives of this project are the following; the satellite image of the study area was classified using ERDAS Imagine2015. The existing analog boundary map was converted into digital format through digitizing using ArcGIS 10.5 application software.

3.6.2. Supervised classification

Supervised classification can be used to cluster pixels in a dataset into classes corresponding to user-defined training classes or the process of using samples of known identity (i.e., pixels already assigned to informational classes) to classify pixels of unknown identity. This classification type requires that the researcher select training areas for use as the basis for classification. Various comparisons are then used to determine if a specific pixel qualifies as a class member. Types of supervised classification include Paralleloped, Minimum distance, Mahalanobis distance, Maximum likelihood, spectral angle mapper, etc.

3.6.3. Maximum likelihood classification algorithms

This classification assumes that the statistics from each class in each band are normally distributed and calculates the probability that a given pixel belongs to the specific classes. Moreover, it quantitatively evaluates both the variance and covariance of the category of spectral response patterns when classifying unknown pixels after computing the probability in each category the pixel would be assigned to the most likely class that is to the highest probability values. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). If the highest probability is smaller than the threshold you specify, the pixel remains unclassified (Anderson, et al, 2009).

Calculated land use and land cover types of each land use by using in the simple formula were generated.

$$\text{LULC types} = \frac{\text{Rate of land use}}{\text{The total study area}} * 100 \quad (3)$$

3.7. Accuracy Assessment

The process of doing an accuracy assessment involved generating a set of points from the classified image and comparing the positions of points whose location was determined by the ground truth data and corresponding coordinates from the original maps (ERDAS, 2009). In this study, these sets of points were selected with random sampling. Random sampling was used to select a set of points. Training points used in image classification were not used for accuracy assessment. The reference points for 1990, 2000, and 2010 were collected from the corresponding key informant, FGDs, Topo map, and Google Earth; original Landsat images, previous reports and maps, and field observation for 2020. Information from interviews and group discussions supported us in getting the historical LULC, for example, forest lands, bare land, agriculture land, and built-up area. There are no high-resolution images in Google Maps for 1990; it is Landsat the common way to represent classification accuracy is in the form of an error matrix. An error matrix is a square array of rows and columns and presents the relationship between the classes in the classified and reference data. The reference data used for accuracy assessment was obtained from field observations and a topographic map. Sets of reference points have been taken to assess its accuracy.

Overall accuracy is computed by dividing the total correct number of pixels (i.e. summation of the diagonal) by the total number of pixels in the matrix (total). Various standard threshold levels were applied to the lower and higher tail of each distribution to find the threshold value that produced the highest change classification accuracy (Behailu, 2010). The producer's accuracy refers to the probability of a reference pixel being classified correctly. It is also known as omission error because it only gives the proportion of the correctly classified pixels. It is obtained by dividing the number of correctly classified pixels in the category by the total number of pixels of the category in the reference data. User's accuracy assesses the probability that the pixels in the classified map or image represent that class on the ground (Lu and Weng, 2007). It is obtained by dividing the total number of correctly classified pixels in the category by the total number of pixels on the classified image table 4. The Kappa coefficient was also used to assess classification accuracy. It expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification (Roy *et.al*., 2015). The Kappa statistic incorporates the off-diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance.

3.8. Dynamic Process

After the classification of land use and covers, remote sensing data were converted into thematic maps. To assess temporal and spatial land of dynamic in the study area Land-use and Land-cover were consecutively be analyzed using datasets of remotely sensed Landsat imageries. Next, area change between two consecutive study periods was computed using the classified imageries. Then, the post-classification comparison dynamic technique was applied in 1990, 2000, 2010, and 2020 using Erdas software. These land-cover maps were compared pixel by pixel with the results showing both dynamic-no-dynamic information as well as 'from to' land-cover dynamic information.

3.9. Model Selection

As observed from the literature outlined in section 2.5, various categories or classifications of LULC change models have been identified by different researchers. The diversity of these categories is due to differences in scientific disciplines, model objectives, modeling techniques, theoretical backgrounds, research questions, and scales of application. (Araya, 2009) argue that despite the availability of a wide range of modeling approaches, there is no single approach that is superior to model land use. They further allege that the selection of a model is highly dependent on the research or policy questions that need answers, the availability of data, and the characteristics of the study area.

3.9.1. Model Selection Criteria

After completing the initial selection of models, the final step was to assess whether the models met a set of requirements for them to effectively model LULC change in the study area. The set of requirements was in the form of a list of modeling criteria created based on knowledge of the area the understudy together with a selection guide extracted from a report by the Environmental Protection Agency (Malczewski, 2018). The following are the requirements

Relevance: A relevant model must model and project outcomes for scenarios that relate to the community and its needs. Relevance is determined by the LULC changes which will be evaluated and questions or issues to be addressed. For this study, it was observed that LULC changes were mostly due to political, economic, demographic, and environmental drivers. A relevant model must therefore be able to incorporate these drivers and output transition maps for each LULC category.

Linkage Potential: Linkage potential is concerned with whether the model can be linked to other models or GIS presentation software. A model with high linkage potential will allow data outputs to other models or software for further analysis or presentation. This is important since a hybrid model is the best method to model LULC changes.

Transferability: This is the ability of the model to be transferred or applied to environments other than the one for which it was developed. Some models may have been designed for specific environments or regions, leading to intensive efforts in adapting them to other areas.

Data Requirements: Many LULC change models are data-intensive and require certain data to function. In some instances, the data can be available or might require significant time and resources to obtain. A model may therefore be constrained by the availability of data. The performance of the model is therefore influenced by the quality and scope of available data (Palmer et al., 2009).

3.9.2. Modeling LULC Dynamics

To model, LULC change CA-Markov chain analysis that is implemented in IDIRIS was used. Cellular automata-Markov can predict transition among any number of classes. It also maintains similar frameworks regarding assembly, testing, validation, and calibration CA-Markov chain analysis indicates the difference in one land-use to another land-use and further uses this to predict the future. Modeling land-use and land-cover dynamics (LULCD) is an essential role in understanding the concepts of land-use dynamics. Cellular Automata can be conceptually understood as a ’cell-based approach for modeling dynamic gravity processes at the micro-level (Han et.al., 2015).

The Modeling and Simulation of land-cover change are fundamental to the evaluation of successive environmental effects. To calibrate the model and simulate land-use dynamics for the future, drivers of dynamic along with the land-use maps of the years 2000 and 2010 were used. The predictive model output for 2020 will then be validated using a “real” land-cover map.

3.9.3. Modeling LULC Change with CA-Markov

CA operates on grid-based cells and transition rules are applied to determine the state of a cell. Markov Chain Analysis, on the other hand, is a system in which the future state of a system is modeled based on the immediate proceeding state. These two are termed as the two simulation techniques used to produce land-use predictions (Shalaby and Tateishi, 2007). The simulation refers to the process of land-use change between two points in time and extrapolating this change into the future (Roy *et.al.*, 2015). Factors and constraints LULC Map Of 2000 LULC Map of 2010 Calibration and Modeling MCE suitability Map Reference LULC 2020 Simulated LULC 2020 Validation Prediction LULC for 2030 CA-Markov Chain analysis for simulating land-use was implemented in IDIRIS Andes. It can predict transition among any number of classes. The transition rules were based on the factors that have impacts on LULC change. These factors include slope, proximity to the road, growing population, and land use. Other factors like rainfall and aspect are taken constantly throughout the study area because of its small extent. The biophysical factor, altitude, was also ignored due to its small range.

3.9.4. Model Calibration

A transition probability matrix was first developed using the Markov module in Idrisi for each land-use and land-cover class between 2000 and 2010 to use as an input for projecting land-use change for 2020 (Table 4). The off-diagonal elements indicate the probability of several cells that are expected to change between the two periods from the existing to new classes.

Table 4: Transition probability matrix for the projection of 2020 land-use and land-cover

LULC Class type 2000/2010	Bare land	Agriculture land	Built-up area	Forest land
Bare land	**0.0296**	0	0.5143	0.0889

Agriculture land	0.2056	**0.5524**	0.2309	0.1338
Built-up area	0.0389	0.5143	**0.7198**	0.0731
Forest land	0	0.0334	0	**0.0825**

3.9.5. Modeling LULC for 2020 with CA-Markov

A cellular automaton is an agent or object that can change its state based upon the application of a rule that relates the new state to its previous state and those of its neighbor (Mahmoud and Divigalpitiya, 2017).In this study, a CA filter was used to develop a spatially explicit contiguity weighting factor to change the state of cells based on their neighbors. It combines both the concept of a CA filter and the Markov change procedure. A transition areas table and suitability image from Markov was used by the CA Markov to predict land-cover change for 2020. Based on these inputs, the module determines the location of change, the number of pixels that must undergo each transition, and selects the pixels according to the largest suitability for a particular transition. The initial analysis used the 2000 and 2010 land-cover maps to "predict" for the year 2020. Agricultural was taken as a constraint for Settlement field expansion. This was created from the land-use map of the year 2010, which was used as a base for simulation. This was created from the land-use map of the year 2020, which was used as a base for simulation.

3.9.6. Model Validation

Model validation refers to comparing the simulated and reference maps. Sometimes the simulated maps can give ambiguous results. In that case, it is necessary to validate the projected/simulated map with the base/reference map (Eastman, J. R., 2009). For validating the output of the simulated LULC map in 2020, two maps were compared the reference LULC map of 2020 and the simulated LULC map of 2020. Several 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) (Fekadu, 2017).

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).

The Kappa statistics (K) is defined according to the following equation (Hagen, A., 2002).

$$K = \frac{P\ (A) - P\ (E)RL}{1 - P(E)RL} \quad (4)$$

Where (A) = Percentage of cells in the map that are identical; P (E) RL = Random location (RL) conditional to the observed distribution in both maps. The calculation of kappa is based on the "contingency table" (Han et al., 2015)).

$$P(A) = \sum_{n=1}^{m} pnn \quad (5)$$

$$P(E)RL = \sum_{n=1}^{m} pm * pn \quad (6)$$

Where, Pnn. = the proportion of cells that is of category 'n' in map A and 'm' in map B.

Pmn = the proportion of cells that is of category n in map A and category m in map B.

Based on the matrix table the following equations be able to be derived from table 8 (Han et al., 2015).

Table 5: Strength of Agreement for Kappa Statistic

Kappa Statistic	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, Klocation, and Khisto

The 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.

It depends strictly on the spatial distribution of the categories on the map. It indicates how well the grid cells are located in the landscape (Behailu, 2010).

$$P(A) = \sum_{n}^{m} = 1\, pnn \quad (7)$$

$$P\ (E)\ RL = \sum_{n}^{m} 1{=}1\ Pn * Pm \qquad (8)$$

Where, P (max) = the maximum success rate P (E) RL = the fraction of expected agreement for the whole map, where RL stands for random location.

Kno is a statistic similar to Kappa, but better capable of expressing similarity both in quantity and location (Hagen, A., 2002) “Klocation indicates how well the grid cells are located on the landscape(Roy et.al., 2015).

$$(Max) = \sum_{n=1}^{m} \min\ (Pn * Pm) \qquad (9)$$

$$Klocation = \frac{P(A)-P(E)}{P(max)-P(E)} = \frac{\sum_{n=1}^{m}(Pn-Pm)}{\sum_{n=1}^{m}(\min(Pn*Pm)-(Pn*Pm)} \qquad (10)$$

Where, P (max) = the maximum success rate, P (E) RL = the fraction of expected agreement for the whole map, where RL stands for random location. Khisto can be calculated directly from the histograms of two maps (Hagen, A., 2002).

$$Khisto = \frac{P(max)-P(E)}{1-P(E)} = \frac{\sum_{n=1}^{m}(\min\ (Pn*Pm)-(Pn*Pm)}{1-\sum_{n=1}^{m} \min\ (Pn*Pm)} \qquad (11)$$

In the case of this research before predicting for the 2030 year, prediction for 2020 is first made for validation. using 2000 and 2010 classified Ambo Town predict for 2020, then validate predicted 2020 with classified 2020, when the value of validation is acceptable, with the same procedures predicting for 2030 Ambo Town LULC classes. The flow chart for the general methodology is shown in Figure 4.

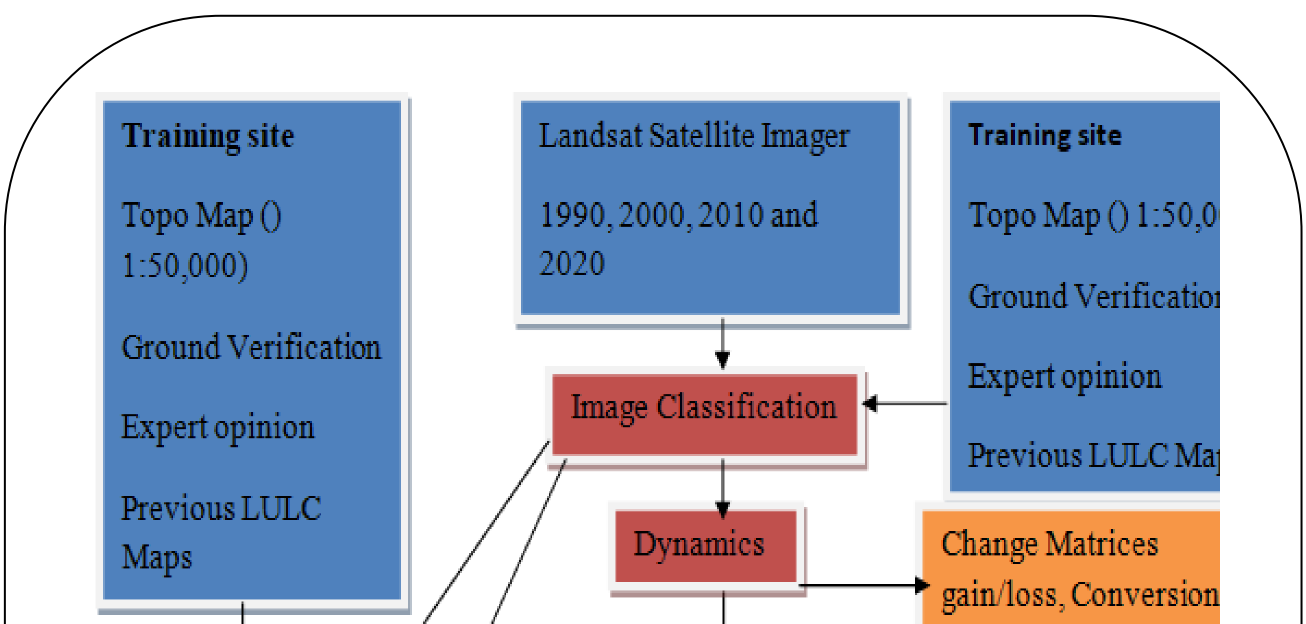


Figure 4: General procedures of the study

3.9.7. Change analysis and prediction modeling

Land-use and land-cover change 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 can use to predict future changes. Land-use change prediction in Land Change Modeler (LCM) is an empirically driven process that moves in a stepwise fashion from Change Analysis to Transition Potential Modeling and from transition modeling to Change Prediction. The Change Prediction (simulation) modeling for 2030 was based on the Cellular Automata. The validation of the model accuracy is needed, to achieve acceptable accuracy, this study had employed an approach to simulate LULC of 2020 (time t3) from the historical LULCD process for time one (2000) and for time two (2010) and then the simulated result was compared with the reference LULC map of 2020 (classified LULC map

2020). The reference map is usually considered more accurate in the study area at time three (Mienmany, 2018)

3.9.8. Change Detection Analysis

Remotely sensed images are vital in land-use and land-cover change detection as it provides spatial and temporal information of the land-use, and cover condition of the Town. In this research thesis, 30-year time span (1990-2020) and four-period change detection (1990-2000, 2000-2010, 2010-2020, and 1990-2020) these periods were chosen based on the availability of satellite images and other data in the town. This method is widely used and easy to understand (Fasika et al., 2019). The advantage of this method includes the detailed from-to information that can be extracted. Change detection and comparison were done for 1990 -2000, 2000 – 2010, 2010 -2020, and the fourth 1990-2020 to get from-to information of changes in LULC and especially to see the rate (trend) of the built-up area, agricultural land, forest, and bare land coverage of the study area. Change statistics would be computed by comparing the values of the area of one data set with the corresponding value of the second data set in each period. The value was presented in terms of hector and percentage. Quantification of the rate of change has been applied to generate information about the land use and land cover change of the study area.

3.10. Future Prediction map

Using Land Change Modeler, GEOMOD, Markov chain analysis, and cellular Automata, it is possible to determine the future Land-use and cover project maps. Using this neural network analysis, it is possible to determine the weights of the transitions that will be included in the matrix of probabilities of the Markov Chain for future prediction. The future Land-use and cover project maps of (2030) may be hard classifiers (Traditional classifiers) since they yield a hard decision about the identity of each pixel and soft classifiers express the degree to which a pixel belongs to each of the classes being considered. For this research, a hard classification of the Future predicted map is generated.

CHAPTER FOUR

4. RESULTS AND DISCUSSIONS

4.1. Land-Use and Land-Cover Dynamics in the Past Three Decades

4.1.1. Land-Use and Land-Cover change

As indicated in the classification scheme built-up area, agricultural land, bare land, and forest lands are the major LULC classes for the study area. Table 6 and figure 10 show the LULC of Ambo town in 1990, 2000, 2010, and 2020. In 1990, agricultural land was the dominant LULC covering 60.2% followed by forest land (21.9%); whereas, built-up area and bare lands covered 13.7%, and 4.2%, respectively. This result is in line with the findings of Lencho, A (2019) who concluded that built-up areas and agricultural lands were the dominant LULC types in Burayu Town, built-up area continuously increased whereas agriculture continuously decreased.

The LULC classification result of 2000 indicated a decline in agricultural land by 16.1%, while results from the rest of the LULC types, built-up, forest, and bare land increased by 8.8%, 3.6%, and 3.6%, respectively (see Table 6 and Fig. 10). In the LULC classification of 2010, the built-up area became the dominant LULC class covering 34.3%, followed by forest land (33.3%), agricultural land (26.5%), and bare land (5.9%). The comparison of the 2000 and 2010 LULC classification results indicated a decline in agricultural land by 17.6% and bare land almost by 2%; while forest land and built-up area increase by 7.8% and 11.8%, respectively.

In the LULC classification of 2020, a built-up area further increased to 56.9% followed by forest land, agricultural land, and bare lands, which constituted 22.5%, 11.8%, and 8.8%, respectively. The comparison of the 2010 and 2020 LULC classification results indicated a decline in agricultural land by 14.7% and forest land by 10.8%; while bare land and built-up area indicated an increase by 2.9% and 22.6%, respectively.

Generally, the LULC change results of Ambo Town in the past three decades (1990-2020) showed a declining trend only in agricultural lands, while the rest of LULC types indicated an increasing trend. Agricultural land was declined by 48.4%, while built-up area, bare land, and forest land, were increasing by 43.1%, 4.6%, and 0.7%, respectively (Table 9). Similarly, Ayele in his LULC change detection study in Hawassa Town (1995 – 2017), reported the increasing trend of built-up areas, forests, and bare lands, while agricultural land showed a decreasing trend. Likewise, the LULC change study in Burayu Town by Lencho A, (2019) indicated an increase in built-up/settlement areas and a decrease in agricultural land.

The increment in the built-up area may be connected to the natural population growth, and/or migration of the rural population particularly of the young generation in search of better livelihood and job opportunities, which intern may also lead to informal settlements. The increase in forest land may be explained by the fact that the government of Ethiopia gave great attention to tree plantation under the Climate Resilient Green Economy Strategy (CRGE); where the Ambo Town Municipality in collaboration with Ambo University undertake reforestation and tree plantation with the aim of urban greening, gave attention campaign of forest tree plantation after Millennium encourage, mainly along the roadside, that is evident still now. For instance, forest land is just like the cover in the study along the roadside in Ambo Town.

Figure 5: Forest land in the study area /in Ambo Town

Figure 6: Bare land and forest land

The increase in bare land was mainly attributed to road expansion, reservation for construction materials like red ash, Ambo granite, and fine aggregate gravels. For instance, indicate the bare land of the study area figure below.

Figure 7: Bare land cover by source Ambo granite and fine aggregate

Figure 8: Bare land cover by coarse aggregate and source of Ambo granite

Figure 9: Bare land, it is Ambo granite shape

Particularly, the excavation of recently invented Red sand, which was replacing River in the sand as a building material, and the increasing demand for Ambo granite throughout the country, extremely increases the proportion of bare land in the study area. On the other hand, the decrease in agricultural land is mainly attributed to urbanization processes, particularly the expansion of the built-up areas, which was mainly at the expense of agricultural lands.

Table 6:1990, 2000, 2010 and 2020 Ambo Town classification result

LULC type	1990		2000		2010		2020	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Bare land	43	4.22	80	7.84	60	5.88	90	8.82
Forest	223	21.86	260	25.49	340	33.33	230	22.54
Agriculture	614	60.19	450	44.11	270	26.47	120	11.76
Built-up area	14	13.73	230	22.54	350	34.31	580	56.86
Total	1020	100	1020	100	1020	100	1020	100

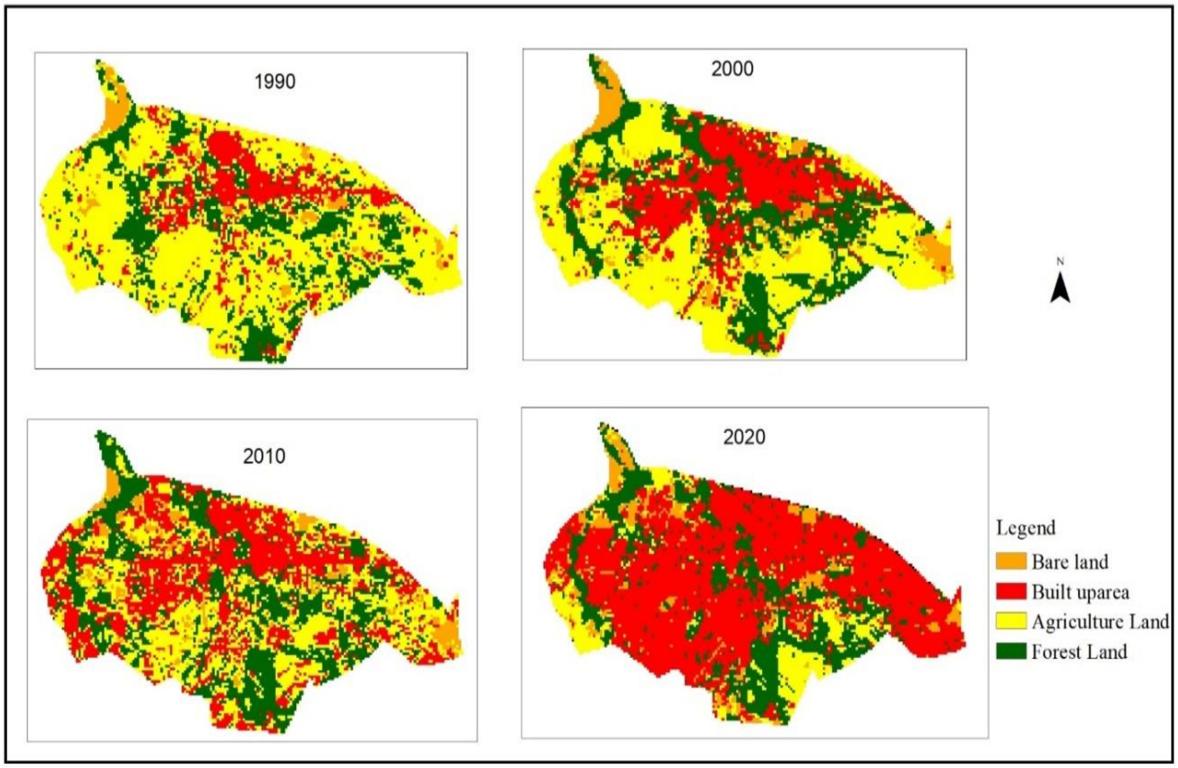


Figure 10: Classified LULC of 1990, 2000, 2010, and 2020 for Ambo Town

4.1. 2. Accuracy assessment classified land-use and land-cover image

The overall result of the current study for kappa coefficient, user accuracy, producer accuracy, and overall accuracy of 1990, 2000, 2010, and 2020 was presented in Table 9. Accordingly, the overall accuracy ranges from 85.5% (1990) to 90% (2020) which is at the acceptable range of accuracy assessment. Similarly, producer's and user's accuracy for almost all the classified images of the respective study years falls within the acceptable ranges, except for user accuracy for the year 2020, which is 83%. Kappa coefficient that associates the classified images to the reference data also showed a strong agreement (fall between 84% and 86%) for the study years. Furthermore, the result of an assessment of each classified land-use and land-cover accuracy is shown that in table 7 and appendix 1-4 in detail.

Table 7: Classification accuracy of (Overall, user's, producer's) accuracy and Kappa coefficient

Year	Overall accuracy (%)	Producer Accuracy (%)	User Accuracy (%)	Kappa coefficient
1990	88.5	84	85.7	0.84
2000	88.5	94	88.6	0.84
2010	89	88	86.2	0.85
2020	90	94	83	0.86

Table 8: Gain and losses matrix and appendix 5 show the gain and loss of an area change in Km^2 and percentage changes for individual LULC classes between 1990 and 2020 in Ambo Town. The quantified results indicate that Ambo Town has experienced considerable changes in LULC. Based on the LULC datasets used; there has been a rapid decrease in agricultural land over the past 30 years. Contrary to these decreases, there have been increases in settlement /built-up area, forest, and bare land.

Table 8: Ambo Town LULC gain and loss between 1990 and 2020 in ha

LULC Classes	1990	2000	2010	2020	Gain (1990-2020)	Losses (1990-2020)
Built up area (ha)	140	230	350	580	440	
Built up area (%)	13.73	22.54	34.31	56.86	43.13	
Agriculture land (ha)	614	450	270	120		494
Agriculture land (%)	60.19	44.11	26.47	11.76		48.43
Bare land(ha)	43	80	60	90	47	
Bare land (%)	4.22	7.84	5.88	8.82	4.60	
Forest land(ha)	223	260	340	230	7	
Forest land (%)	21.86	25.49	33.33	22.54	0.68	
Total (ha)	1020	1020	1020	1020	0	
Total (%)	100	100	100	100	0	

Generally, area change of LULC classes in three decades (1990-2020) built-up area, forest land, and bare land were increased by 440 ha (43.13%),0.07 (0.32%), and 50 ha (4.60%), agriculture land was decreased by 494 ha (48.43%) and respectively. The current finding agrees with the result of Lencho A, (2019) who concluded that built-up area increased by (44%) whereas agricultural lands decreased by (5%). Similarly, (Ayele, 2017) also reported that the built-up area increased in Hawassa town at the same time as an agricultural land decreased during 1995-2017.

The LULC change results also indicate that there have been Ambo Town increases in settlement area or built-up areas with about 8.82%, a 5% increase in bare land and forest. An assessment of the individual kebele in the Ambo town however provides a clearer picture of the actual LULC changes and shows that the increase in urban areas in the past 30 years is concentrated in the Awaro kebeles area and the adjacent Sanqale and Faris kebeles. Despite the 57.8% Ambo Town has experienced 250 hectares loss (-24.51%) in agriculture land to other LULC classes showed in table 9, and appendix 6.

Table 9: Ambo Town LULC area, net change, and percentage change between 1990 and 2020 (ha)

LULC Classes	1990-2000	2000-2010	2010-2020	1990-2020
Built up area (ha)	+90	+120	+230	+440
Built up area (%)	+8.81	+11.77	+22.55	+43.13
Agriculture land (ha)	-164	-180	-150	-494
Agriculture land (%)	-16.08	-17.64	-14.71	-48.43
Bare land(ha)	+37	-20	+30	+47
Bare land (%)	+3.62	-1.96	+2.94	+4.6
Forest land(ha)	+37	+80	-110	+7
Forest land (%)	+2.63	+7.84	-10.79	+1

Generally, area change of LULC classes in three decades (1990 - 2020) increased for the built-up area by 440 ha (44%), agriculture land decreased by -499 ha (-49 %) and forest land increased by 7 ha (0.68 %) and bare land was increased by 47 ha (4.6%).

4.1.3. Land Use and Land Cover Dynamics

The land-cover change comparison matrix gives the general information of major changes of the land-cover classes analyzed for the two periods. In the direction of clearly understand the major land-cover source and destination of the cover class's change, the conversion matrix for each period was analyzed. The rows of the tables show the initial stage and the column represents the final stage. For example, column one in Table 13 indicates that from a total of 614 ha agricultural land in 1990,340 ha remained as agricultural land, 45 ha changed to bare land, 119 ha changed to built-up area land, 110 ha converted to forest land. Similarly, as seen clearly in the matrix, a total of 223 ha forest land in 1990, 60 ha and 20 ha converted to agriculture land and bare land, respectively table 10.

Table 10: Gain and losses matrix of Ambo Town for 1990/2000 (ha)

LU/LC Types		2000 LULC Class				
		Agriculture land	Bare land	Built-up area	Forest land	Total
1990 LULC Class	Agriculture land	**340**	45	119	110	614
	Bare land	20	**5**	9	9	43
	Built-up area	30	10	**50**	50	140
	Forest land	60	20	62	**91**	223
	Total	450	80	230	260	1020

The 2000/2010 land cover matrix for Ambo Town, as shown in Table 11, indicated a similar trend in a loss of agricultural land, bare land, and forest land for built-up area land. For example, the first column shows that, from a total of 450 ha agricultural land in 2000, 20 ha converted to bare land and 140 ha changed to built-up area land in 2000. Similarly, from 260 ha forest land in 2000, 40 ha and 30 ha converted to agriculture land and built-up area land, respectively. The lowest and highest unchanged classes in both 1990/2000 and 2000/2010 land cover matrix are bare land and forest land and built-up area and forest land table 13 and 14 respectively.

Table 11: Gain and losses matrix of Ambo Town for 2000/2010 (ha)

LU/LC Types		2010 LULC Class				
		Agriculture land	Bare land	Built-up area	Forest land	Total
2000 LULC Class	Agriculture land	**210**	20	140	80	450
	Bare land	20	**20**	10	30	80
	Built-up area	20	10	**170**	30	230
	Forest land	20	10	30	**200**	260
	Total	270	60	350	340	1020

The 2010/2020 land cover matrix for Ambo Town, as shown in Table 12, indicated a similar trend in a loss of agricultural land, bare land, and forest land for built-up area land. For example, the first column shows that, from a total of 120 ha agricultural land in 2020, 40 ha converted to built-up area and 20 ha changed to forest land in 2020. Similarly, from 230 ha forest land in 2020, 40 ha and 20 ha converted to agricultural land and built-up area land, respectively. The lowest and highest unchanged classes in both 2000/2010 and 2010/2020 land cover matrix are bare land and built-up area and forest land table 11 and 12 respectively.

Table 12:Gain and losses matrix of Ambo Town for 2010/2020 (ha)

		2020 LULC Class				
LU/LC Types		Agriculture land	Bare land	Built-up area	Forest land	Total
2010 LULC Class	Agriculture land	**50**	40	140	40	270
	Bare land	10	**10**	30	10	60
	Built up area	40	20	**270**	20	350
	Forest land	20	20	140	**160**	340
	Total	120	90	580	230	1020

Although agricultural land intensification is a common trend elsewhere in the rapid such as the Ambo area (Lench, A,2019), the situation in the current study area was remarkable in Ambo Town. This was most likely caused by the expansion of built-up areas to migration from Guder, Goro sole, and Ginch town in 2000 and the high rate of population growth (Angessa et.al., 2019). It should also be stressed that forest lands continuously up to 2010, except for 2020. In general, LULC change is an indirect measure of population pressure; it provides robust evidence on the footprints of active human impacts on natural resources. The latter is usually manifested through the expansion of built-up areas and new bare land following forest clearings. However, in the current study area forest has increased by about 7 ha.

The current study clearly illustrates human-driven changes in the LULC of the study areas. The growing population and increasing socio-economic necessities create pressure on certain land use and land cover. This pressure results in unplanned and uncontrolled changes in LULC.

The 2020/2030 land cover matrix for Ambo Town as shown in Table 13 indicated a similar trend in a loss of bare land and agriculture land for settlement and forest land. For example, the first column shows that, from a total of 620 ha built-up area in 2030, 30 ha converted to agriculture land and 550 ha unchanged land in 2030. Similarly, from a total of 245 ha forest land in 2030, 35 ha and 10 ha converted to agriculture land and bare land/built-up area, respectively.

Table 13: Gain and losses matrix of Ambo Town for 2020/2030 (ha)

		2030				
LU/LC Types		Agriculture land	bare land	built up area	Forest land	Total
2020	Agriculture land	**45**	10	30	35	120
	bare land	20	**30**	30	10	90
	built up area	10	10	**550**	10	580
	forest	20	10	10	**190**	230
	Total	95	60	620	245	1020

Table 14: Ambo Town LULC classes change in a built-up area for three decades in table form in ha.

	Changed to the Built-up area (ha)				
LULC Classes	1990-2000	2000-2010	2010-2020	1990-2020	Total
Agriculture land	90	140	230	30	490
Bare land	20	10	20	30	80
Forest land	50	30	90	10	180
Total	160	180	440	70	850

4.1.4. Land-use and land-cover conversion matrix classification

As shown from the map most land use and land cover of the study area were unchanged. However, areas that had been agricultural land in 1990 were highly changed to built-up areas in 2000. Moreover, areas located in the northeast of the area were highly changed.

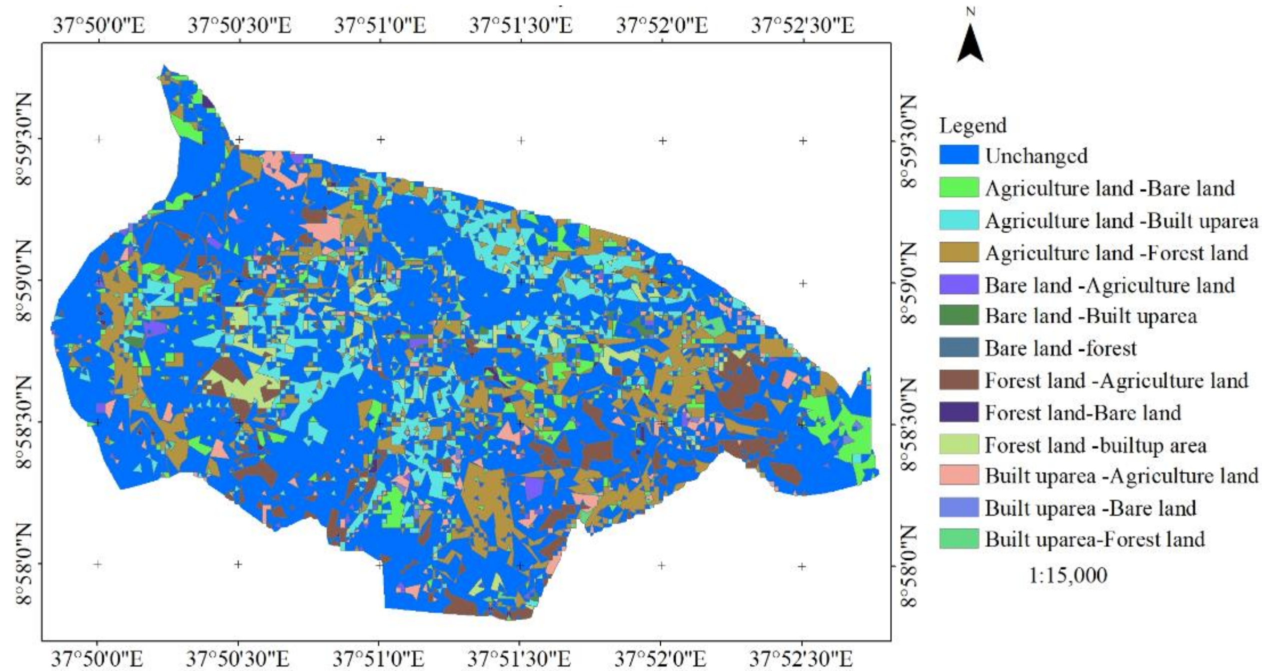


Figure 11: Land-use the land conversion matrix of 1990 – 2000

As shown from the map most land-use and land-cover of the study area were unchanged. However, areas that had been agricultural land in 2000 were highly changed to built-up areas in 2010. Moreover, areas located southwest of the area were highly changed.

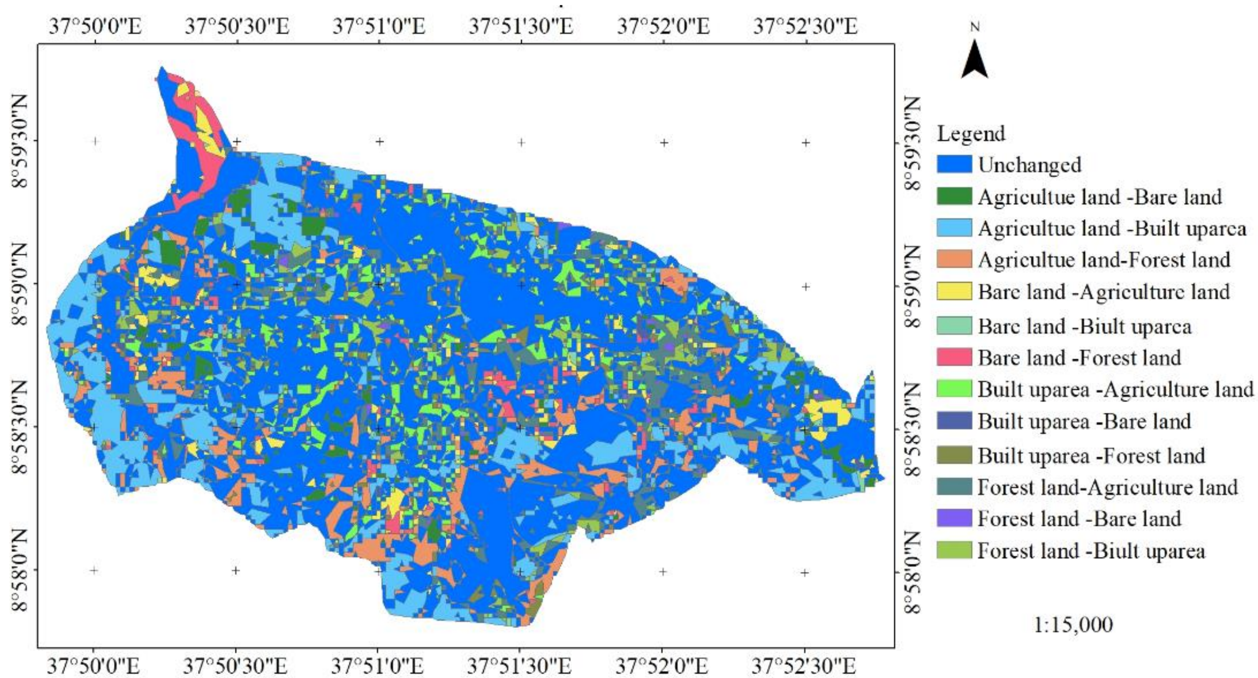


Figure 12: Land-use the land conversion matrix of 2000 -2010

As shown from the map most land-use and land-cover of the study area were unchanged. However, areas that had been agricultural land in 2010 were highly changed to built-up areas in 2020. Moreover, areas located at the southwest of the area were highly changed. The built-up area has been changed to the bare, forest, and agriculture land was insignificant, these mean results show that 1.9 %, and 3.9 % respectively. The measurement of southwest and northeast is based on the position/direction of the Maps.

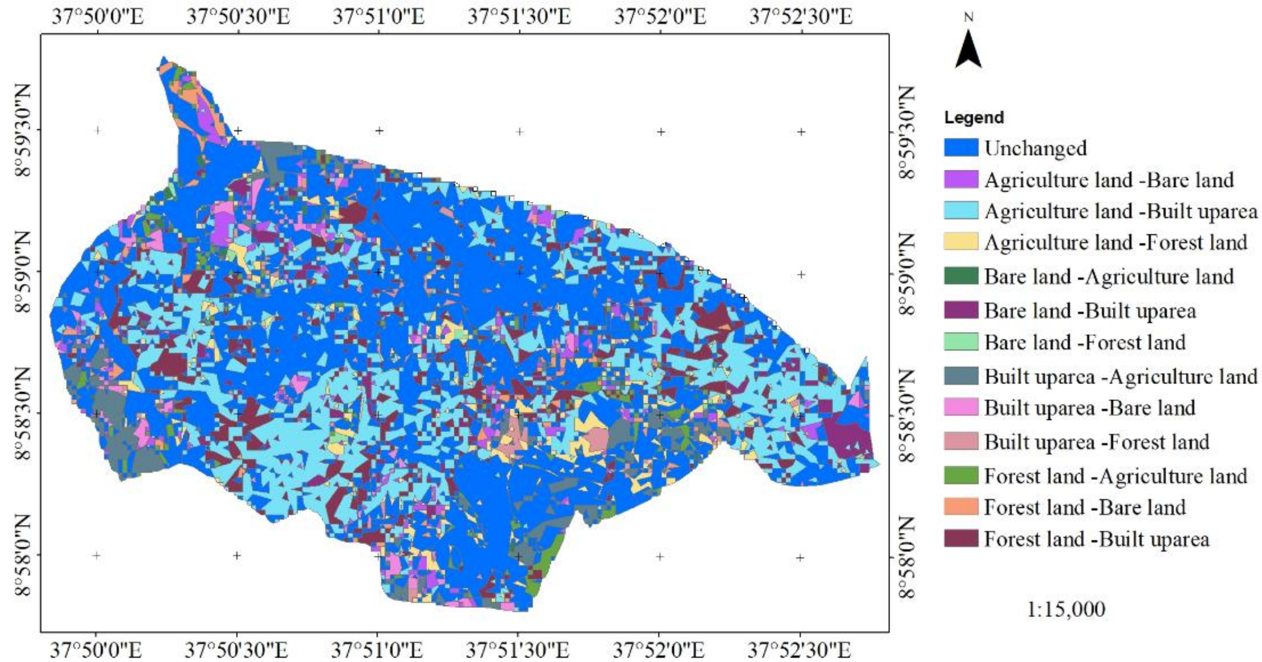


Figure 13: Land-use the land conversion matrix of 2010 - 2020

4.1.5. Future Prediction and Modeling for 2020

Markov model was selected for simulating the land-cover map of Ambo Town for the year 2020 for validation and predict the final land-use and land-cover map for 2030. Two basic models of change prediction are the 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 research is based upon the hard prediction model.

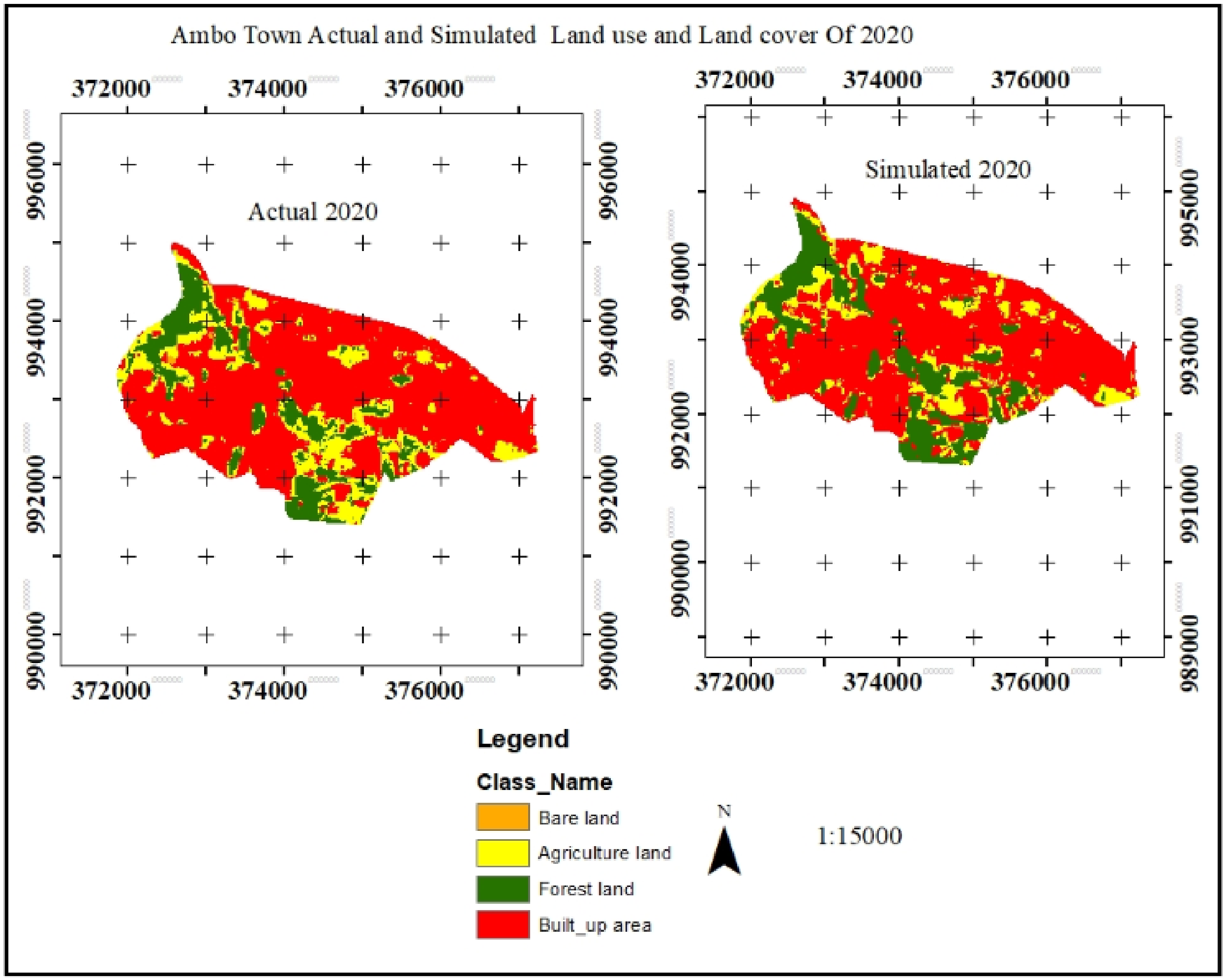


Figure 14: Predicted vs. Classified for Ambo Town 2020

4.1.6. Model Validation

The kappa statistics demonstrate that in appendix 8 conducted includes kappa histogram (0.84) that is an estimation of the frequency distribution of the simulation, Kappa location (0.9903) that is the simulation ability to perfectly specify location between the reference map and the simulated map, and Kappa overall (0.5626) that is the total accuracy of the number pixel correctly classified between the reference map and simulated map.

All of these Kappa values can be referred to Landis and Koch (1997), which explained the kappa value range. The value between 0.41-0.6 corresponds to a moderate agreement between the reference map and the simulated map. The total correctness value is 53.41%, which indicates that the moderate accuracy of the simulated LULC map in 2020 Validate.

figure 10-shows the output graph generated by running validates using the 2020 LULC map as the reference map and the 2020 simulated map as the comparison map. As explained above, this comparison method is of main interest since it indicates the accuracy of the model at simulating LULC changes. The graph below shows traditional Kappa statistics, Kstandard, Kno, and Klocation. Kstandard indicates agreement extent in terms of each category, Kno indicates overall agreement and is used to evaluate the overall success of the simulation and Klocation shows agreement between reference and comparison map in terms of location of each category. Kappa statistics of 0 indicate an agreement due to chance and 1 indicates perfect agreement. The accuracies of the Western Cape model were Kno =0.7701, Kstandard= 0.9930, and Klocation = 0.9930, indicating that the model is acceptable for future predictions.

4.1.7. Change Prediction Modeling for 2030

The Change Prediction (simulation) modeling for 2030 was based on the Cellular Automata. The validation of the model accuracy is needed, to achieve acceptable accuracy, this study had employed an approach to simulate LULC of 2020 (time t3) from the historical LULCD process for time one (2000) and for time two (2010) and then the simulated result was compared with the reference LULC map of 2020 (classified LULC map 2020). The reference map is usually considered more accurate in the study area at time three. The simulated LULC in 2020 was successful in both correctness value and multi-resolution. The correctness value was 53.31% that is a moderate agreement between the reference map and the Predicted (simulated) map.

The multi-resolution indicated the perfect location and medium quantity information between the reference map and the simulated map, which means that the historical LULCD process from 2000 to 2010 is accurate and reliable to predict LULC patterns in 2030. However, the validation of the simulated map is a challenge because there is no criterion to assess the performance of the different LULC dynamics models. Another problem is parameters to indicate the overall accuracy, parameters for comparing different modeling results, and the minimum accuracy standard (Muzein, 2006). Therefore, this research was considered to simulate LULC for the short period. So with similar procedures using Ambo Town 2010 and 2020 LULC generating the potential transition of all land-use and land-cover classes by using factors/constraints and change prediction of Ambo Town LULC of 2030. As shown from map 12 most land use and land cover of the study area were unchanged. However, areas that had been agricultural land in 2020 were highly changed to built-up areas in 2030. Moreover, areas located at the southwest of the area were highly changed. Built-up area change into agriculture, bare and forest land this indicates by percent all are equal percents this means 0.98/1, due to this insignificant area from them.

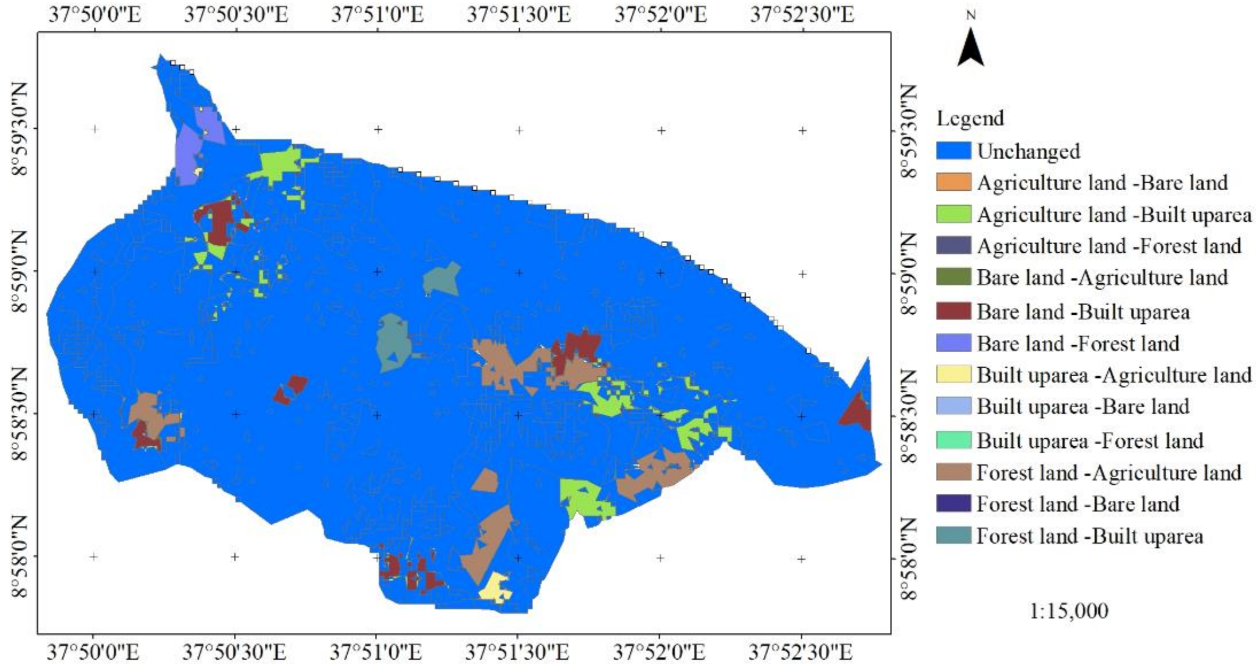


Figure 15: Land-use the land conversion matrix of 2020 -2030

The predicted Ambo town LULC map is indicated that in Figures 12 and 13. The predicted Ambo Town LULC in 2030 consists of 620 (ha) (60.5%) of built-up area, 245 (ha) (24.2%) of forest land, 95 (ha) (9.31%) of agriculture land, and 60 (ha) (6%) of bare land. Based on the predicted result the built-up area increased from 580 (ha) (56.86%) in 2020 to 620 (ha) (60.5%) in 2030 this is the predicted result by considering factors and constraints.

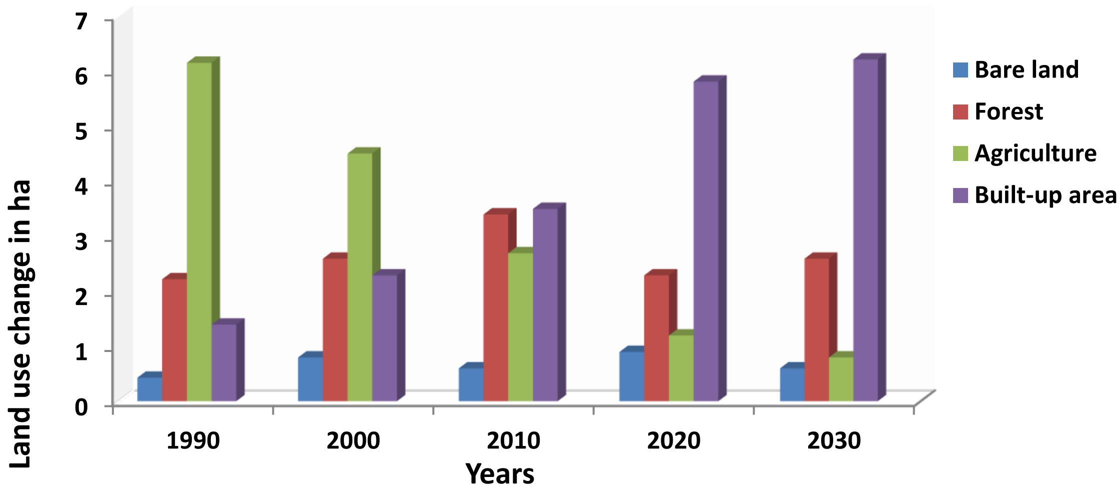


Figure 16: Ambo Town LULC Classes for three decades and predicted 2030.

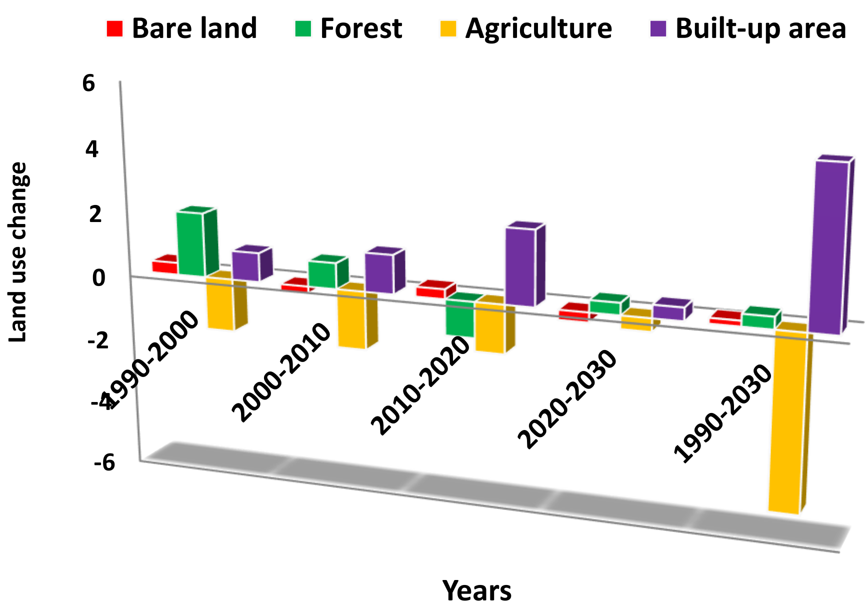


Figure 17: LULC Change (ha) for Ambo Town

In Ambo Town significant changes in land-use, the Land-cover was observed over the last three decades particularly, built-up area, forest land, and bare land were increased for the predicted year while other land-uses such as after the predicted agriculture land was decreased within 1990- 2030. Generally, there is continuous land-use and land-cover change-taking place for most parts of Ambo Town in the last 30 years.

4.2. Models of Future Land Use Dynamics under Two Scenarios

This objective was achieved by conducting a literature review on land-use change models and selecting a model that could be adapted in the study area. Modeling approaches were combined into Cellular Automata models. Cellular Automata models that were shortly were Cellular Automata (CA) and Markov, which was referred to as CA_Markov.

These models were shortlisted based on a multitude of publications and literature, which suggests their wide applications in various topics in different regions and countries. 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.

This was achieved by using GIS software to analyze LULC maps derived from remote sensing imagery. The LULC quantitative analysis results indicate that there were significant LULC changes between 1990 and 2020 characterized by a decline in Agriculture land. In contrast, urban/settlement classes exhibited increases. The LULC change results also show that there was an Ambo Town increase in built-up areas with about form 13.73 % to 56.86% increase with past three decades. However, analyses of individual district municipalities' LULC changes reveal that the increase in settlement areas was concentrated in the Ambo Town area. The increase in urban areas was due to rising infrastructure demands generated by population growth and informal expansion.

In this study, the CA-MARKOV model was used to predict two scenarios-businesses as usual scenarios (BAU) and policy reform scenario-of the future LULC system in Ambo Town using historical maps from 1990 to 2020. The BAU scenario kept the development trend in the past decades, and there is still a relatively high speed of urban expansion. Based on this scenario, agricultural and bare land areas will be significantly decreased whereas built-up area, forest land, areas will be increased. The simulation results indicate that the agricultural land and bare land will decline and would have an extremely high level for a long time in Ambo Town. Under the BAU scenario, which assumed that the current socioeconomic development trends would continue, urbanization is projected to increase significantly in 2030. If this scenario persists, it will have a rigorous impact on the environment, soils, and the deterioration of climate.

Therefore, the government should take the appropriate measures or policies at different stages to meet the real requirements of socio-economic development. Therefore, the baseline scenario is not suitable for future agricultural land control.

The policy reform scenario refers to when the government provides different innovative strategies to overcome the BAU scenario. Reform and innovation are key drivers of any town's remarkable economy. (PRS) will be designed implementation of spatial policies in which assumed that the policy reform (condominium buildings and apartment, reforestation, and plantation) would be leading to the competition of the remaining LULC types to obtain the demands for LULC types in 2030. The model in this study is the first one for the Ambo town and essential as it can be useful for LULC planners and agriculture land managers to identify the delicate environmental systems and take proper measures. The accuracy of the model is tested by comparing the actual 2020 LULC map with its simulated matching part using the 1990 and 2000 LULC maps. The CA–Markov model can be used to simulate future LULC in Ambo Town. If a reform scenario is applied, agricultural land and forest land areas will increase as the government might measure conserve and plant forests.

In addition, the government will encourage the vertical expansion of the town through the apartment and condominium buildings hence, the built-up area and bare land will decrease in the coming ten years. Finally, if this scenario is applied, the livelihood of the society will be enhanced as the changes might bring modernization and changes in the Mode of living through industrialization, commercialization, social benefits and services, and employment opportunities, which will be environmentally sustainable and economically profitable for the Ambo Town

4.3. Qualitative Analysis Using the Driver Pressure State Impact Response (DPSIR) Change framework between 1990 and 2020

The following sections provide a summary of LULC change qualitative results obtained from interviews with municipality town planners. The findings from the interviews are organized into themes which are presented using components of the Dpsir framework illustrated in Figure 18. The Dpsir framework is used to emphasize the relationship between human activities and land-use change. Drivers are social, economic, demographic changes in societies, including consumption, lifestyle, and production patterns. These forces lead to human activities and processes which exert pressure on land resources resulting in various states of the environment. The change in the state of the environment has consequences which are indicated in the framework as impacts that elicit responses. Responses are actions by individuals, society, and the government to prevent and adapt to negative impacts (Akintola, 2018). The arrows between components of the Dpsir framework represent causal chains that show sequential processes that link causes of problems with their effects (Tizora, 2018).

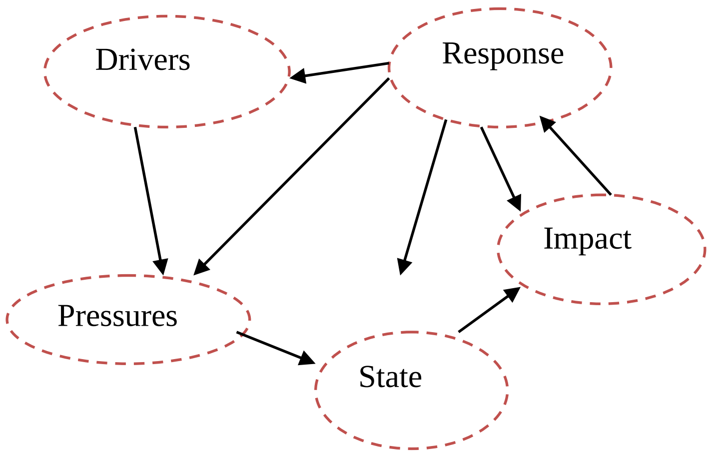


Figure 18: The Dpsir Framework Tizora (2018)

4.5.1. Driving Factors of LULC Change

According to the investigated result shows, the determination of driving factors of land-use change in the Ambo Town was accomplished by interviewing municipality Town planners to obtain deeper insights on LULC change dynamics, and Ground–truth data were gathered on the ground to be used for image classification and confirmation of the satellite imagery.

This research identified both underlying and proximate driving factors of LULC change in the study area in the years 1990 and 2020. Proximate factors are infrastructure expansion, agriculture, and informal house expansion and whilst underlying factors are political, economic, technological, demographic, environmental, and cultural factors. Underlying factors will be explained in detail as they are relevant to the scale of the study. A summary of all determining factors is provided in Table 14.

Answering this question will involve influential the driving factors of LULC change by examining historical expansion patterns and exploring the in progress condition of LULC change by reviewing the literature on factors that pressure land-use decisions in Ambo Town. Policies such as Provincial Spatial Development Framework (PSDF) which determines future LULC change will also be reviewed. Interviews will be conducted to further supplement the secondary literature on historical and current drivers of LULC change and to determine important factors which will influence future change. The interview participants will be municipality town planners and their responses will be based on their past experiences and knowledge on current land issues in Ambo Town. The questions will focus on why LULC change has been taking place in the town, what future changes are likely to occur and what is driving LULC change. The findings of driving factors of LULC change obtained from literature search and the interview will be very significant in this study as they determine the data needs of the research.

Table 15: Driving Factors of LULC change in Ambo Town

Proximate Driving Factors		
✓ Infrastructure	✓ Forestry	✓ Agriculture
Transport (roads, railways) Settlements expansion (e.g. new residential developments) Market Infrastructure any construction on the earth surface	Plantations Plantation farming Afforestation Reforestation	Diversification Proactivity (tourism e.g. wine tasting, farm tours, farm accommodation)
Underlying Driving Factors		
✓ Demographic	✓ Cultural factors	✓ Technological
Population growth (natural increment and migration) Population Density Population Distribution In general increment of population size	Public attitudes, values, and beliefs (e.g. unconcern about the environment)	Agrotechnological change (e.g. mechanization) Agricultural Production Factors (e.g. related factors and labor)

4.3.2. Pressures

The demographic, economic, technological, environmental, political, and cultural factors discussed lead to human activities which use pressure on land resources. The most prominent pressures emerge from sectors with high economic development opportunities which occur in the Ambo Town district municipalities. Pressure Population from urban expansion in illegal is in the form of land, water availability, and reservation of raw material. The agricultural sector attracts both inter-provincial and circular temporary migrants within the province, which exerts pressure on transport, housing, and services.

4.3.3. State

LULC change drivers coupled with pressures on resources affect the state of land in Ambo Town. The change in the state of land has been demonstrated with the results presented from the desktop analysis which shows the changes that have taken place in LULC between 1990 and 2020. LULC maps also show that most infrastructure developments are concentrated along the awaro kora and sanqale fi faris, in the Ambo Town, and core agricultural towns. Based on the interview respondents, most land-use changes and associated impacts occur in agricultural, urban expansion, and industry-related areas.

4.3.4. Impacts

The change in the state of land use has both positive and negative consequences. Agriculture promotes food security, economic stability, job creation, inputs to other industries surrounded by other advantages. However poor farming practices, overgrazing, and land clearance can lead to erosion and land degradation. Droughts and declining farming profitability have led to proactivity as farmers engage in non-agricultural activities to supplement their income. If more profitable, this could contribute to farm exits and change in land- use. The conversion of plantations to another land -uses has led to job losses and dried trees from clear-felling have fuelled fires leading to biodiversity loss.

The perception of Ambo Town as a better province in terms of employment and access to basic services has led to in-migration leading to pressure on transport, accommodation, and other essential facilities. This consequently leads to congestion, increased crime, informal settlements, housing, urban sprawl, infrastructure developments, and other issues which negatively impact the environment.

4.3.5. Response

Responses are actions which the society or government undertake as a result of detrimental impacts which can take place at stages between driving factors and impacts in the DPSIR framework. Such responses in the study area have been in the form of policies and monitoring projects. An example is the monitoring of the state and changes of ecosystem functioning of the Wadesa Daku Factory (WDF) and water resource minerals by the establishment of the Water mineral Quality in Ambo(WMQA) (Yimesgen and Daba, 2019).

4.3.6 Adapted Dpsir Framework

LULC aspects and issues which emerged from interviews with municipality town planners and document readings were grouped into themes of Driving Factors, Pressures, State, Impacts, and Responses. An adapted dpsir framework for LULC change in the Ambo Town is presented in figure 19.

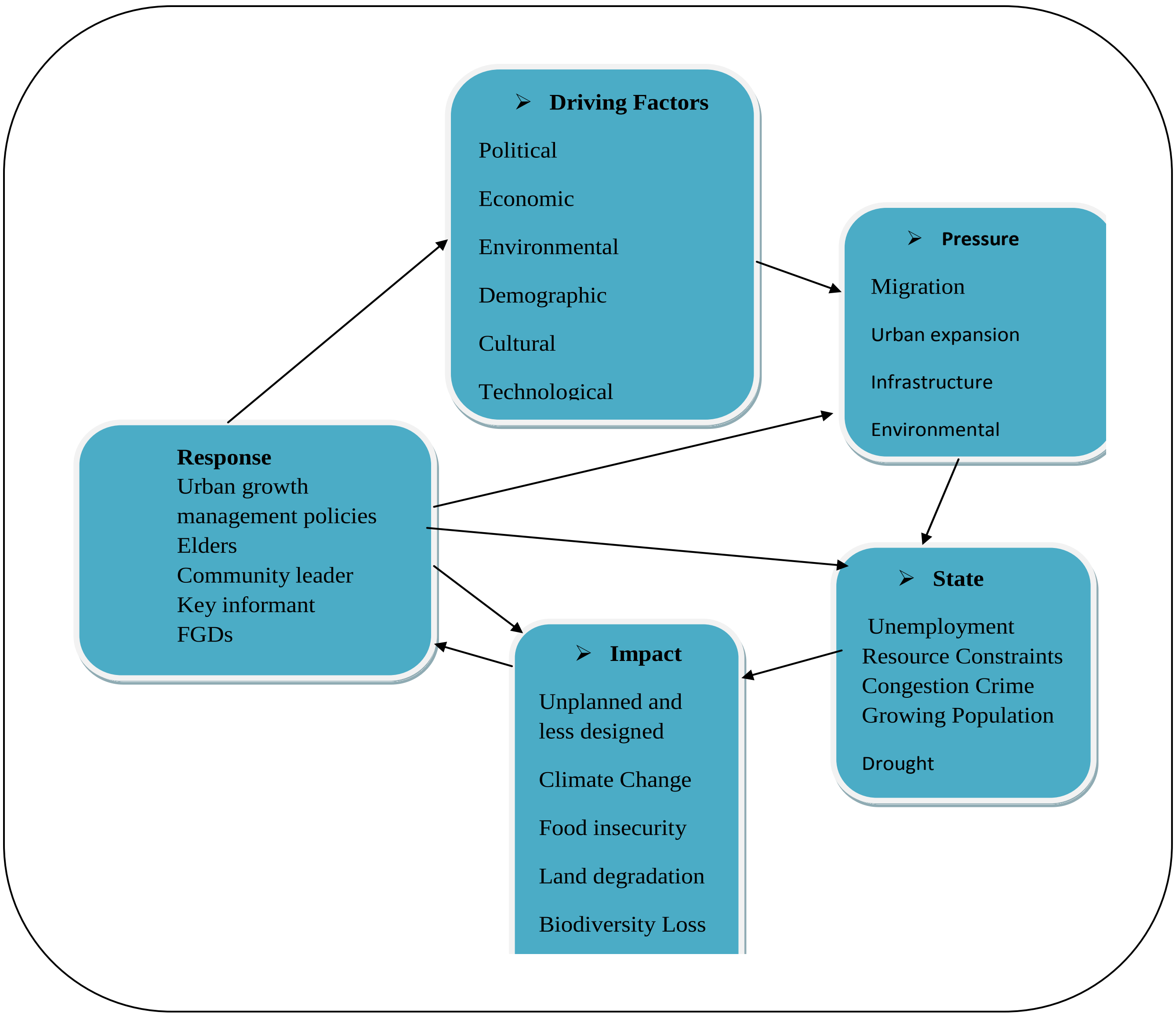


Figure 19: Dpsir Framework for LULC change in the Ambo Town

Strategies and policies based on responses to major drivers of LULC and their impact are, therefore, recommended to avoid undesirable impacts of changes in LULC. The period 1990 to 2020 showed a dramatic change in several LULC categories including built-up area (440 ha.) or (44%), bare land (47 ha) or 6%), and forest land (7 ha) or (1%) were increased and agricultural

Based on interviews and document analysis, proximate causes were identified as infrastructure, agriculture, expansion of Ambo University for instance Hacalu Campus, and forestry changes. To understand these drivers, the Focus group discussions (FGDs) and key informants, community leader and the trend of an urban expansion in Ambo Town interviews were adapted to show how driving factors lead to human activities, which exert pressure on resources resulting in various states of the environment, which have significant impacts and require responses. Strategies and policies based on responses to major drivers of LULC and their impact are, therefore, recommended to avoid undesirable impacts of changes in LULC. The period 1990 to 2020 showed a dramatic change in several LULC categories including built-up area (440 ha.) or (43.13%), bare land (47 ha) or 4.6 %), and forest land (7 ha) or (0.68%) were increased and agricultural land (-494 ha.) or (-48.43%) was decreased.

The result of 2020 obtained for each land-use bare, forest, agriculture, and built-up area (8.82%,22.54%,11.76%, and 56.85%) and in the 1990 result of each land-use with that point (bare, forest, agriculture, and built-up area) (4.22%, 21.86%,60.19%, and 13.73%) respectively showed that figure 7 and table 9. These data expressly stated that an increase in a built-up area, bare land, and forest land coverage of the town resulted in population pressure on land and some policies encourage management of reservation for construction material and forest land for the safety population in town. Expansion of informal construction of grabbing land, commercial constructions material, Ambo University expansion, and Ambo international sports ground are good percentage increase of built-up area.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Remotely sensed images are vital in land-use and land-cover change detection as it provides spatial and temporal information of the land-use and land-cover condition for rapidly developing towns including Ambo Town. The main objective of this study was to assess the dynamics of urban land-use and land-cover of Ambo Town using Landsat satellites of 1990, 2000, 2010, and 2020 and predictions for 2030. Image classification and change detection assessment was also made to evaluate the change transitions. The accuracy assessment of 1990, 2000, 2010 and 2020 were 88.5%, 88.5%, 89% and 90% respectively. At the same time, the kappa coefficient of 1990, 2000, 2010, and 2020 were 0.84, 0.84, 0.85, and 0.86 respectively. The results of this study revealed the existence of significant land-use and land-cover changes in the last 30 years particularly the expansion of built-up land area increased and the declining of agricultural lands. The land-use transition from 1990 to 2020 has shown a dramatic change in several LULC categories. Built-up area, bare land and forest land increased by 580 ha (56.86%) ,47ha (4.9 %)and 7 ha (0.69 %). On the other hand, agriculture showed a reduction of- 494 ha (-48.94 %) and respectively. Accordingly, more land was converted to the built-up area. The result indicated that an increase in a built-up area and bare land coverage of the town resulted from population pressure. There are also conducive government policies for encouraging and increasing green areas including afforestation. CA_Markov modeling approach was also used to predict a land-use change in the future. To use the model for short-and long-term forecasting, the predictive ability of the model was also assessed. Regardless of the factors that might have had an impact on the simulation output, it was inferred that the current trend of expansion of the built-up area would continue in the future. The Ambo Town urban land-use and land-cover change (built-up area) more expanded in Ambo kora, Sanqele, and faris, and Awaro,Gosu, and Areda kebele with alarming rate since 1990 that cause many problems such as deteriorating environmental quality, loss of prime agricultural lands, displacement of farm communities, enclosing surrounding rural land to the urban territory, overexploitation of usual possessions. As urban land, use is expanding to agricultural land and forest, alternative land use is disproportionality affected, which has an impact on productivity and environmental services. Therefore, the town administration has to apply the policy reform scenario suggested by this study that tremendously reduces urban expansions.

5.2. Recommendations

Based on the above results and conclusions the following recommendations are forwarded:-

- Land use and land cover change (LULC) mapping and detection of changes shown here may not provide the real figure of classes due to the low resolution of the imagery but it serves as a base to understand the patterns and magnitude of LULCCs in the area. Therefore, such LU/LC detections using high-resolution satellite images would be more dependable.
- The increase in bare land over time will affect the urban development effort; hence the administration shall rehabilitate this land use for development purposes.
- The future expansion of the town should incorporate technology-based land use planning and the selection must be based not only on current needs but also on projected needs.
- Rapid settlement increase has played a major role affecting LULC change and there should be strategic planning to monitor abrupt urban expansions of the town from concerned governmental and nongovernmental bodies (offices).
- Ambo Town administration should give attention to the main problems of housing, infrastructure services, and losses of Agriculture land by modifying land policy and giving land for housing.
- Government should give attention to the Provision of tenure security and Facilitate special attention to the provision of land for the poor, ethnic minority, women.
- Further studies should be conducted to find out whether the Land Change Modeler (LCM), Earth Trends Modeler (ETM), GEOMOD, and CA-MARKOV, ARCGIS kinds of models are suitable for future prediction.

References

Ackom, E. K., Amaning, K., Samuel, A., & Odai, N. (2020). Monitoring Land Use and Land - Cover Changes Due To Extensive Urbanization In The Odaw River Basin Of Accra, Ghana, 1991 – 2030. *Modeling Earth Systems And Environment*, *0123456789*. Https://Doi.Org/10.1007/S40808-020-00746-5

Akintola, L. (2018). *Land Use / Land Cover Change Analysis Using Markov-Based Model For Eleyele Reservoir BELLO , HO ; * OJO , OI ; GBADEGESIN , AS DOI : Https://Dx.Doi.Org/10.4314/Jasem.V22i12.8*.

Al-Ahmadi, F. S., & Hames, A. S. (2009). Comparison Of Four Classification Methods To Extract Land Use And Land Cover From Raw Satellite Images For Some Remote Arid Areas, Kingdom Of Saudi Arabia. *Journal Of King Abdulaziz University, Earth Sciences*, *20*(1), 167–191. Https://Doi.Org/10.4197/Ear.20-1.9

Angessa, A. T., Lemma, B., & Yeshitela, K. (2019). Land-Use And Land-Cover Dynamics And Their Drivers In The Central Highlands Of Ethiopia With Special Reference To The Lake Wanchi Watershed. *Geojournal*. Https://Doi.Org/10.1007/S10708-019-10130-1

Araya, Y. (2009). *Urban Land Use Change Analysis And Modeling: A Case Study Of Setúbal And Sesimbra, Portugal*. *September*, 72.

Ayele, A. (2017). Land Use And Land Cover Change Detection Analysis Using Remote Sensing Techniques : The Case Of Hawassa Town, Southern Ethiopia. *A Thesis Project, Hawassa University, Ethiopia*.

Behailu, A. (2010). Land Use And Land Cover Analysis And Modeling In South-Western Ethiopia: The Case Of Selected Resettlement Kebeles In Gimbo Woreda. *A Thesis Project Submitted To Addis Ababa University, Ethiopia*.

Bekele, T. (1993). Vegetation Ecology Of Remnant Afromontane Forest On The Central Plateau Of Shewa, Ethiopia. *Acta Phytogeographica Suecica*, *79*, 66.

Berhanu, A. (2017). *Vegetation Ecology And Conservation Status Of Evergreen Afromontane Forest Patches In Awi Zone Of Amhara Region, Northwestern Ethiopia*. 188.

Cervantes-Godoy, D., Dewbre, J., PIN, Amegnaglo, C. J., Soglo, Y. Y., Akpa, A. F., Bickel, M., Sanyang, S., Ly, S., Kaiser, J., Ama, S., Gautier, B. P., Officer, E. S., Officer, E. S., Eberlin, R., Officer, P., Branch, P. A., Oduro-Ofori, E., Aboagye Anokye, P., … Swanson, B. E. (2014). The Future Of Food And Agriculture: Trends And Challenges. In *The Future Of Food And Agriculture: Trends And Challenges* (Vol. 4, Issue 4). Https://Doi.Org/10.2307/4356839

Deng, X., Jiang, Q., Zhan, J., He, S., & Lin, Y. (2010). Simulation On The Dynamics Of Forest Area Changes In Northeast China. *Journal Of Geographical Sciences*, *20*(4), 495–509. Https://Doi.Org/10.1007/S11442-010-0495-0

Eastman, J. R. (2003). IDRISI Kilimanjaro: Guide To GIS And Image Processing. *Clark University: Worcester, MA, USA*, *1*(May), 87–131. Https://Doi.Org/10.1109/TGRS.2002.802519

Ehsan, S., & Kazem, D. (2013). Analysis Of Land Use-Land Covers Changes Using Normalized Difference Vegetation Index (NDVI) Differencing And Classification Methods. *African Journal Of Agricultural Research*, *8*(37), 4614–4622. Https://Doi.Org/10.5897/Ajar11.1825

ERDAS. (2009). *ERDAS Field Guide TM - Tutorial*. *November*, 810.

Fasika, A., Motuma, T., & Gizaw, T. (2019). Land Use Land Cover Change Trend And Its Drivers In Somodo Watershed South Western, Ethiopia. *African Journal Of Agricultural Research*, *14*(2), 102–117. Https://Doi.Org/10.5897/Ajar2018.13672

Fekadu, D. (2017). *Addis Ababa Institute Of Technology Addis Ababa Institute Of Technology*. *June*, 1–100.

Foody, G. M. (2001). Monitoring The Magnitude Of Land-Cover Change Around The Southern Limits Of The Sahara. *Photogrammetric Engineering And Remote Sensing*, *67*(7), 841–847.

Gorokhovich, Y., & Voustianiouk, A. (2006). *Accuracy Assessment Of The Processed SRTM-Based Elevation Data By CGIAR Using Field Data From USA and Thailand And Its Relation To The Terrain Characteristics*. *104*, 409–415. Https://Doi.Org/10.1016/J.Rse.2006.05.012

Green, E. P., Mumby, P. J., Edwards, A. J., & Clark, C. D. (2000). Remote Sensing Handbook For Tropical Coastal Management. *Coastal Management Sourcebooks 3*, *January 2000*, X + 316.

Ha, T. V. (2011). The Linkage Between Land Reform And Land Use Changes: A Case Of Vietnam. *Journal Of Soil Science and Environmental Management*, *2*(3), 88–96. Http://Www.Academicjournals.Org/JSSEM

Han, H., Yang, C., & Song, J. (2015). Scenario Simulation And The Prediction Of Land Use And Land Cover Change In Beijing, China. *Sustainability (Switzerland)*, *7*(4), 4260–4279. Https://Doi.Org/10.3390/Su7044260

Hansen, M. C., & Loveland, T. R. (2012). A Review Of Large Area Monitoring Of Land Cover Change Using Landsat Data. *Remote Sensing Of Environment*, *122*, 66–74. Https://Doi.Org/10.1016/J.Rse.2011.08.024

Haque, I., & Basak, R. (2017). The Egyptian Journal Of Remote Sensing And Space Sciences Land Cover Change Detection Using GIS And Remote Sensing Techniques : A Spatio-Temporal Study On Tanguar Haor, Sunamganj, Bangladesh. *The Egyptian Journal Of Remote Sensing And Space Sciences*, *20*(2), 251–263. Https://Doi.Org/10.1016/J.Ejrs.2016.12.003

Karsidi, A. (2004). *Spatial Analysis of Land Use / Land Cover Change Dynamics Using Remote Sensing and Geographic Information Sytems : A Case Study In The Down Stream And Surroundings Of The Ci Tarum Watershed Of*. *May*.

Kindu, M. (2013). *SYNTHESIS OF RESEARCH ON LAND USE AND LAND COVER*. 1–39.

Kindu, M., Schneider, T., Döllerer, M., Teketay, D., & Knoke, T. (2018). Scenario Modelling Of Land Use/Land Cover Changes In Munessa-Shashemene Landscape Of The Ethiopian Highlands. *Science Of The Total Environment*, *622–623*, 534–546. Https://Doi.Org/10.1016/J.Scitotenv.2017.11.338

Koranteng, A., Zawila-Niedzwiecki, T., & Adu-Poku, I. (2016). Remote Sensing Study Of Land Use / Cover Change In West Africa. *Journal Of Environment Protection And Sustainable Development*, *2*(3), 17–31.

Kousalya, P., Mahender Reddy, G., Supraja, S., & Shyam Prasad, V. (2012). Analytical Hierarchy Process Approach – An Application Of Engineering Education. *Mathematica Aeterna*, *2*(10), 861–878.

Leemhuis, C., Thonfeld, F., Näschen, K., Steinbach, S., Muro, J., Strauch, A., López, A., Daconto, G., Games, I., & Diekkrüger, B. (2017). Sustainability In The Food-Water-Ecosystem Nexus: The Role Of Land Use And Land Cover Change For Water Resources And Ecosystems In The Kilombero Wetland, Tanzania. *Sustainability (Switzerland)*, *9*(9). Https://Doi.Org/10.3390/Su9091513

Lencho, A, Modeling Spatio-Temporal Urban Land Use Land Cover Change: A Case Of Burayu

Town Using Remote Sensing And Gis Techniques.

Lepers, E. (2014). *D Dynamics Of L And -U Se And L And -Cover Change In Tropical Regions*. *June*. Https://Doi.Org/10.1146/Annurev.Energy.28.050302.105459

Li, X., Wang, Y., Li, J., & Lei, B. (2016). Physical And Socioeconomic Driving Forces Of Land-Use And Land-Cover Changes: A Case Study Of Wuhan City, China. *Discrete Dynamics In Nature And Society*, *2016*(2014). Https://Doi.Org/10.1155/2016/8061069

Lu, D., & Weng, Q. (2007). A Survey Of Image Classification Methods And Techniques For Improving Classification Performance. *International Journal Of Remote Sensing*, *28*(5), 823–870. Https://Doi.Org/10.1080/01431160600746456

Mahmoud, H., & Divigalpitiya, P. (2017). Modeling Future Land Use And Land-Cover Change In The Asyut Region Using Markov Chains And Cellular Automata. *Green Energy And Technology*, *November*, 99–112. Https://Doi.Org/10.1007/978-3-319-44899-2

Malczewski, J. (2018). *Review Article On The Use Of Weighted Linear Combination Method In GIS : Common And Best Practice Approaches*. *January 2000*, 4–22. Https://Doi.Org/10.1111/1467-9671.00035

Mienmany, B. (2018). *Analysis Of Land Use And Land Cover Changes And The Driving Forces: A Case Study In Kaysone Phomvihan District, Laos*. 136.

Muzein, B. S. (2006). *Remote Sensing & GIS For Land Cover / Land Use Change Detection And Analysis In The Semi-Natural Ecosystems And Agriculture Landscapes Of The Central Ethiopian Rift Valley*. *November 2006*.

Palmer, D., Fricska, S., Wehrmann, B., Augustinus, C., Munro-Faure, P., Törhönen, M.-P., & Arial, A. (2009). *TOWARDS IMPROVED LAND GOVERNANCE In Collaboration With* (Issue September). Http://Www.Fao.Org/3/A-Ak999e.Pdf

Pickett, S. T. A., Cadenasso, M. L., Rosi-Marshall, E. J., Belt, K. T., Groffman, P. M., Grove, J. M., Irwin, E. G., Kaushal, S. S., Ladeau, S. L., Nilon, C. H., Swan, C. M., & Warren, P. S. (2017). Dynamic Heterogeneity: A Framework To Promote Ecological Integration And Hypothesis Generation In Urban Systems. *Urban Ecosystems*, *20*(1), 1–14. Https://Doi.Org/10.1007/S11252-016-0574-9

Roy, S., Farzana, K., Papia, M., & Hasan, M. (2015). Monitoring And Prediction Of Land Use/Land Cover Change Using The Integration Of Markov Chain Model And Cellular Automation In The Southeastern Tertiary Hilly Area Of Bangladesh. *International Journal Of Sciences: Basic And Applied Research*, *24*(October), 125–148.

Shalaby, A., & Tateishi, R. (2007). Remote Sensing And GIS For Mapping And Monitoring Land Cover And Land-Use Changes In The Northwestern Coastal Zone Of Egypt. *Applied Geography*, *27*(1), 28–41. Https://Doi.Org/10.1016/J.Apgeog.2006.09.004

Tizora, P. C. (2018). Modeling Land Use And Land Cover Change In The Western Cape Of Province. *Dissertation Submitted To University Of Pretoria, South Africa, February*.

Wen, Y., Khosrowpanah, S., & Heitz, L. (2011). Land Cover Change Of Watersheds In Southern Guam From 1973 To 2001. In *Environmental Monitoring And Assessment* (Vol. 179, Issues 1–4). Https://Doi.Org/10.1007/S10661-010-1760-5

Yimesgen, Y., & Daba, T. (2019). Perceived Effects Of Poverty On Urban Socio-Economic Development In Ambo Town, Ethiopia. *American Journal Of Theoretical And Applied Business*, *5*(4), 97. Https://Doi.Org/10.11648/J.Ajtab.20190504.13

Appendix 1: matrix of the 1990 LULC classification of Ambo Town (in pixels)

Referenced Data 1990

	LULC	Agricultural land	Forest land	Built-up area	Bare land	Rw total	UA	PA
	Agricultural land	45	1	2	2	50	88.2%	90%
	Forest land	2	44	3	1	50	91.6%	88%
	Built up area	2	3	42	3	50	85.7%	84%
	Bare land	2	0	2	46	50	88.4%	92%
Classified Data	Column total	51	48	49	52	200		

number of lULC correctly classified =177

over all classification =(45+44+42+46)/200=177/200*100=88.5%

overall kappa coefficient=0.84

Appendix 2: Error matrix of the 2000 LULC classification of Ambo Town (in pixels)

Referenced Data 2000

	LULC	Agricultural land	Forest land	Built-up area	Bare land	Rw total	UA	PA
	Agricultural land	46	1	1	2	50	85.1%	92%
	Forest land	3	43	1	3	50	93.4%	86%
	Built up area	2	0	47	1	50	88.6%	94%
	Bare land	3	2	4	41	50	87.2%	82%
Classified Data	c.total	54	46	53	47	200		

number of lULC correctly classified =177

over all classification =(46+43+47+41)/200=177/200*100=88.5%

overall kappa coefficient=0.84

Appendix 3: Error matrix of the 2010 LULC classification of Ambo Town (in pixels)

Referenced Data 2010

	LULC	Agricultural land	Forest land	Built-up area	Bare land	Rw total	UA	PA
	Agricultural land	42	3	3	2	50	87.5%	84%
	Forest land	1	47	2	0	50	90.3%	94%
	Built up area	2	2	44	2	50	86.2%	88%
	Bare land	3	0	2	45	50	91.8%	90%
Classified Data	c.total	48	52	51	49	200		
	number of lULC correctly classified =178							
	over all classification =(42+47+44+46)/200=178/200*100=89%							
	overall kappa coefficient=0.85							

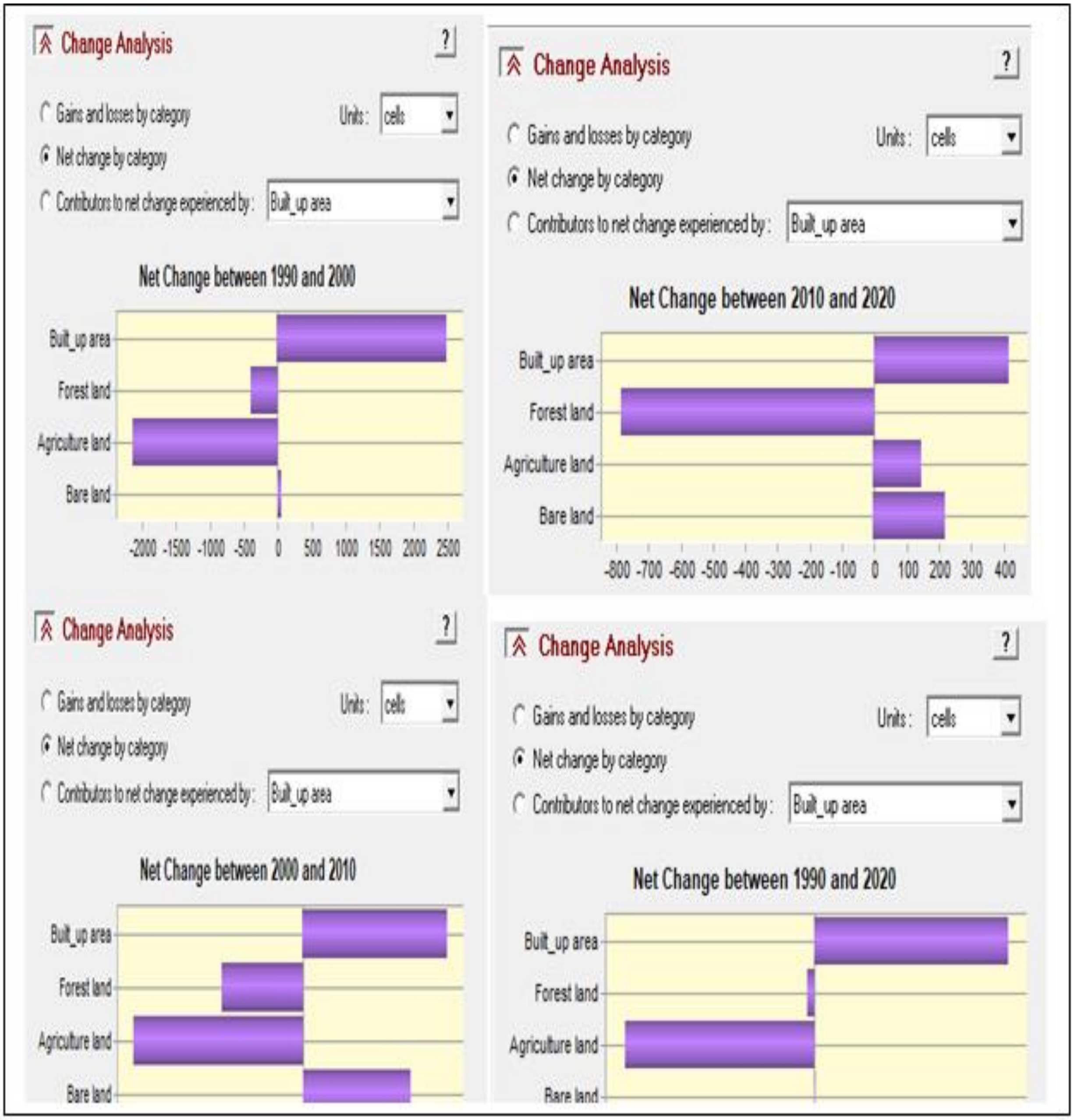
Appendix 4: Error matrix of the 2020 LULC classification of Ambo Town (in pixels)

Referenced Data 2020

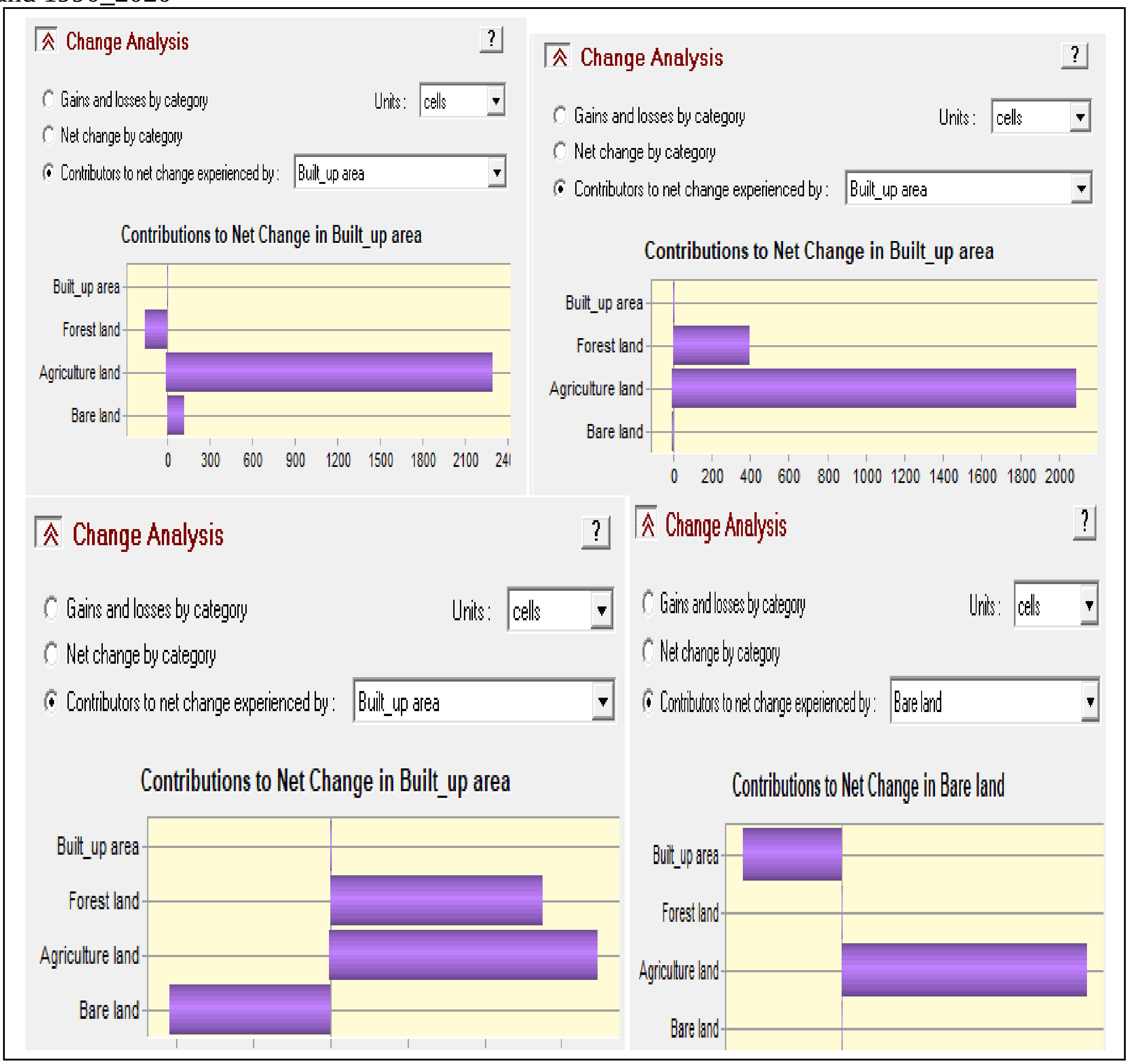
	LULC	Agricultural land	Forest land	Built-up area	Bare land	Rw total	UA	PA
	Agricultural land	42	3	2	2	50	91.3%	84%
	Forest land	0	46	3	1	50	92%	92%
	Built up area	1	1	47	1	50	83%	94%
	Bare land	3	0	2	45	50	91.8%	90%
classified Data	c.total	46	50	54	49	200		
	number of lULC correctly classified =180							
	over all classification =(42+46+47+45)/200=180/200*100=90%							
	overall kappa coefficient=0.86							

Appendix 5: Gain and Losses (1990_2000, 2000_2010, 2010_2020 and 1990_2020)

Appendix 6: Net Change (1990-2000, 2000-2010, 2010-2020 and 1990_2020)



Appendix 7: Contributors to net Change by Built-up area (1990_2000, 2000_2010, 2010_2020 and 1990_2020



Appendix 8: Ambo Town LULC classified vs. Predicted 2020 Validate view as Bar graphs