Impact of Land Use and Land Cover Change on Carbon Storage and Sequestration: The Case of Addis Ababa City and Surrounding Oromia Special Zone

By: Ribka Olana Aga

A Thesis Submitted to

The Department of Geomatics Engineering

School of Civil Engineering and Architecture

Presented for Partial Fulfillment of the Requirement for the Degree of Master's in Geo-informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

November, 2020

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By: Ribka Olana Aga

Advisor: Tilahun Erduno (PhD)

Co-Advisor: Daniel Alemayehu (PhD)

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DECLARATION

I declare that the work which is being presented in the thesis entitled "Impact of Land Use and Land Cover Change on Carbon Storage and Sequestration: The Case of Addis Ababa City and Surrounding Oromia Special Zone" Submitted to Adama Science and Technology University, School of Civil and Architectural Engineering in partial fulfillment of the requirements for the award of the degree of master of science in Geo-informatics Engineering is entirely my own work carried out from January to October, 2020 under supervision of Tilahun Erduno (Ph.D.) (Advisor) from Adama Science and Technology University, school of civil and Architecture Engineering lecture. All references, including citation of published and unpublished sources, have been appropriately acknowledged in the work. I further declare that the work has not been submitted for the purpose of academic examination, either in its original or similar form, anywhere else.

Ribka Olana	________________	________________
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.

Tilahun Erduno (Ph.D)	________________	______________
Advisor	Signature	Date
Daniel Alemayehu (Ph.D)	________________	______________
Co-Advisor	Signature	Date

ADVISOR'S APPROVAL SHEET

To: Geomatics Department

Subject: Thesis Submission

This is to certify that the thesis/dissertation entitled "Impact of Land Use and Land Cover Change on Carbon Storage and Sequestration: The Case of Addis Ababa City and Surrounding Oromia Special Zone" submitted in partial fulfillment of the requirements for the degree of Master's in Geo-informatics, the Graduate Program of the Department of Geomatics Engineering, and has been carried out by Ribka Olana Aga Id. No PGR/18227/11, under my/our supervision. Therefore, I/we recommend that the student has fulfilled the requirements, and hence hereby he/she can submit the thesis/dissertation to the department.

Tilahun Erduno (Ph.D.)	____________________	____________
Name of major Advisor	Signature	Date
Daniel Alemayehu (Ph.D.)	____________________	____________
Name of Co Advisor	Signature	Date

BOARD OF EXAMINERS APPROVAL SHEET

We, the undersigned, members of the Board of Examiners of the final open defense Ribka Olana Aga have read and evaluated his thesis entitled: Impact of Land Use and Land Cover Change on Carbon Storage and Sequestration: The Case of Addis Ababa City and Surrounding Oromia Special Zone and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Master of Science in Geo-informatics.

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LIST OF ACRONYMS

AUC	Area under Curve
CA	Cellular Automata
CAD	Computer-Aided Design
ETM+	Enhanced Thematic Mapper plus
GHG	Green House Gases
GIS	Geographic Information System
InVEST	Integrated Valuation of Environmental Services and Tradeoffs
IPCC	Intergovernmental Panel on Climate Change
LCM	Land Change Modeler
LULC	Land Use Land Cover
MC	Markov Chain
MCA	Markov Chain Analysis
MLP	Multi-Layer Perceptron Neural Network
NEE	Net Ecosystem Exchange
NDVI	Normalized Difference Vegetation Index
OLI	Operational Land Imager
ROC	Relative Operating Characteristic
RS	Remote Sensing
TM	Thematic Mapper
UNCCD	United Nations Convention to Combat Desertification
UNFCCC	United Nations Framework Convention on Climate Change
UNEP	United Nations Environment Programme
US	United States
USGS	United States Geological Survey

ABSTRACT

Land use land cover (LULC) change is the key factor that triggers declines in terrestrial carbon stocks all over the world. LULC change particularly in urban areas is becoming the major factor in reducing regional carbon sequestration capacity. While LULC change detection has been the focus of numerous studies in Addis Ababa city and the surrounding Oromia special zone, few efforts have been made on assessing LULC change impacts on carbon storage and sequestration. Therefore, this study aims at analyzing the impact of LULC change on carbon storage and sequestration. The study employed Landsat images from 1990 to 2020 and employed Land Change Modeler (LCM) model to explore the LULC dynamics in the study area to assess where LULC changes are expected to occur in 2050 under business-as-usual (B-a-U) scenario and green scenario. Afterward, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model was employed to estimate carbon stored in the study area, analyzing their variations over time (2020–2050) under the two scenarios. The results from predicting the B-a-U scenario indicates that a decrease in forest and shrubland, by -29% and -50%, respectively and an increase in built-up, grassland, and cropland by 92%, 17%, and 2%, respectively in 2050. The green scenario indicates an increase in forest land roughly by 19% in 2027. However, the long-term effect of the greenery planning in 2050 reveal that the forest land will decline by -15% between 2027 and 2050.Cosequently, the result observed from modelling carbon storage showed that the total carbon stocks decreasing from 39.1 Tg C in 2020, to 33.6 Tg C in 2050 under the B-a-U scenario. According to the model, if the trend detected in this analysis continues, sequestered carbon it is expected to be -5.5 Tg C in 2050. Correspondingly, observed result depicts sequestered carbon (-2.11 Tg C) by the end of 2050 under the green scenario. The results of the study thus infer that changes in land cover have an effect on carbon stocks, with considerable decline in carbon stocks under the B-a-U scenario in 2050s. Similarly, the green scenario has less impact on the landscape in the long run (2050). If this trend is expected to continue in the coming decades, the consequences will be substantial environmental degradation and decline in carbon storage unless proper measures will be taken. Therefore, a potential policy measures should be taken to mitigate negative effects of LULC change on carbon stocks within the study area.

Key Words: Addis Ababa, Carbon storage and sequestration, InVEST, LCM, LULC

CHAPTER I: INTRODUCTION

1.1. Background of the Study

Over the past century, land use land cover changes initiated by human activities such as fossil fuel burning, deforestation, and urbanization have led to high concentrations of CO_2 and other greenhouse gasses in the atmosphere (Brennan et al., 2009). Higher CO_2 levels are likely to alter the global climate and also likely to have significant effects on plant growth and physiology, regardless of climate impact. Likewise, any land-use changes essentially forest deforestation, and environmental degradation has a direct impact on carbon storage (Giri, Mandla and Ravibabu 2017).

Land-use change is the key driver of global change (Feddema et al., 2005). It is estimated that nearly half of the earth's land area has been converted or deteriorated to accommodate human requirements (Vitousek, Mooney, Lubchenco and Melillo 2008). Changes in land use and land cover are influenced by human activity and population growth, socioeconomic factors, forest development, urbanization, natural factors such as insects, and agricultural activities (Contador L.F.J., Schnabel S., 2008). Accordingly, the rate of LULC change is influencing the amount of carbon sequestration in the atmosphere and is becoming a significant indicator of human disturbance (Kennedy and Spies, 2005). Carbon stocks are an essential part of a functioning ecosystem that is directly or indirectly influenced by LULC effects (IPCC, 2006; F. Zhang, Zhan, Zhang, Yao, and Liu, 2017).

Land cover changes also contribute to climate change and variability, and when combined, may have profound effects on the Earth's habitability. The United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto protocol initiated research on the carbon cycle, land-use, land-use change, and biological/ecological processes concerning that it is a critical issue (Pouliot, 2012). Land cover information plays a major role in carbon balance modelling studies, which at a basic level includes the type and extent of vegetation. It has been recognized that Remote Sensing can contribute by providing systematic observations and temporal data archives that may reduce uncertainties in reporting on terrestrial carbon budgets (Pouliot, 2012).

With the acceleration of urbanization, LULC is playing a significant role in natural ecosystems. In other words, the impact of LULC change onto the growth and development of the ecosystem is among the most critical issues in the ecosystem (F. Zhang et al., 2017). Thus, the current rapid urbanization is responsible for the complex and uncontrolled pattern of urban physical growth and the continuous LULC changes which have been taking place in developing countries.

Land cover changes aligned with urbanization, decrease carbon storage (Hutyra, Yoon, Hepinstall-Cymerman, and Alberti, 2011). However, considering that biomass and soil carbon stocks vary across multiple land covers within urbanized areas, such rapid growth in urban carbon reservoirs driven by land use and cover change is often at the cost of even more severe reduction in carbon stocks from peri-urban and rural areas, which become the main cause of decreased carbon sequestration potential in regional ecosystems (Tao, Li, Wang, and Zhao, 2015).

Land cover changes specifically forest changes and deterioration over the past century is reported from various parts of Ethiopia. This, in turn, made the landscape structure to be modified and lose its origin. Environmental factors like deforestation, overharvesting of crops above the carrying capacity of the land, and permanent conversion to other forms of land use are leading to the shrinkage of forest resources (Yitebitu, 2010).

Uncontrolled built-up area expansion and haphazard land developments are one of the crucial problems in Addis Ababa City which is experiencing rapid urban expansion towards surrounding regions that is causing environmental degradation and rural-urban land-use changes. Therefore, this study chooses Addis Ababa City and surrounding regions for analysis because of its notable spatial expansion, developmental activities, and population growth.

There are several situations to demonstrate the issue of the horizontal expansion of Addis Ababa towards the peri-urban areas. Due to high rapid informal settlements with increasing built-up areas, the urban land is getting expanded to the mountains in central Ethiopia surrounding Addis Ababa and the large tracts of natural green areas and prime agricultural lands are now resettled (Feyissa and Gebremariam, 2018; Mohamed and Worku, 2019). Therefore, the focus of this research is aimed at analyzing the impact of LULC change on carbon storage and sequestration for improving capacities of urban vegetation carbon accounting for developing carbon sequestration strategies and alternative response options.

1.2. Problem Statement

Human activities have changed the LULC type and directly impacted urban carbon storage and sequestration. Urban development, increased demand for construction land, and urban expansion are major factors reducing regional carbon sequestration capacity (W. Zhang, Huang, and Luo, 2014). Nowak et al. (2013) have also suggested that in the coming decades, more terrestrial carbon stocks will be contained in human settlements, simply because urbanized areas are continuing to expand at an unprecedented rate.

Urban Expansion in African Countries is approaching a demographic climax as the number of fresh urban inhabitants is expected to increase by more than 300 million between 2000 and 2030, twice the number of rural inhabitants (UNCCD, 2017). As it is admitted in many developing countries, raised issues caused by rapid urbanization are causing degradation of the atmosphere and causing land-use changes in Ethiopia as well (Mohamed and Worku, 2019).

Addis Ababa the capital city of Ethiopia can be taken as a good example to this crucial issue whereas firstly, the city is a densely populated city where urbanization took place under an insufficient plan for land development that prompted uncontrolled urban expansion towards the peri-urban areas (Mohamed and Worku, 2019). Secondly, due to urbanization, a rapid transition of land use is experienced in the city including the surrounding Oromia Special Zone (Girma, Terefe, Pauleit, and Kindu, 2019b). Thirdly, deforestation activities have been carried out within the City and surrounding Oromia Special Zone for settlement and other purposes (Feyissa and Gebremariam, 2018; Yitebitu Moges, 2010).

Likewise, Abdissa and Degefa (2011) documented that between 1961 and 1984, the region of Addis Ababa expanded by 400 ha between 1984 and 1994 appears to be approximately 30,814 ha, and in 2005 its entire area was 54,000 ha. However, this expansion has occurred with the expense of forest degradation, loss of agricultural property, and deterioration of the livelihoods of periphery populations (Girma, Terefe, Pauleit, and Kindu, 2019a). Moreover, Mohamed et al. (2019) LULC change analysis indicates, Addis Ababa and the neighboring Oromia Special

Zone depicts the existence of a significant change in the 2015 LULC map and the most dynamic type of land cover is built-up.

Accordingly, while LULC change detection has been the focus of numerous studies in the city, a few efforts have been made on assessing LULC change impacts on carbon storage and sequestration (Seyum, Taddese, and Mebrate, 2019; Solomon, Pabi, Annang, Asante, and Birhane, 2018). There have not been attempts to quantify the carbon storage and sequestration capacity of the city and surrounding regions. For this reason, these issues need to be more analyzed to examine LULC dynamics and its consequent impact on carbon storage and sequestration.

In fact, carbon stock analysis was explored by (Muluken, Teshome, and Eyale, 2015; Tura and Eshetu, 2013; Yohannes, 2015) within a specific land cover type which is the forested land cover, though other land cover types such as shrubland grassland, cropland land also contribute to carbon storage and sequestration (M. Zhao, Kong, Escobedo, and Gao, 2010). Therefore, it is advantageous to examine the contribution of other land cover types for carbon storage and sequestration.

Although urban spaces are the main centers for energy consumption and CO_2 emissions, they also contribute to sequester some of the very same emissions they generate, notably foliar and woody biomass in urban soils (Mcpherson, Simpson, Peper, Maco, and Xiao, 2006; Nowak and Crane, 2002). Thus, the effort to map urban vegetation cover properly and quantifying their abilities to store carbon can help planning authorities to locate places where urban greening projects have the greatest beneficial impact on communities (Raciti, Hutyra, and Newell, 2014).

Hence, this study analyses the impact of LULC change scenarios on carbon storage and sequestration within the study area to identify appropriate measures associated with carbon storage and sequestration.

1.3. Research Objectives

1.3.1. General Objective

The general objective of this study is to analyze the impact of LULC change on carbon storage and sequestration.

1.3.2. Specific Objective

The specific objective of the study is to:

- analyze LULC dynamics within Addis Ababa City and Surrounding Oromia Special Zone
- predict future LULC map of the study area in 2050
- model carbon storage and sequestration level of the study area
- propose future possible measures concerning carbon storage and sequestration

1.4. Research Question

1. What is the LULC change trend within the study area?
2. What is the extent of the predicted LULC map of the study area in 2050?
3. What is the level of carbon storage and sequestration of the study area?
4. What are the possible measures to be taken in the study area regarding carbon storage and sequestration?

1.5. Significance of the Study

In Ethiopia, new settlements in natural forests are increasing which is a cause for the conversion of forested land into agricultural and other land-use systems. Again this rapid growth in the number of urban dwellers transforms wide areas of land into urban use (Yitebitu Moges, 2010). Though viable urban carbon sinks are likely to be small, urban vegetation is a crucial element of urban ecosystems and the carbon cycle, while offering urban residents with aesthetic, financial, and ecological value (Nowak and Crane, 2002).

Since Ethiopia heavily relies on biomass fuels for its energy, the main challenge facing the country is to enhance natural forest management for various goals, including carbon forestry (Moges, 2010). Moreover, Since Ethiopia is planning to become a middle-income, carbon - neutral, and resilient economy by 2025 (UNFCCC, 2016), city planners and those who want to implement green area policies benefit from urban vegetation mapping and quantifying their capabilities to store carbon.

Even though there have been researches in developed countries considering the impact of LULC on carbon storage due to the difference in culture and development, the results of studies conducted in developed countries can not merely be generalized to our country. Therefore, monitoring current patterns of land use/land cover spatial distributions and developmental trends as well as analyzing their impact on terrestrial carbon storage is beneficial for the city. Additionally, integrating up-to-date information into carbon storage and sequestration models can assist concerned authorities to make any developmental plans and to implement policies and programs. The result of this study is expected to have the following significances for:

- ✓ city policy makers by visualizing change trends among different years and providing reference information for the advancement of policies.
- ✓ government and nongovernment organizations, researchers and professionals by providing valuable information about the impact of LULC change on carbon storage.
- ✓ city administration by providing a scientific basis for the development of carbon policies and urban and peri-Urban land planning (Z. Li, Zhong, Sun, and Yang, 2017).
- ✓ policymakers to investigate economic value associated with carbon storage (Sallustio, Quatrini, Geneletti, Corona, and Marchetti, 2015).

1.6. Scope of the Study

The scope of the study was spatially limited in the Addis Ababa City and the Surrounding Oromia Special Zone. It covers an area of 4986.73 sq. km. The study focused only on analyzing urban dynamics in the past three decades and predict future land cover map as well as model the carbon storage of current land cover and future land covers according to secondary carbon pool data. Generally, the study emphasizes on the impact of urban land use land cove change on carbon storage and sequestration within the study area using mainly LCM and Integrated Valuation of Ecosystem Services and Tradeoffs model (InVEST).

1.7. Limitation of the Study

Difficulty to get high resolution images for better, high accuracy and precision result on mapping and classifying LULC map of the study area. Bureaucracy and limited accesses to get data from different governmental organizations were the major limitation to get structural map of towns within the study area. Not all carbon pools in land cover types within the study area were available; hence, the study used average value of carbon pool data employed in different literatures within the country. Nevertheless, current study provides valuable information and insight that can be of great importance for the relevant information of current and future carbon storage value.

1.8. Organization of the Thesis

This study is organized into five chapters. The first chapter elaborates the background of the study, statement of the problem, general and specific objectives, significance, limitation and scope of the study. The next section, chapter two, focuses on theoretical and conceptual framework of literature review and related work for this study. This section presents brief understanding on LULC change and predicting LULC changes as well as carbon storage and sequestration modelling. The third chapter focuses on the general methodology followed, the data sets used in this study and detail explanation of the study area. This chapter highlights all the procedures and techniques applied for analyzing LULC change and predicting future land cover as well as carbon storage modelling. The fourth chapter deals with the results and discussion which presents the quantified results from image classification, LULC change modeling and carbon storage modelling. The last chapter presents conclusions and recommendations this chapter elaborates the key findings and critical points that need further treatment has been forwarded as a recommendation for future work.

CHAPTER II: LITERATURE REVIEW

Practices of land use usually evolve over a long period under various environmental, political, demographic, and socio-economic circumstances (Muttitanon and Tripathi, 2005). There is tremendous confusion as to the degree or types of land-use transitions to be anticipated (Seto, Güneralp, and Hutyra, 2012). Drivers, such as technological innovation, advancements in the energy sector, environmental public choices, and local-to-federal policies, all play an important role in defining land-use evolution (Seto et al., 2012).

Changes in land use and land cover can influence global atmospheric circulation, cause local climate change, and affect carbon sequestration (Verburg, Neumann, and Nol, 2011). Carbon storage in the landscape can be disturbed by each land cover type, therefore; changes in land cover proportions affect net ecosystem exchange (NEE) (Gibson, Münch, Palmer, and Mantel, 2018).

Future land cover predictions of the C40 Large Cities Climate Leadership Group stated that 80% of the world's largely CO_2-based anthropogenic greenhouse gases (GHGs) are released from cities and overall urban emissions are growing at a rate of 1.8% annually (W. Zhang et al., 2014). Besides, it is estimated that GHG released from cities in developing countries will rise above the average rate (W. Zhang et al., 2014).

Subsequently, the carbon balance in urban areas has become a major research problem and a major policy issue in efforts to resolve anthropogenic climate change, since cities are both drivers of increasing atmospheric carbon dioxide emissions and also major players in the investigating efficient strategies to make human society more sustainable (C. Liu and Li, 2012; Pataki et al., 2006; M. Zhao et al., 2010).

However, urban vegetation can assist in local carbon reduction strategies and can also impact on ecosystem functions such as pollution removal (Escobedo, Kroeger, and Wagner, 2011; Nowak and Crane, 2002; Nowak et al., 2013). Thus the accurate assessment of the urbanization impact on the carbon cycle needs detailed information concerning the types and locations of land-cover changes, as well as analysis of the carbon densities in different types of pre-urban and urban land-cover (Yan, Zhang, Hu, and Kuang, 2016).

With increasing awareness of their potential economic value and political interest in their environmental services, urban forests have started to draw more and more focus in recent decades (Hubert de Foresta, Eduardo Somarriba, August Temu, and Gauthier, 2013). Wherefore, Remote sensing (RS) and Geographic Information System (GIS) can provide efficient instruments for enhanced LULC change monitoring together with carbon storage and sequestration modelling (Mas, Kolb, Paegelow, Camacho Olmedo, and Houet, 2014). A wide range of LULC change models has been created over the past two decades to help with land management and to better explore, assess and project LULC changes' future role in earth system functioning (Mas et al., 2014).

2.1. Land Use Land Cover Change

The Earth's surface is experiencing rapid LULC changes as a result of numerous socio-economic activities and natural phenomena (Cheruto, Kauti, Kisangau, and Kariuki, 2016). Nowadays the rapid growth and expansion of urban areas, rapid population growth, land scarcity, increasing production demands, and growing technology are some of the drivers of LULC change (Barros, 2004).

Anthropogenic disturbances, such as changes in land use through agriculture, forestry, and urbanization, have a significant influence on the function of the landscape and ecosystems. Similarly, the development of urban settlers in agricultural and forest regions can lead to land degradation and desertification (Adel and Tateishi, 2007). Accordingly, rates of land cover changes and declines in terrestrial carbon stores are anticipated to accelerate rapidly in the coming decades as the population increases from all over the world (Montgomery, 2008).

From across the tropical regions, many countries face major struggles in meeting the needs of rapidly increasing populations and sustaining reliable ecosystem services while resolving climate change impacts with mitigation and adaptation strategies (Capitani et al., 2019). Moreover, (Seto et al., 2012) indicated that the urban expansion in Africa will be tough by 2030 within five regions: Egypt's Nile River, the coast of West Africa on the Gulf of Guinea, Kenya, and Uganda's northern shores of Lake Victoria, and Rwanda and Burundi, the Kano region in northern Nigeria, and Addis Ababa, Ethiopia. In order to appropriately understand the triggers of present environmental problems, an assessment of natural resources and environmental changes over time has become the main concern of researchers around the world. Accurate and up-to-date analysis of land use/cover is crucial to update land use information and for environmental planning to identify the effect on the terrestrial ecosystem (Muttitanon and Tripathi, 2005). The main purpose of the LULC change analysis is to enhance the understanding of dynamic changes between land-use and land cover within a defined area. Remote sensing can be used for a better assessment of natural or anthropogenic disturbance and to monitor changes across wide areas for advancing carbon storage estimation (Myeong, Nowak, and Duggin, 2006).

2.2. Predicting Land Use Land Cover Changes

Since, changes in LULC are the major anthropogenic drivers of environmental changes, monitoring and mitigating the negative consequences of LULC and maintaining the development of essential resources, has become an important priority for researchers to evaluate the future dynamics and its impacts on the environment.

Modelling is the most appropriate way of assessing the dynamics of a defined area which is through analyzing the processes of interactions among natural factors and human factors. Especially if carried out using a spatially specific method, it is a significant method for projecting and exploring alternative future scenarios, conducting research that enables to understand and describe key procedures quantitatively and as well intensify the estimate of future carbon storage (Gibson et al., 2018). LULC change models can assist decision-makers to manage financial and demographic frameworks that often work at a national level and generate decision-making scenarios (Aguiar et al., 2016).

Therefore, studies of LULC change must assimilate RS and GIS, modelling and simulation analysis using different scenarios as well as future predictions of LULC change (Beckline, 2017). In that matter, developing LULC change scenarios can assist discover the uncertainties of land practices in a range of probable futures along with the possible effects and interactions in a dynamic environment (Ho, 2008).

Formerly, scholars apply different approaches to model the urban spatial processes such as Markov Chain Analysis (MCA), Cellular Automata (CA), CA_MARKOV, LCM.

Cellular Automata (CA)

A Cellular Automata (CA) model is a dynamic geo-simulation that represents the development of space and time in the system which is described with discrete units and where space is usually regarded as a regular two-dimensional grid (Kumar, Kumari, and Bhaskar, 2016). Prediction of future changes depends on changes within adjacent cells. In other words, CA models determine changes in space and time in terms of local relations (Barros, 2004). Additionally, the CA model with efficient spatial measures can be used to efficiently simulate the spatial variation of the system. However, the literature indicates that CA modelling is more suitable in the context of statistical analysis for the assessment of land-use changes.

Markov Chain Analysis (MCA)

Markov Chain Analysis (MCA) is an aggregate, macroscopic, stochastic, modelling process that calculates the probability of a cell representing a particular type of land use at a given time being subjected to changes within a specified period from one land use category to one another (Kumar, Kumari, and Bhaskar, 2016). Prediction of future changes is based on the previous LULC change trend at different spatio-temporal scales. MCA enables to quantify conversion states and transfer rates between different land cover types. However, it fails to consider the causes of land-use changes and it is difficult to predict the spatial pattern of land-use changes (Sang, Zhang, Yang, Zhu, and Yun, 2011).

CA_MARKOV

In predicting LULC change RS and GIS approaches have received a wide range of affirmation among researchers by encompassing the Markov Chain (MC) and Cellular Automata (CA) function. CA Markov can perform effective simulation towards temporal as well spatial variations and the MC model offers proper results in land-use changes in quantity to be transformed to spatially explicit results using the CA function (S. Q. Wang, Zheng, and Zang, 2012).

Land Change Modeler (LCM)

LCM is an inductive model integrated with Terrset software which provides the tools for the analysis and prediction of land cover change. LCM uses a Markov Chain prediction method which estimates the amount of change based on previous observations together with transition susceptibility which specifies the area of land to be subject to changes in the future. Changes in land use found between the two maps (Time 1 and Time 2) represent changes from one land cover to another and are used to determine losses and gains for each land-use class (Eastman, 2016).

LCM multi-layer perceptron can model multiple transitions as well as generate different results for each simulation utilizing its stochastic elements. LCM provides a detailed analysis of accuracy and competence for each transition and persistence category (Eastman, 2016). It also includes a lot of information about each variable's importance to the system, including a step-by-step analysis that makes it easy to evaluate the most circumspect model (Eastman and Toledano, 2018).

Many researchers promote TerrSet's LCM tool for its ability to analyze land cover change, empirically model land cover relationship with its explanatory variables, and predict future changes (Eastman, 2016). Furthermore, it provides a user-friendly interface and multiple accuracy testing and validation tools (Mas et al., 2014). Considering this Pechanec et al. (2018) employed LCM to assess dominant land-use changes and used a multi-layer perceptron (MLP) neural network to create transition potential models. Gibson et al. (2018) as well applied Terrset’s LCM used Multi-layer Perceptron (MLP) with explanatory spatial variables to create transition potential maps to predict the future land cover change in South Africa.

2.3. Land Use Land Cover Change and Carbon Storage

Changes in LULC is the major driving force for global environmental change (Gurung, Yang, and Fang, 2018). The complex interactions between humans and the environment are the key driver for LULC change which has a serious impact on soil, water, and atmosphere (Schaldach and Priess, 2008). Historical cumulative C losses due to global land-use changes were estimated as 180–220 PgC before 1850 (IPCC, 2001).

Literature contends that the primary cause of changes in carbon storage is LULC change. Likewise, land procurements by urban development induce both an initial loss of carbon stock and a permanent reduction of carbon capture capacity of the land (Hutyra et al., 2011). Consequently, changes in land use and land cover have become a key factor of present natural resource management and environmental monitoring policies (Muttitanon and Tripathi, 2005).

Ambiguities in the quantitative interpretation of LULC change impact on the global carbon cycle draw uncertainties in atmospheric CO_2 and climate forecasts and ultimately influence pollution reduction strategy formulations (Strassmann, Joos, and Fischer, 2008). Therefore, LULC change assessments ease the process of quantifying carbon stored by urban trees by the means of the dynamic spatial pattern of the urban ecosystems due to anthropogenic and natural factors (Myeong et al., 2006).

Although urban areas occupy a small proportion of the global land surface, the structures and functions of their ecosystem have a huge impact on global change (J. Wu, Jenerette, Buyantuyev, and Redman, 2011). Through a process called photosynthesis, urban trees and shrubs can turn CO_2 into above as well as below-ground biomass and sequester and store carbon in the form of stems, branches, or roots (Nowak and Crane, 2002).

Wherefore, changes in LULC produces variations of terrestrial carbon storage within the ecosystems, and become the major consequences for both the climate system and human life (C. Li, Zhao, Thinh, and Xi, 2018). Changes in LULC impact surface temperatures indirectly through NDVI; implying that, researchers are insisting that the promotion and protection of urban greening, such as new planting in public areas and green infrastructure is remarkably important (Muthee, Mbow, and Macharia, 2017).

2.4. Urban and Peri-Urban Areas and Carbon Storage

Scientific assessment of the effect of landscape changes on carbon storage confirmed that greenhouse gas emissions had increased within the atmosphere (H. Wu, Guo, and Peng, 2003). Subsequently, about ~75% of global anthropogenic carbon dioxide (CO_2) emissions are caused by cities (Seto et al., 2012). Despite their relatively small area (>3% of the global terrestrial surface), there is increasing awareness that urban ecosystems and their resources are particularly critical for their proximity to human activity and occupancy (Grimm et al., 2008).

Most recent studies have been carried out in quantifying the carbon sequestration of urban vegetation (Seto et al., 2012). On account of their investigations literature revealed that urban biomass maps are capable of promoting our understanding of urban ecological systems and can be used as model inputs to analyze landscape function, surface-atmosphere exchanges, and patterns of adjacency between urban and peri-urban areas (Raciti et al., 2014).

Urban ecosystem play a major role by enhancing the quality of the environment and human health (Nowak and Crane, 2002) and assisting climate regulation/cooling effects (Elmqvist et al., 2015). Furthermore, urban vegetation can act as a carbon sink by absorbing carbon through photosynthesis and storing carbon as biomass (Nowak and Crane, 2002; Nowak et al., 2013). Shrublands indeed contribute to terrestrial carbon storage (Hui_Feng, Zhi_Heng, Guo_Hua, and Bo_Jie, 2006)

Rowntree and Nowak (1991) was the first study to estimate urban carbon storage which resulted in between 350 and 750 million tones which were based on an extrapolation of carbon data for Oakland, CA. Again Nowak (1993), comprises data from a second city (Chicago, IL), estimated between 600 and 900 million tons of national carbon storage by urban trees. In later studies, Nowak et al. (2013) confirmed that urban trees in the 50 US states store a total of 643.2 million tons of carbon with a gross sequestration rate of 25.6 million tons per year. Similarly, the total carbon stored in 35 cities' urban green infrastructure vegetation in China was estimated to be 18.7 million tons (Chen, 2015).

Since urban forests sequester CO_2 and affect urban CO_2 emissions, urban forests can play a significant role in helping to mitigate increased levels of carbon dioxide in the atmosphere (Nowak and Crane, 2002), advancing urban forest management will significantly impact on their capacity of carbon storage and sequestration (M. Zhao et al., 2010) and for the avoidance of carbon emissions from fossil-fuel power plants through energy conservation from properly located trees (Nowak, 1993).

In other words, it is not merely desirable to invest in the restoration, preservation, and enhancement of green infrastructure and ecosystem services in cities for ecological and social purposes (Gurung, Yang, and Fang, 2018), as long as it upgrades economic values (Elmqvist et al., 2015; G. Liu and Zhao, 2018). UNEP (2011) as well confirmed that investing in urban greening initiates significant contributions that cities can make to the 21st century Green Economy agenda of the United Nations.

Hence, it is important to model the carbon storage of urban vegetation to develop our understanding of the role of urban green area in the carbon balance (Tang, Chen, and Zhao, 2016) and assess their role in avoiding carbon emissions from fossil-fuel power plants through energy conservation from properly located trees (Nowak, 1993).

2.5. Carbon Storage and Sequestration Modelling

The carbon cycle has become an increasingly popular concept in Global climate change and earth sciences in the past decades (He, Zhang, Huang, and Zhao, 2016; C. Li et al., 2018). Since many researchers have been quantifying carbon storage and sequestration, estimation of carbon storage accuracy has improved (Eswaran, Van Den Berg, and Reich, 1993). Global carbon is mainly stored in the soil, terrestrial vegetation, and atmosphere; about 1400–1500 Gt of carbon is contained in the soil, about 500- 600 Gt of carbon is found in terrestrial vegetation, and about 750 Gt of carbon is contained in the atmosphere(Z. Zhao et al., 2018).

Carbon sequestration is the act of removing and storing atmospheric CO_2 in other long-lived carbon pools (aboveground biomass, belowground biomass, soil organic, and deadwood) or otherwise released in the atmosphere (Rattan Lal, M. Suleimenov, B.A. Stewart, D.O. Hansen, 2007). More recently, several towns use urban forests as a carbon offset strategy (M. Zhao et al., 2010). The quantification of urban tree carbon storage can thus contribute to a better understanding of the relationship between urban trees in global carbon accounting for greenhouse gas emissions and improved urban planning and management (Myeong et al., 2006). Carbon is absorbed from the atmosphere by plants through their biological carbon cycle photosynthesis (C. Liu and Li, 2012).

The Assessment of carbon storage and sequestration of landscapes must include data on the quantity and location of carbon already stored, the amount of carbon sequestrated or lost over time, and the relationship between land-use change and its impact on carbon storage and sequestration over time (Oulehle et al., 2011). Commonly employed carbon storage assessment methods include field surveys (Hutyra et al., 2011), Remote Sensing (RS) (Myeong et al., 2006), and models (C. Li et al., 2018; Pechanec et al., 2018).

2.5.1. Contact Measurements Method

This method involves the harvesting of sample trees within a defined area and measuring the weight of the various components of the harvested tree, such as the tree trunk, leaves, and branches, and measuring their weight after drying it (Supriya Devi and Yadava, 2009). The common approach for carbon storage estimates are generated from allometric equations using several parameters to measure tree biomass: breast height diameter (dbh), tree height, the density of wood, moisture content, index of site and plant condition (Lal and Augustin, 2012). Contact measurement methods always provide more accurate results (Schneider, Lerner, McGroddy, and Rudel, 2018), but they are costly, time-consuming, and incompatible for large area assessments (Gibbs, Brown, Niles, and Foley, 2007).

2.5.2. Remote Sensing Method

Remote Sensing permits a faster and effective way of mapping larger areas using a temporal database of satellite imagery that enables monitoring of urban forest dynamics (Myeong et al., 2006). The Normalized Vegetation Index (NDVI) and other vegetation indicators derived from RS platforms are common indicators used to monitor biophysical conditions and vegetation cover (Gibbs et al., 2007). However, no Remote Sensing technology can accurately measure forest carbon stocks and hence additional ground-based data collection is required (DeFries et al., 2007).

Different studies estimate carbon content from high-resolution remote sensing images together with estimates of aboveground carbon from field inventories. Myeong (2006) used Landsat TM imagery from Syracuse, NY to measure the aboveground carbon storage of urban trees of Syracuse, NY, USA using ground samples and NDVI data to estimate per pixel biomass. Raciti (2014) used quite high-resolution images from the IKONOS and QuickBird commercial satellites to map urban vegetation to further advance classification accuracies, together with LiDAR-based tree height data to estimate biomass in forested systems.

2.5.3. InVEST Carbon Model

Integrated Valuation of Environmental Services and Tradeoffs (InVEST) model allows for biophysical and economical evaluation of ecosystem services and has been used in various case studies around the world, mostly in close cooperation with local decision-making processes (Krkoška lorencová, Harmáčková, Landová, Pártl, and Vačkář, 2016). The InVEST carbon model method depends on linking selected areas and pre-prepared tables of carbon stock production for each land cover type according to defined classification. Tabulated values are derived from previous field measurements and different literature results (Pechanec et al., 2018). Accordingly, the model is used to perceive existing carbon stocks and their future development using carbon pools (aboveground biomass, underground biomass, dead wood, and soil) (Nelson et al., 2014). The carbon sequestration and release cycle are not explicitly taken into account in the model, but the model can consistently estimate carbon storage in the landscape (Z. Zhao et al., 2018). Prediction of the future carbon storage is based on the changes in future land cover (Pechanec et al., 2018). Scholars promote the InVEST model for it can use multi-scale models and can simulate numerous scenarios, it requires fewer input data than other methods and generates more output data (Z. Zhao et al., 2018).

Different studies have confirmed that the InVEST model is convenient for calculating carbon storage. For example (Sallustio et al., 2015) employ the InVEST model to assess land take by urban development and its impact on carbon storage in Italy from 1990–2008, C. Li et al. (2018) studied the effects of urban expansion on terrestrial carbon storage Xuzhou, China from 2015–2025 by adopting the InVEST model, Hernández et al. (2019) also applied the InVEST model to investigate the impact of land use and changes in land cover related to carbon storage in a western basin in Mexico from 1990–2050, Zhang (2017) analyzed the impacts of LULC change on terrestrial carbon stocks from 2006- 2010 for Uganda using InVEST model.

Model Description

The InVEST carbon storage model analyzes the quantity of carbon stored in four carbon pools: above-ground biomass, below-ground biomass, soil, and dead organic matter to produce cumulative carbon storage (Nelson et al., 2014). The model provides a map of total carbon storage by summing these four carbon pools in millions of grams per hectare (mg per ha) for each grid cell based on its corresponding LULC type (Nelson et al., 2014). The model assumes that while the carbon storage level of each LULC type is equal to the average of measured storage levels within that land cover type, the amount of carbon level varies linearly over time as the LULC is changed to another (Nelson et al., 2014).

Model Inputs

Current land use/land cover (required): Raster of land use/land cover (LULC) for each pixel, where each unique integer represents a different land use/land cover class.

Future landcover (required for sequestration and valuation): Raster of land use/land cover (LULC) for each pixel, where each unique integer represents a different land use/land cover class.

Carbon pools (required): A CSV (comma-separated value) table of LULC classes, containing data on Carbon stored in each of the four fundamental pools for each LULC class

- Carbon Above: Carbon density in aboveground biomass [units: megagrams/hectare]
- Carbon Below: Carbon density in belowground biomass [units: megagrams/hectare]
- Carbon Soil: Carbon density in soil [units: megagrams/hectare]
- Carbon Dead Wood: Carbon density in a dead matter [units: megagrams/hectare]

Model Outputs

- *Current/Future Stored Carbon (Mg):* Raster showing the amount of carbon, in Mg, stored in each pixel across the landscape. This value is the sum of carbon stored in each pool included in the model.
- *Sequestered Carbon (Mg):* Raster showing the total sequestered carbon for each pixel based on the difference in stored carbon from current to future land-use scenarios.

2.6. Conceptual Framework

Nowadays, LULC changes are drawing attention since they become major causes for anthropogenic disturbance to the environment and microclimate changes. Literature contends that LULC changes affect the carbon stock and decreases the capacity of landscapes to capture carbon. Most commonly urban areas are documented to be principal front drivers of LULC on account of their dynamic nature (Grimm et al., 2008). Similarly, different scholars assert that cities are major contributors to CO_2 emission (Pataki et al., 2006; Seto et al., 2012; W. Zhang et al., 2014).

LULC change is an eventual process and it is a major issue, particularly in developing countries including Ethiopia (Arsiso, Mengistu Tsidu, Stoffberg, and Tadesse, 2018). Studies are reporting that LULC change is becoming a serious issue in Addis Ababa, the capital city of Ethiopia, and surrounding regions (Arsiso et al., 2018; Leulsegged, Gete, Dawit, Fitsum, and Andreas, 2012; Mohamed and Worku, 2019).

The City and surrounding regions have experienced massive transitions led by excessive agricultural, industrial, and urban expansion activities. These land-use modifications damaged the ecosystem in terms of land cover, land quality and strength, weather and climate, land quantity that can be maintained, and population and socio-economic determinants (Tadesse, Tsegaye, and Coleman, 2001). This is mostly because of the rapidly increasing built-up area that conquered large tracts of natural green spaces and prime agricultural lands (Mohamed and Worku, 2019).

Since researches began to insist that LULC changes are impacting on carbon storage level of cities, different studies are emerging to take strategic measures to mitigate CO_2 emissions that are generated from the urban area. Thus, it is important to analyze the LULC dynamics of the city and surrounding regions together with its impact on the carbon storage level.

Regardless of land use prediction analysis, researchers apply Markov Chain Analysis (MCA) for the prediction of geographical features without after-effects. Apparently, the literature reveals that CA modelling is suitable in the context of statistical analysis for the assessment of land-use changes. Therefore employing Terrset's LCM is the proper approach in quantifying the dynamics and determining the spatial and temporal trends of LULC changes together with predicting land-use changes within the study area, while it integrates MCA with MLP referring to that Markov reveal the conversion state and transfer rate of changes between land use and MLP predict as well as determine the likely situation of future LULC change patterns and enable to model multiple transitions.

In consideration of carbon storage and sequestration modelling few studies consider that the contribution of urban vegetation to minimize GHG emissions directly through carbon sequestration is very low (Velasco, Roth, Norford, and Molina, 2016); referring to that, they insist that urban ecosystems have limited ecological value since they are relatively small in size unlike old-growth forests and are frequently modified by humans and are.

Whilst, particular scholars argue that urban forests assist in carbon storage and significantly impact on CO_2 emissions produced by the cities; in fact, land cover types such as shrubs and soils of urban forests were found to be greater in their abilities to store carbon than the rural counterparts; implying that, they suggest urban heat island can be mitigated through green area developments such as greenways, community garden and street garden (Hui et al. 2006; Nowak and Crane, 2002).

However, carbon storage and sequestration estimations of urban areas in North America and China where most research has been carried out regarding this particular issue cannot simply be replicated to Ethiopia, since urban configurations and human management activities vary remarkably among cities. On that matter, detailed maps of LULC dynamics and estimates of carbon storage across cities need to be developed to assess the impact of LULC change on the level of carbon storage. Besides, in light of some studies, carbon storage varies greatly among cities due to differences in the estimation approach (Grafius et al., 2016). Therefore, it is preferable to quantify the level of carbon storage at Addis Ababa City and surrounding regions as well as assess the impact of LULC change on the level of carbon storage to ensure the advancement of successful resource management policies.

Since the estimates of carbon storage have been introduced in urban and sub-urban areas studies employ different approaches to assess carbon storage. There are three commonly used approaches such as contact (field measurement) method, contactless measurements using the Remote Sensing method, and using Models. Studies usually employ field measurement methods for estimating carbon storage of forested land use; likewise, as it is mentioned in the previous section field measurement methods are more accurate methods of quantifying carbon storage but it is costly and incompatible to assess carbon storage of large areas. Wherefore, considering that the study area consists of different land cover types and covers a large area field measurement method is not a convenient method.

While the Remote Sensing method provides a broader view of the inaccessible area beyond it enables to capture the spatial variability within a defined area, it requires incorporating field measurements to make it more accurate and it fails to account for soil and dead wood carbon pools. Besides, studies that manipulate the Remote Sensing method mostly used high-resolution satellite images depending on their abilities to accurately distinguish urban forests. However, even if high-resolution satellite images are advisable for feature variability recognitions they are not freely available.

The third method of estimating carbon storage is the InVEST model which works on the basis of previously defined carbon storage data. It inspects carbon storage under four carbon pools (aboveground biomass, belowground biomass, soil, and deadwood) for each land cover type. Since a particular amount of carbon can be sequestered by soils in urban green areas (Jo, 2002; Nowak, 2006), it is important to include carbon stored by urban soils and other components of the urban area that can contribute to carbon storage. Thus, on account of secondary data, the study includes four carbon pools, accordingly; the InVEST model is compatible to estimate carbon storage of the study area. Another impressive advantage of the InVEST model is that it can use multi-scale models and can simulate numerous scenarios, it requires fewer input data than other methods and generates more output data (Z. Zhao et al., 2018).

CHAPTER III: MATERIALS AND METHODS

This section explains the data used to achieve the objective of the study as well as how the process of analyzing it was carried out. The present section gives the procedure that was followed in completing the results discussed in the result section.

3.1. Study Area Description

3.1.1. Location

The study area is found in the center of the country. Addis Ababa City is located in the heart whereas; the Special Zone of Oromia Surrounding Addis Ababa is situated surrounding the city boundary of Addis Ababa. The geographical coordinates of the region are 8°25'N to 9°25'N latitude and 38°25'E to 39°07'E longitude with a total area of 4986 sq.km as shown in (Figure 3.1). It covers the capital city Addis Ababa and surrounding areas (six Oromia Special Zone districts). In this research, it is referred to as Addis Ababa and the Surrounding Oromia Special Zone (Mohamed and Worku, 2019).

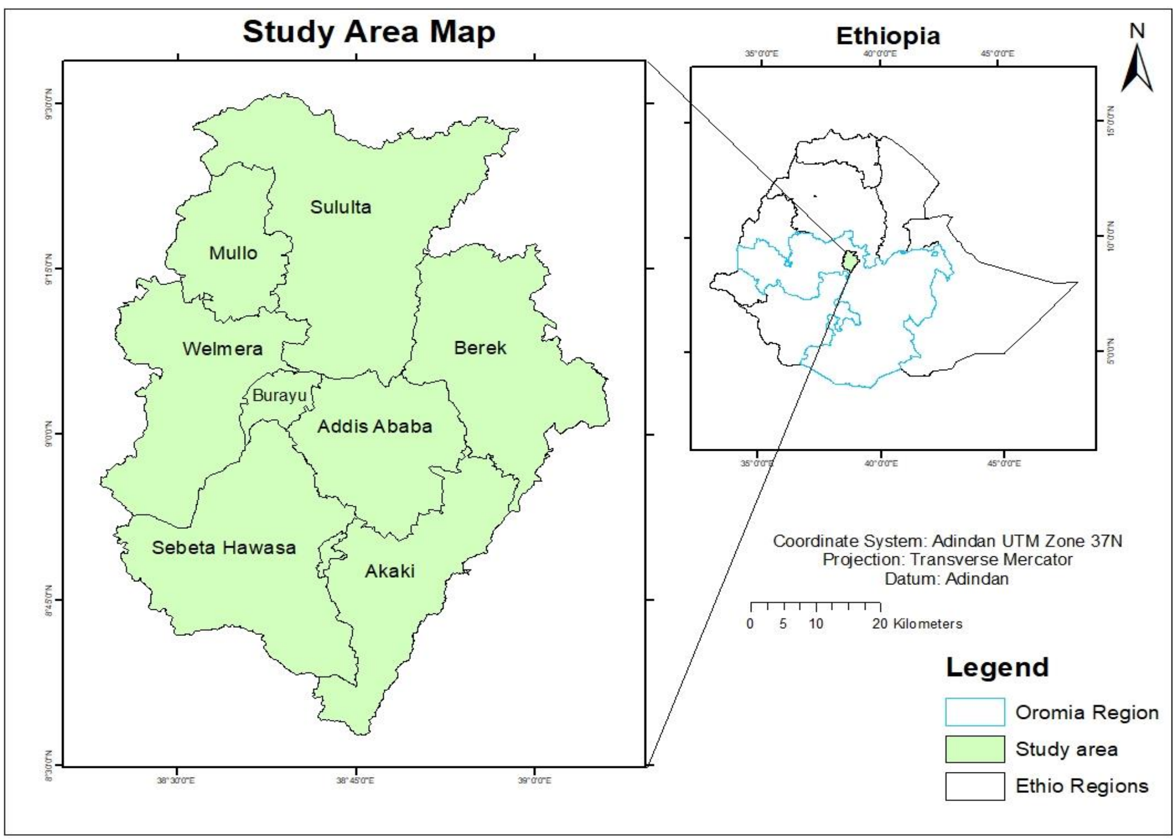


Figure 3. 1 Location Map of the Study Area

3.1.2. Land Use

In Addis Ababa and the surrounding Oromia special zone major land use categories are residential, commercial, mixed-use, grasslands, manufacturing and storage, recreational, open space, forest, and others. In Addis Ababa, the built-up area is the major land use category. Likewise, the surrounding Oromia special zone encompasses mixed land cover types which are built up, forest, agriculture, shrublands, and grasslands.

3.1.3. Climate

Addis Ababa has a humid subtropical mild summer climate that is mild with dry winters, mild rainy summers, and moderate seasonality. The mean annual temperature is 15.9 degrees Celsius. During summer average high temperatures are 21°C (69.8°F) and average low temperatures are 10°C (50°F) (Climatemaps.com, 2017). Throughout the year, 1,200 mm (49 in) of rainfall, with a maximum from June to September, this is the only remarkably rainy period. From November to February, there is little rain, and rare showers occur; from March to May, afternoon showers become a bit more frequent, occurring for 6/7 days per month, while in July and August, they occur on average every other day (Climates to travel, 2018).

According to the physiographic classification of the country, the Oromia special zone is found in the central highlands where the climate especially temperature is from cool to moderate. The mean annual cool temperature ($11^{o}c$ - $16^{o}c$) covers 60 percent of the zone. About 38 percent of the zone has a mean annual temperature of $16^{o}c$ - $21^{o}c$ and the remaining 2 %, especially in the southern part of the zone, has a temperature amount of $21^{o}c$ - $26^{o}c$ The rainfall pattern of the zone has a uni-modal characteristic where the majority 80 percent of this zone experiences maximum rainfall from June to September (Tabor, 2019).

3.1.4. Population

Addis Ababa is the largest city in the country by population, with a total population of 3,384,569 according to the 2007 census. However, it is believed that this number was inaccurate when recorded and underestimated the city’s population. The city has through recent years seen a robust annual growth rate, and population counts as of 2017 are growing closer to 4 million (Population Stat, 2019).Table 3.1 illustrates the population of the surrounding Oromia Special Zone.

Table 3. 1 Population of Oromia Special Zone Source (Tabor, 2019)

Towns	Districts	Year of Estab. EC/GC	Area (ha)2009	Population size				
				2007/8	2009/10	2011/12	2013/14	2015
Burayyu	Walmara	1954 (1954)	6650	66526	72180	78333	85030	88598
Dukam	Akaki	1988 (1996)	3586	6976	7632	8351	9137	9557
Galan	Akaki	1978(1986)	750	-	9686	10598	11595	12128
Holota	Walmara	1894 (1902)	5500	32112	34859	36323	41107	42842
L/TafoL/ Dadhi	Barak	1998 (2007)	-	-	13270	14518	15885	16616
Sabata	S/Hawas	1936 (1944)	9500	58713	64239	70285	76900	80437
Sandafa	Barak	1929 (1937)	8800	11245	12303	13461	14728	15405
Sululta	Sululta	1929 (1937)	4400	13025	14251	15592	17059	17844
Total	-	-	39186	178497	228420	247461	271441	369,441

3.2. Data Source and Materials Used

This section encompasses gathering both spatial and non-spatial data from actual fieldwork and secondary sources of data. Table 3.2 delineates the types of data to be used in the study, formats and where the data were gathered from;

Table 3. 2 Data Source

S.No	Data	Source	Data Type	Cell Size/Scale
1	Satellite Image	USGS	Tiff	30m
2	Carbon Pool	EFCCC and Soil Grid	Excel Sheet	__
3	Addis Ababa Green area Development Plan	Urban Planning Office	Shape file	__
4	Structural Plan of Oromia Special Zone	Oromia Bureau	CAD file	__

Table 3. 3 Characteristics of satellite data used in this study

Acquisition Date	Path	Row	Landsat	Sensor	Spatial Resolution
10-01-90	168	54	Landsat 5	TM	30 m
25-02-00	168	54	Landsat 7	TM	30 m
15-01-10	168	54	Landsat 7	ETM+	30 m
27-01-20	168	54	Landsat 8	OLI	30 m

Materials Used

Table 3. 4 Materials Used

No.	Material Name	Source	Purpose
1	ArcGIS 10.5	-	Data processing and thematic map preparation
2	ERDAS Imagine 2014	-	Image preprocessing and TM and ETM+ as well as atmospheric correction
3	TerrSet 18.31	-	Change analysis, validation, and prediction of future map
4	InVEST Model	-	Modelling carbon storage and sequestration
5	Google Earth Pro	-	Use as a base map in visual image interpretation, and generate coordinate points for the images
6	Microsoft Word and Excel	-	Integrating attribute data and compositing final thesis

3.3. Data Collection Methods

To achieve the objective of this research, secondary data like satellite images, boundary data, carbon pool data were used to model carbon storage of the current land cover map and future land cover map, and master plan for identifying plans on green area development. The data were collected from the concerned source. Additionally, previous reports and documents, various journal papers, thesis, textbooks, and the internet were also used as secondary data.

3.4. Data Analysis Methods

The study analyzes the LULC dynamics of Addis Ababa City and surrounding as well as models the carbon storage and sequestration using geospatial and remote sensing techniques. Due to the unavailability of high-resolution Remote Sensing data the study employs the Landsat images from the United States Geological Survey (USGS) which covers the entire study area. However, Landsat TM imagery helps to avoid many issues often related to high-resolution imagery used for mapping landscapes such as shadows caused by tall objects and high spectral variation of the same land cover due to diverse spectral signatures of various construction materials found in urban areas (Lu, Li, and Moran, 2014). Therefore, Landsat TM images of 1990, 2000, 2010, and 2020 were downloaded to proceed to subsequent phases.

3.4.1. Image Pre-Processing

Once data are collected, the study undergoes the processes of manipulating, sorting, and preprocessing collected data to analyze the LULC dynamics of the study area and model the carbon storage which is precisely dedicated to achieving the objective of the study. The satellite image of 1990, 2000, 2010, and 2020 was processed using ERDAS Imagine. The coordinate system, image mosaicking, layer stacking, and layer extraction took place. Then Landsat images were corrected for the atmospheric, sensor, and an illumination variance through radiometric calibration procedures.

3.4.2. Land Use Land Cover Classification

Regarding the fact that different urban land-cover types have different carbon storage (C. Zhang et al., 2012), the study analysis classified the Landsat TM images of (1990, 2000, 2010, and 2020) into seven land cover types. The research first applies unsupervised classification based on indices (for water bodies, vegetation cover, bare land, and built-up) to have a brief picture of the region. Consequently, the LULC map was produced with land cover types such as forest, shrubland, cropland, grassland, built-up, bareland and water body for the study area using a maximum likelihood algorithm supervised classification.

Table 3. 5 Description of LULC classes used for classification in this study (UNFCCC, 2016)

S/N	Land Cover Type	Description
1	Built-up	Urban and rural built-up including homestead area such as residential, commercial, industrial areas, villages, settlements, road network, pavements
2	Barren Land	Includes a surface with no vegetation, open land exposed soil, rocks, and sand
3	Water Body	Areas covered by water bodies such as lakes and rivers
4	Grassland	Areas dominated by grasses including grazing areas
5	Croplands	Areas of land used for growing agricultural crops
6	Shrublands	Areas covered by shrubs and short trees mixed with grasses
7	Forest	Trees, natural vegetation including high and low-density forest

3.4.3. Accuracy Assessment

The term accuracy is typically used to express the degree of ‘correctness’ of a map or classification in thematic mapping from remotely sensed data. The objective is to quantitatively evaluate whether pixels were successfully grouped into the correct feature classes in the area under analysis. A classification of the map may be considered accurate if it provides an unbiased representation of the land cover of the region that it represents (Bharatkar and Patel, 2013). One essential indicator of accuracy is the overall accuracy, which is calculated by dividing the correctly classified pixels (sum of the values in the main diagonal) by the total number of pixels checked. Producer’s accuracy measures errors of omission, which is a measure of how well real-world land cover types can be classified. User's accuracy estimates commission errors, which indicates the probability that a classified pixel meets the land cover type of the corresponding pixel real-world location (Rwanga and Ndambuki, 2017). In this study, total test samples of 440 for image 1990, 474 for image 2000, 510 for image 2010, and 449 for image 2020 were randomly selected respectively from Google earth.

3.4.4. Application of LCM for Land Use Land Cover Modelling

Since the study aims to assess the effects of LULC change of the city and surrounding, on carbon storage and sequestration, it is essential to quantify the detailed “from-to” transitions of land-use changes to determine the dynamics and change pattern of the study area. Analyses of LULC change were carried out using LCM a module in TerrSet 18.3.LCM was adopted considering that it is an appropriate method for producing maps of overall potential change within the study area and for it provides an easy way for users to map the changes and define transitions between LULC categories.

3.4.5. Change Analysis

The Panel of Change Analysis provides a fast quantitative assessment of changes so that researchers produce gain and loss evaluations, net change, persistence, and specific transitions both in a map and graphical form. The main issue is to define the dominant changes that can be grouped and modeled, termed sub-models (J. Ronald Eastman, 2016).

In this study, land use and land cover maps of the study area obtained from image classification for the periods of 1990, 2000, and 2010 were used for the analysis. Based on the principle of land change analysis, maps of gains and losses, contributions to net change, transitions of land cover classes between different categories, and spatial trend analysis were examined both in a map and graphical form.

3.4.6. Transition Sub-Models

This panel identifies all transitions that occur between time 1 and time 2 of the land cover maps. In LCM, collection transition Potential maps are grouped within a transition sub-model which is empirically evaluated and has the same driver variables. A transition sub-model may consist of a single land cover transition or a group of transitions which are considered to have the same underlying driver variables (Eastman, 2016).

Since it can execute multiple transitions up to 9 per sub-model, the study implemented Multi-layer Perceptron neural network (MLP). To obtain the best modelling results, the model has been run multiple times by selecting a sub-model with MLP and various variables. Additionally, the study examined all of the variables in the dataset in each sub-model and in each transition to evaluate their potential to be incorporated into the model.

3.4.7. Model Variables Development

To model the vulnerability of the study area to changes, explanatory variables were selected based on their potential for describing the transitions that occurred within the study area. Researchers contend that the best method for variable selection is based on the characteristics of the study area, observed LULC overtime, and expert knowledge of the study areas (Mishra and Rai, 2016). Therefore, all modelling variables as spatial characteristics were selected by taking into consideration the area's development pattern by using an overview of the study region.

Constraints

Constraints refer to the criteria that limit the expansion of a land cover class. The constraints are explained in Boolean maps: the areas that are excluded from future land-use changes being assigned a value of 0 (not suitable) while those considered for land-use changes being assigned a value of 1 (suitable) (Eastman, 2016). The constraints considered in this study were existing built-up areas and major roads derived from image classification of land cover.

Factors

Factors are not 'hard rule' like constraints are criterion that enhances or detracts from the suitability of a specific alternative for the activity under consideration. It gives a degree of suitability for an area to change such as in many cases on a distance basis (Eastman, 2016). They are not reduced to simple Boolean constraints. It is therefore most commonly measured on a continuous scale. Physical factors, topographic factors, socioeconomic factors, neighborhood factors, and planning have been widely identified as significant determinants of land cover changes (Wang and Maduako, 2018).

The Cramer's V, which measures the association for nominal variables developed with the overall classes, has a range of values from 0 to 1. A value of 0.15 or higher is considered to be important whereas 0.4 or greater are considered to be good (Eastman, 2016). After screening the potential explanatory power of variables employing the Cramer V analysis, variables were defined as static and dynamic. Variables can be defined as static and dynamic based on their influence. Static variables are variables that don't change over time while dynamic variables change and are calculated over time throughout the prediction (Wang and Maduako, 2018).

3.4.8. Change Prediction and Validation

LULC scenarios were modeled using the Markov Chain based built-in module in TerrSet software to conduct all spatial analyses and modelling as long as it contains tools for land cover change analysis, identify class transition and trends also it comprises tools with the possibility of modelling several transitions at a time. LCM model was used since it also predicts future landscape scenarios by incorporating user-specified change drivers (Eastman, 2016; Pérez, Mas, and Ligmann, 2012). Likewise, the Markov Chain model was chosen since it encompasses Spatial and temporal elements, tackling dynamism (Kamusoko, Aniya, Adi, and Manjoro, 2009).

Since the result of this model is a future scenario, typical land cover validation methods cannot be employed since time 3 is a future time step. Other indicators are thus required to assess the prediction. Accordingly, the transition probability matrix for the period 2000–2010 was computed to assess the exchange rate of land cover using Markov chains with the LULC map. The prediction of the Markov chain is carried out by creating a matrix for calculating the region of each LULC type for the future and the amount of change for each transition (J. Ronald Eastman, 2016).

Multi-Layer Perceptron (MPL) Neural Network model was used for modelling multiple class transitions since it reveals major LULC transitions that occurred in the study area. Simulations for the year 2020 were executed using transition potentials from 1990-2000 and 2000-2010 respectively. The procedure determines exactly how much land would be expected to change from the earlier dates to the prediction date (2020) based on a projection of the transition potentials into the future and creates a transition probabilities file. Afterward, the outputs from the LULC maps of previous years were used to predict the 2020 LULC map.

Subsequently, the validation module in TerrSet was used to statistically assess the quality of the 2020 simulated map against the 2020 actual map. Three methods were used to validate the model. The first method employed was a comparison of the simulated and the reference LULC map of 2020. In this method, LULC classes of the simulated map were checked against LULC classes of the corresponding reference LULC map of 2020.

ROC / AUC (Relative Operating Characteristic/Area under Curve) module of IDRISI TerrSet was the second method used for scoring the accuracy of the model. The ROC curve is the true positive fraction vs. false positive fraction and the AUC is a measure of overall performance (Nahib et al., 2018). This method is used to validate a soft simulation, particularly the map of projected potential for transitions, mapping the places most prone to change (Ballatore, McClintock, Goldberg, and Kuhn, 2020).

The third method employed was computing the kappa coefficient using the validate module in Terrset software. Kappa variation techniques were used in the validate module as the statistical validation procedure. Kappa statistics are used for testing accuracy in terms of location (Kappa for location) and quantity of correct cells (Kappa for quantity) (Kura and Beyene, 2020). Using the tool k_{no}, $k_{location}$, k_{strata}, and $k_{standard}$ were calculated to know the correctness of the model in terms of forecasting future LULC. Based on the validation carried out in the above section the prediction of 2027 and 2050 LULC maps were produced.

Business-as-usual (BAU) Scenario

This is the default scenario set in the Markov chain probability matrix. The Business-as-usual (BAU) scenario in the study indicates what would happen if the past trend in 1990–2000–20010–2020 were to continue until 2027 and 2050.

Ecosystem Conservation (Green) Scenario

Addis Ababa and the surrounding region's planning office target to increase existing green areas such as Forest, green areas in park places, and Grasslands according to structural plans specified for 2027. The study considered the incentives that planners are promoting in certain areas to encourage the naturalization of land for various purposes (for example, to expand forest, park areas, urban agriculture). Therefore, plan maps concerning green area expansion within the study area were obtained from Addis Ababa and the surrounding region's planning office and fed into LCM. Consequently, the study assumed that the current trend of LULC classes converting to the green area proposed by 70% for predicting 2027 and 2050.

3.4.9. Carbon Storage and Sequestration Modelling

Carbon storage of land cover types within the study area was estimated by using the InVEST model. The decision to use InVEST was for it is organized in different tiers of difficulty of use and input data availability; it can assess several ecosystem services. The InVEST carbon Storage and Sequestration model incorporate the amount of carbon stored in carbon pools: aboveground biomass, belowground biomass, soil, and dead organic matter according to land use maps and classifications provided.

Additionally, the model estimates the net amount of carbon stored in a land parcel over time and the market value of the carbon sequestered in remaining stock using maps of land use and land cover types and the amount of carbon stored in carbon pools (Nelson et al., 2014). The amount of sequestered carbon within a particular time span was calculated by subtracting carbon stored at the beginning of the period from the carbon stored at the end of the time period. Therefore, the study used secondary data for aboveground biomass, belowground biomass, and dead wood for forest land cover types that are available and average value of different studies for other land cover types (Appendix VI). Figure 3.2 demonstrates the whole research process work flow.

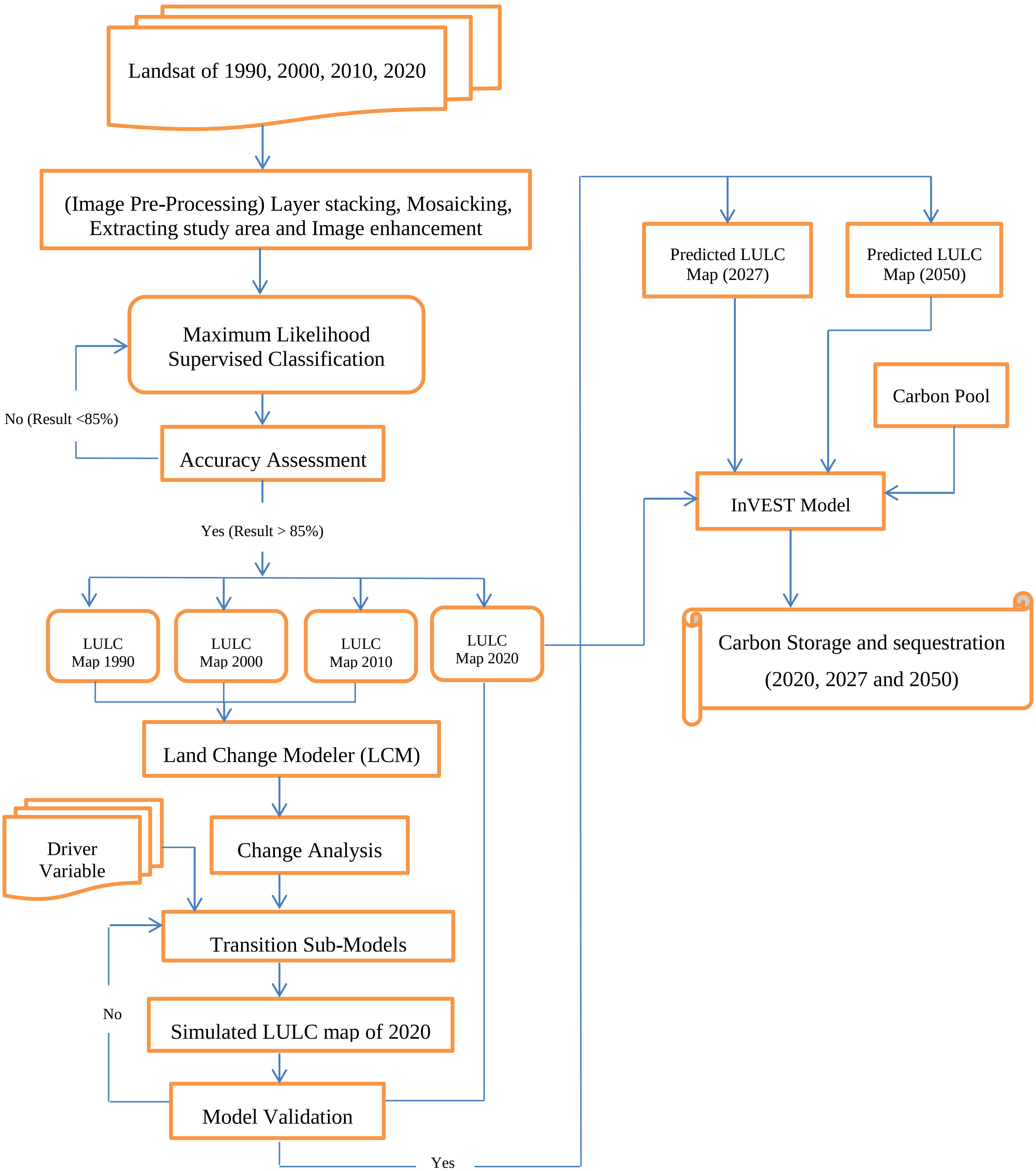


Figure 3. 2 Technological Scheme of the Study (Work Flow Chart)

CHAPTER IV: RESULT AND DISCUSSION

In this section, based on the data gathered data analysis performed output images of LULC images developed for the years 1990, 2000, 2010, and 2020 presented in the following Figure.4.1 and Table 4.6 shows the statistical change analysis of LULC between the years 1990 and 2020. An overall change in LULC in all the four years is shown in Figure 4.2. Additionally, the future scenario namely the green scenario and business as usual scenario for the years 2027 and 2050 were presented in the following Figure.4.4 and Figure 4.5.

4.1. Land Use Land Cover Classification

The study first classified Landsat satellite images of 1990, 2000, 2010, and 2020 to compute the LULC change trend of Addis Ababa and the surrounding Oromia special zone. The produced maps configure seven major LULC types. These are bare land, built-up, cropland, grassland, forest, shrubland, and water bodies. The land cover maps generated after running a maximum likelihood supervised classification, as well as a post-classification algorithm, are presented in figure 4.1 below. Over the period 1990–2020, the dominant land cover type in the study area was Cropland ranging between 55% and 63% of the total area.

4.2. Accuracy Assessment

Accuracy assessment in this study revealed the overall accuracies of 87%, 86%, 86%, and 87% were calculated for 1990, 2000, 2010, and 2020, respectively. This implies that all classifications are in acceptable range because an overall accuracy of each year is greater than 85% and kappa coefficient greater than 0.80 represents strong (almost perfect) agreement (Rwanga & Ndambuki, 2017) is an indicator for a strong accuracy. Most of the LULC classes have a larger producer’s accuracy than overall accuracy except the classes of grassland and shrubland. The lower accuracy for these two classes can be attributed to the limited Landsat image resolution and the lack of comprehensive ground truth data. The details of error matrix tables’ results are shown in Table 4.1, Table 4.2, Table 4.3, and Table 4.4.

Table 4. 1 Confusion matrix for the land cover map of 1990

Reference Map									
Classified Data	Bare Land	Grass Land	Water Body	Forest	Shrub land	Built-Up	Crop Land	Row Total	Users Accuracy
Bare Land	42	0	0	0	1	0	0	43	97.67%
Grass Land	0	39	0	0	0	1	5	45	86.67%
Water Body	0	0	52	0	0	0	0	52	100.00%
Forest	0	1	0	44	3	3	2	53	83.02%
Shrubland	3	1	0	1	35	0	10	50	70.00%
Built-Up	1	0	0	1	0	71	0	73	97.26%
Crop Land	4	12	0	5	2	0	101	124	81.45%
Column Total	50	53	52	51	41	75	118	440	
Producers Accuracy	84.00	73.58	100.0	86.27	85.37	94.67	85.59		
Overall Accuracy = 87.27% Overall Kappa Statistics = 0.8474									

Classified Map

Table 4. 2 Confusion matrix for the land cover map of 2000

Reference Map									
Classified Data	Bare Land	Grass Land	Water Body	Forest	Shrub land	Built-Up	Crop Land	Row Total	Users Accuracy
Bare Land	38	0	0	0	0	0	1	39	97.44%
Grass Land	0	32	0	0	0	2	4	38	84.21%
Water Body	0	1	50	0	0	0	0	51	98.04%
Forest	4	0	0	75	11	6	1	97	77.32%
Shrubland	3	0	0	0	53	4	4	64	82.81%
Built-Up	0	0	0	0	0	66	0	66	100.00%
Crop Land	10	9	0	2	4	0	94	119	78.99%
Column Total	55	42	50	77	68	78	104	474	
Producers	69.09	76.19	100.00	97.40	77.94	84.62	90.38		
Overall Accuracy = 86.08% Overall Kappa Statistics = 0.8345									

Classified Map

Table 4. 3 Confusion matrix for the land cover map of 2010

Reference Data										
Classified Map	Classified Data	Bare Land	Grass Land	Water Body	Forest	Shrub land	Built-Up	Crop Land	Row Total	User Accuracy
	Bare Land	43	0	0	1	0	0	0	44	100.00%
	Grass Land	0	51	0	0	0	3	6	60	85.00%
	Water Body	0	0	33	0	0	0	0	33	100.00%
	Forest	0	0	0	92	3	9	12	116	79.31%
	Shrubland	0	0	0	0	52	0	6	58	89.66%
	Built Up	5	0	0	0	4	56	0	65	86.15%
	Crop Land	0	9	3	1	10	1	110	134	82.09%
	Column Total	48	60	36	94	69	69	134	510	
	Producers Accuracy	89.58	85.00	91.67	97.87	75.36	81.16	82.09		
	Overall Accuracy = 85.69% Overall Kappa Statistics = 0.8276									

Table 4. 4 Confusion matrix for the land cover map of 2020

	Reference Data									
	Classified Data	Bare Land	Grass Land	Water Body	Forest	Shrub land	Built-Up	Crop Land	Row Total	Users Accuracy
Classified Data	Bare Land	23	0	0	0	1	0	0	24	95.83%
	Grass Land	2	28	0	0	0	0	1	31	100.00%
	Water Body	2	1	18	0	1	0	0	22	81.82%
	Forest	0	1	1	62	0	9	1	74	83.78%
	Shrubland	2	2	0	0	36	0	6	46	78.26%
	Built-Up	1	2	0	0	0	56	0	59	94.92%
	Crop Land	3	7	1	0	0	3	79	93	84.95%
	Column Total	33	41	20	62	38	68	87	449	
	Producer Accuracy	69.70	68.29	90.00	100.00	94.74	82.35	90.80		
	Overall Accuracy = 86.53% Overall Kappa Statistics = 0.8376									

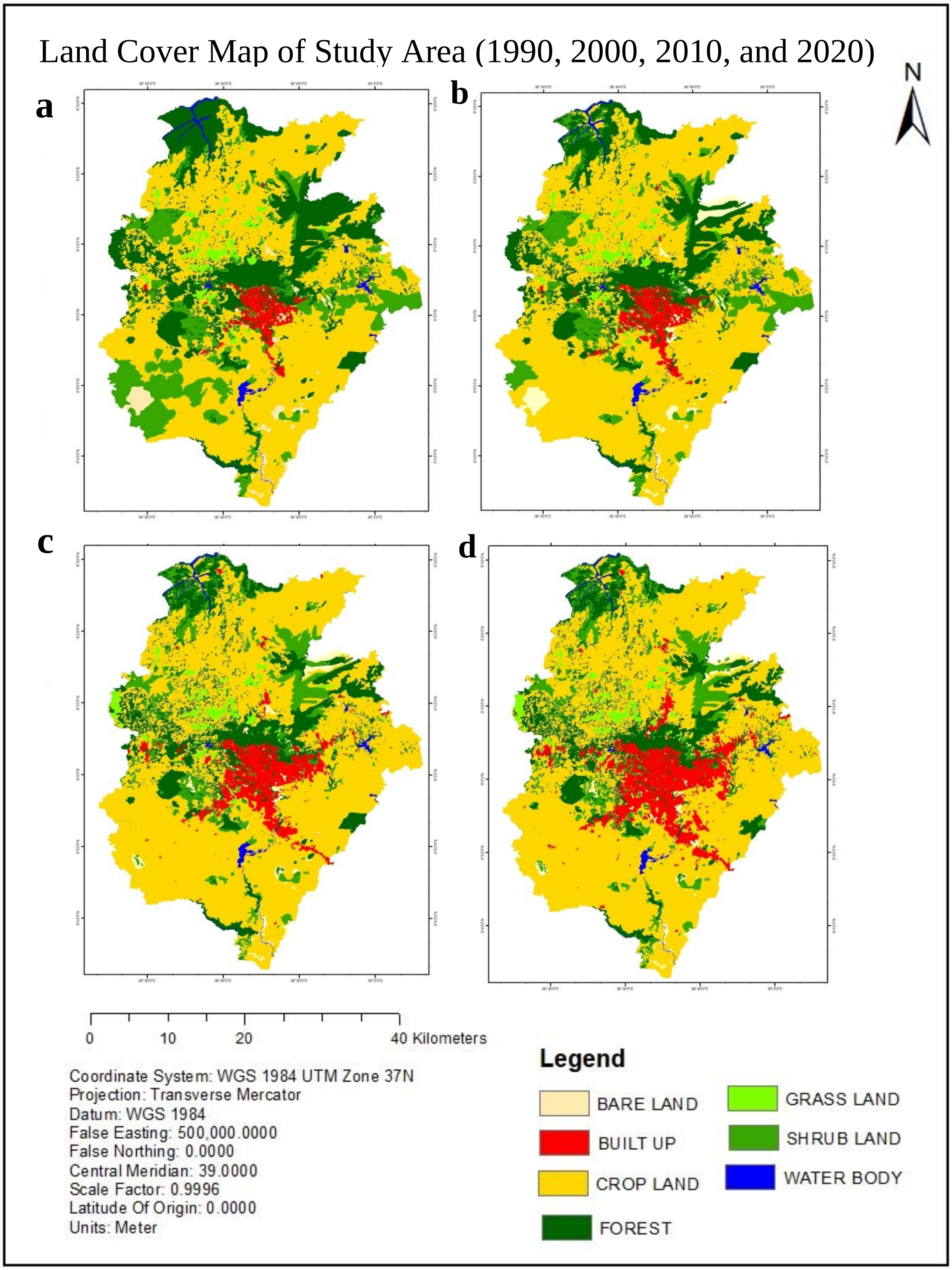


Figure 4. 1 LULC map of study area in 1990 (a), 2000 (b), 2010 (c), and 2020 (d)

4.3. Change Analysis

After the preparation of land use maps, the changes that occurred during the studied periods in each land cover were detected. Over the past decades, land covers in study areas such as forest, shrubland, water body, and bare land were in continuous decline, while cropland and grassland cover types showed a varying pattern. In general, out of the seven LULC types identified in the study area, only one, namely built-up, showed continuous increment over the past 30 years. The extent of change within the study area of the individual land cover categories in square kilometer (km^2) and the percentage they occupied for 1990, 2000, 2010, and 2020 are presented in Table 4.5.

Table 4. 5 Area statistics and Percentage of the land use/cover units from 1990-2020

LULC Types	1990		2000		2010		2020	
	Area (km^2)	%	Area (km^2)	%	Area (km2)	%	Area (km^2)	%
Bare Land	326.56	7	350.81	7	314.17	6	305.8083	6
Grass Land	96.14	2	90.7119	2	94.8375	2	85.3578	2
Water Body	43.32	1	42.9642	1	39.7125	1	36.1332	1
Forest	1074.51	22	902.468	18	784.346	16	729.657	15
Shrubland	670.27	13	512.772	10	404.583	8	406.3482	8
Built Up	118.73	2	177.989	4	308.246	6	460.2618	9
Crop Land	2657.2	53	2909.01	58	3040.83	61	2963.1582	59
Total	4986.73	100	4986.73	100	4986.73	100	4986.73	100

In 1990 the study area was dominated by cropland covering 53% followed by forest land covering 22% of the study area. Built-up, shrubland, water body, bare land, and grassland shared 2%, 13%, 7%, and 2% of the total area respectively. Those areas, which are close to built-up and urban centers, were subjected to significant loss of forest in the last three decades.

Table 4. 6 Overall Amounts and Percentage of Land Cover Change (1990-2020)

LULC Types	1990-2000		2000-2010		2010-2020	
	Change (Δ /Km^2)	(%)	Change (Δ /Km^2)	(%)	Change (Δ /Km^2)	(%)
Bare Land	24.25	7	-36.64	-10	-8.36	-3
Grass Land	-5.43	-6	4.13	5	-9.48	-10
Water Body	-0.36	-1	-3.25	-8	-3.58	-9
Forest	-172.04	-16	-118.12	-13	-54.69	-7
Shrubland	-157.5	-23	-108.19	-21	1.76	1
Built Up	59.26	50	130.26	73	152.01	49
Crop Land	251.81	9	131.82	5	-77.67	-3

Generally, the downward trends observed (Figure 4.2) in the forest, shrubland and bare land, and LULC types during the study period are greater than the other two LULC types that showed a moderate loss, namely, grassland and water body. Most of the area lost from forests, and shrubland was converted to farmland and built-up. Within the study period (1990–2020), the total area of forests, shrubland, and grassland converted to other land cover was estimated at about 381 km ^{2}, 341 km^2, and 10 km^2, respectively. During the same period, cropland and built-up gained about 418 km^2 and 346 km^2. For a better comparison of the changes occurring in these four periods, are shown in Figure 4.2.

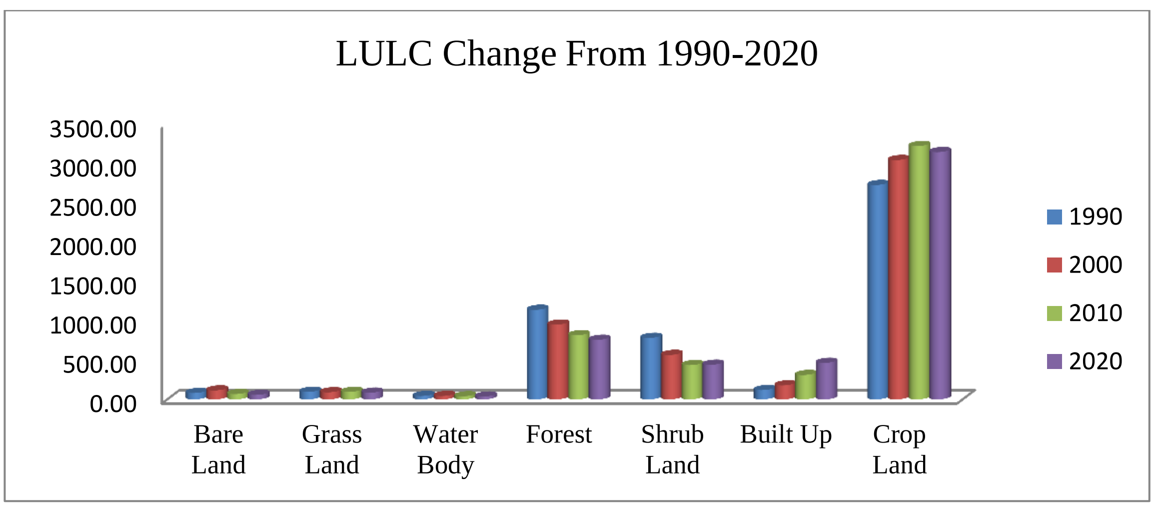


Figure 4. 2 Historical Change Trends of LULC from 1990-2020

4.3.1. Land Use Land Cover Change during 1990–2000

The study observed that during the first period various LULC types were changed into other land cover types. For instance, forest land has lost its predominant position to agricultural land, shrubland, and built-up and maintained its position as the second-largest LULC classes with 19% area cover Land use and land cover trend in the study area. Figure 4.3 revealed that shrubland has been on the decrease recording a reduction of 216 km ^{2} (-5%) in the first period. During the same period, cropland showed a net positive change of 11% with substantial gains from forest land. Likewise, notable expansion in 50% of the total LULC types was observed, particularly in built-up areas.

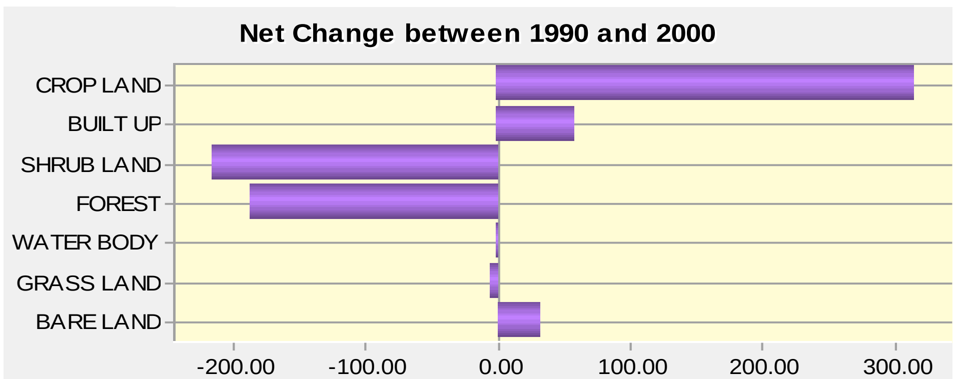


Figure 4. 3 Net Change in LULC from 1990-2000

4.3.2. Land Use Land Cover Change during 2000–2010

The second period witnessed the conversion of LULC types to different land covers. The area of forest declined to the tune of 135 km ^{2} (-14%) in the second period. Likewise, shrubland and bare land declined by 129 km ^{2} (-23%) and 46km^{2} (-41%), respectively. On the other hand, alike the first-period cropland showed an increment of 177km^{2} (6%). In contrast to the previous period grassland gained 5% of its original cover. The most striking change in this period is an increase in the built-up area that revealed a net positive charge of 74%. The trend of changes in the third-period land use revealed a general trend of destruction that was considered except the built-up land cover which showed changes extensively. Figure 4.4 shows the comparison of the net change of land cover during the second period (2000–2010).

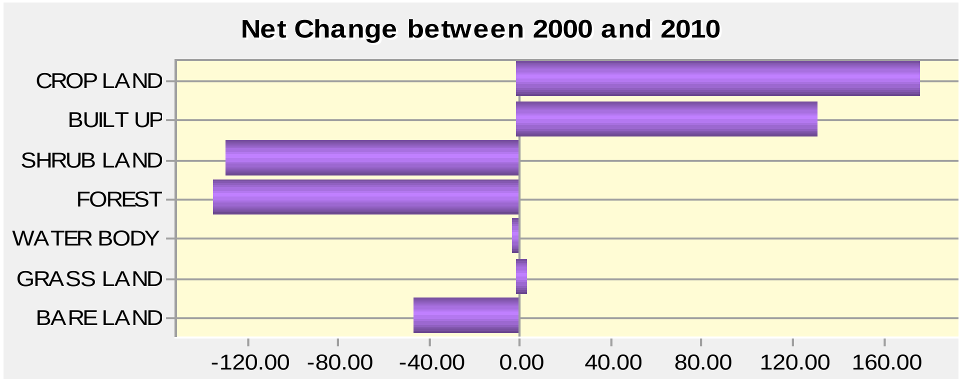


Figure 4. 4 Net Change in LULC from 2000-2010

4.3.3. Land Use Land Cover Change during 2010–2020

The third period was characterized by advanced LULC dynamics where previously intensifying land cover classes such as cropland and grassland declined their net change by -3% and -10% respectively. The built-up area reveals rapid change with a net positive increase of 154.27 km^2 (50%). Hence, the expansion of built-up areas had resulted in a negative change of forest land and croplands. Although shrubland showed a net decline of 28% during the first period and 23% in the second period, in this period it reveals an increment in 5%. Figure 4.5 shows the comparison of the net change of land cover during the third period (2010–2020).

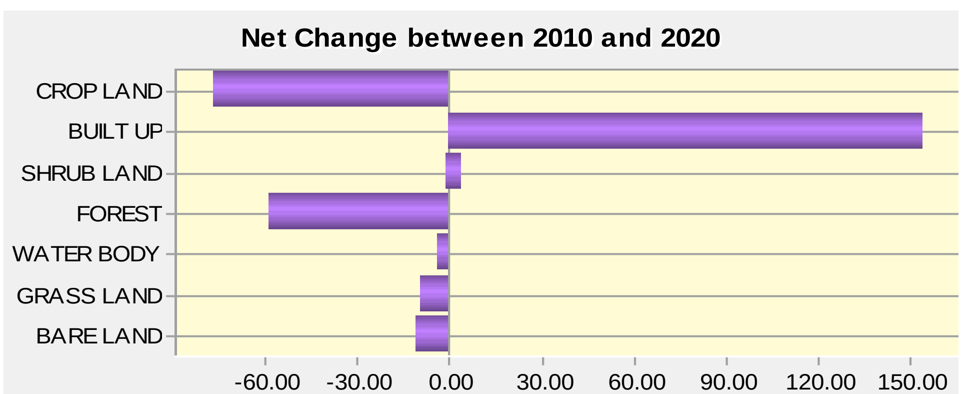


Figure 4. 5 Net Change in LULC from 2010-2020

4.3.4. Land Use Land Cover Change during 1990–2020

Over the course of 30 years (1990–2020), the magnitude and directions of LULC change had become more dynamic. The net change for a forest is negative with varying levels of deforestation during the first and second distinct study periods. This shows a heightened level of deforestation during these periods due to the expansion of built-up area. Due to its small size, the water body did not show significant change but the second and third period was marked decline compared to the first period. A 291% net change of built-up was possibly a triggering factor causing LULC change in the study area, mostly gaining areas from forest land, shrubland, and cropland since the 1990s.

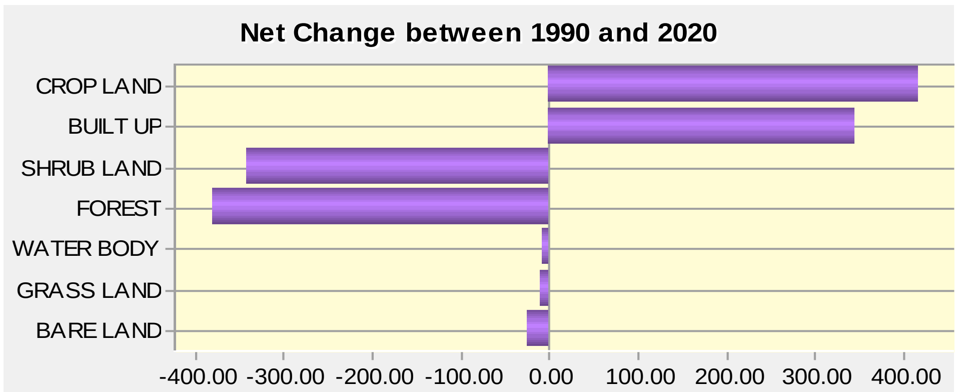


Figure 4. 6 Net Change in LULC from 1990-2020

As shown in Figure 4.6 the change in the area experienced by each land cover class from 1990–2020, the forest area decreased from 22% to 15% while cropland increased from 55% to 63% over the past 30 years. The largest changes from forest and cropland to the built-up area occurred during the second and third periods. The other two affected LULC types were shrubland and grassland. The shrubland decreased from 16% to 9% during the same period. Likewise, grassland lost 11% of its area within the study period. Therefore, the change in LULC can negatively affect the potential characteristics of the area mainly in carbon storage.

4.4. Transition Sub-Models

In the transition potential modelling, of the six sub-models, the Built-up sub-model showed higher accuracy and skill measure compared to other sub-models. Accuracy and skill measure for the deforestation sub-model was 87.25% and 0.8731, respectively, while for the degradation sub-model, observed results are an accuracy and skill measure of 82.99% and 0.8370 (Table 4.7). In the Agricultural intensification sub-model, all the transitions showed a higher skill measure, except the transition from shrubland to cropland which showed relatively lower skill measure (0.7300).

Table 4. 7 Model skill breakdown by transitions

S.No	Transition sub-model	Land Cover Transitions	Skill Measure
1	Agriculture Intensification	Bare Land - Crop Land	0.8866
		Grass Land - Crop Land	0.7850
		Water Body - Crop Land	0.8775
		Shrubland - Crop Land	0.7300
2	Deforestation	Forest- Bare Land	0.9526
		Forest- Grass Land	0.8670
		Forest- Shrubland	0.8478
		Forest- Built-up	1.0000
3	Degradation	Shrubland - Bare Land	0.8522
		Shrubland-Grass Land	0.8591
4	Reforestation	Bare Land – Forest	0.8457
		Grass Land – Forest	0.8619
		Water Body – Forest	0.7832
		Shrubland- Forest	0.8366
		Crop Land- Forest	0.7997
5	Regeneration	Bare Land – Shrubland	0.8006
		Grass Land- Shrubland	0.8290
		Crop Land- Shrubland	0.8160
6	Built-up Intensification	Bare Land- Built-up	0.9758
		Grass Land- Built-up	0.9221
		Shrubland-Built-up	0.8721
		Crop Land- Built-up	1.0000

4.5. Drivers of LULC Change in the Study Area

Cramer's coefficient, which shows the relationship between variables and LULC classes, was calculated, and the results are shown in Table 4.8. In this regard, the study selected those with 0.4 or higher as good, and study included distance from the cropland, digital elevation model, distance from built-up, distance from shrubland, slope, maximum likelihood of change, distance from major road, and distance from forest. Thus, the variables selected in this study, as a dynamic state, were distance to existing built-up areas, distance to major roads, distance to Crop Land, distance to Shrubland, and distance to Forest, whereas, elevation and slope were defined as static variables. The variables distance from road in the urban intensification sub-model and the distance from shrub variable in the degradation sub-model had the highest and lowest Cramer's coefficients with 0.7943, and 0.2108 respectively.

Table 4. 8 Sub-models in the study with associated explanatory variables and performance

Sub-model	Explanatory variables	Cramer's V
Agriculture Intensification	Elevation	0.4213
	Slope	0.3321
	Distance from Crop Land	0.7432
	Distance from Road	0.6934
	Distance from Built-up	0.4572
	Evidence likelihood	0.5834
Deforestation	Elevation	0.3872
	Slope	0.3689
	Distance from Road	0.7854
	Distance from Forest	0.6438
	Distance from Built-up	0.6631
	Distance from Crop Land	0.3201
	Evidence likelihood	0.4302
Degradation	Elevation	0.3187
	Distance from Shrubland	0.2108
	Distance from Road	0.3251
	Evidence likelihood	0.4432
Reforestation	Elevation	0.3568
	Distance from Crop Land	0.4026
	Distance from Road	0.5093
	Evidence likelihood	0.3892
Regeneration	Slope	0.3165
	Distance from Crop Land	0.2992
	Evidence likelihood	0.4679
Built-up Intensification	Elevation	0.3687
	Slope	0.3882
	Distance from Road	0.7943
	Distance from Built-up	0.7743
	Evidence likelihood	0.3679

The result indicated that the changes that occurred between 2000 and 2010 were significant for the modelling and that there is a higher possibility of continued change behavior in the land covers for the future scenario in areas close to those that have already undergone changes in land cover. For the dynamic modelling of land cover, the best training result based on the MLP algorithm, obtained from the iteration of the explanatory variables with the transitions of interest for each sub-model were an accuracy rate more than 80% after 10,000 iterations.

Table 4.9 presents the land cover transition probability matrix of time 2 (2000) for time 3 (2010) obtained by Markov Chain. The results of the diagonal represent the percentages of persistence, while the other results correspond to the percentages of change from one land cover category to another.

Table 4. 9 Matrix of the transition probability of land covers categories for 2000 and 2010

Matrix of the transition probability of land cover categories							
LULC Class	Bare Land	Grass Land	Water Body	Forest	Shrubland	Built-Up	Crop Land
Bare Land	0.0878	0.0011	0.0000	0.0433	0.0221	0.1242	0.7215
Grass Land	0.0001	0.5821	0.0000	0.0219	0.0033	0.1478	0.2449
Water Body	0.0002	0.0050	0.7299	0.0250	0.0192	0.0120	0.2087
Forest	0.0046	0.038	0.0000	0.3838	0.1537	0.0896	0.3304
Shrubland	0.0046	0.0016	0.0000	0.0495	0.1037	0.1040	0.7366
Built Up	0.0000	0.0000	0.0000	0.0012	0.0002	0.9982	0.0003
Crop Land	0.0002	0.0016	0.0000	0.0546	0.0094	0.1117	0.8225

4.6. Model Simulations and Validations

Markov chain model simulations results are based on a transition probability matrix of land-use changes from time 1 (2000) to time 2 (2010). This has become the basis for projection for another time period (2020). Figure 4.7 shows the statistics of actual land cover vs. predicted land cover of 2020. Once the transition potential maps were created with the best possible accuracies, the actual and simulated land cover of the year 2020 through Markov Chain modelling is shown in Figure 4.8 and Figure 4.9.

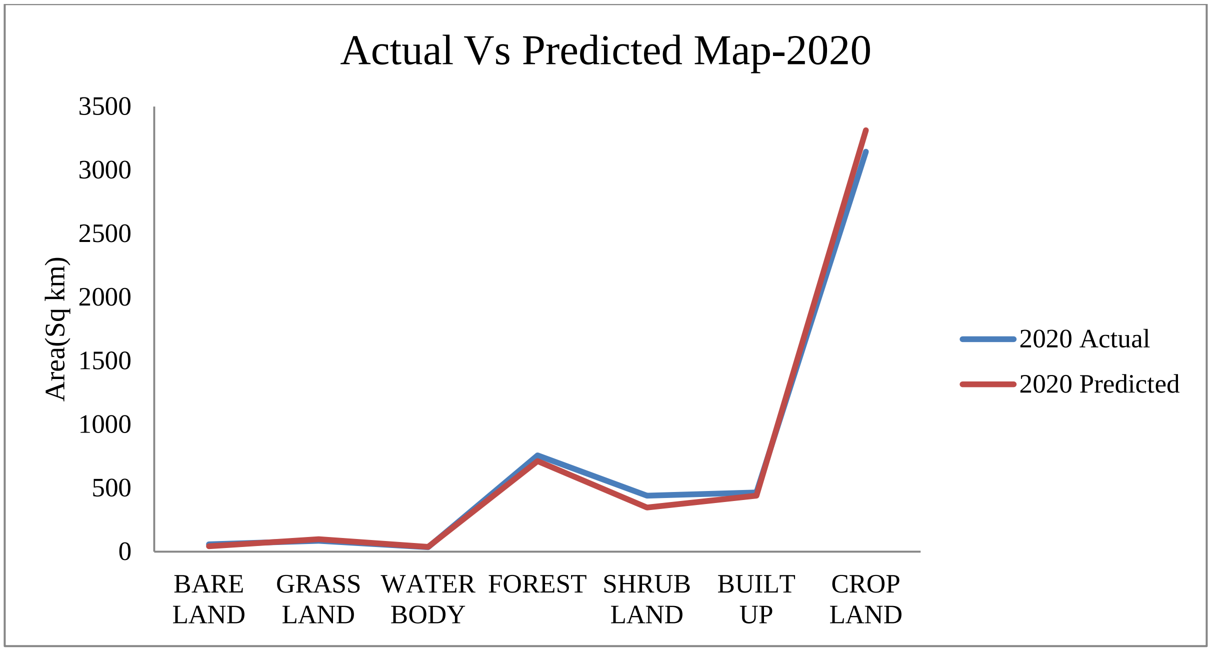
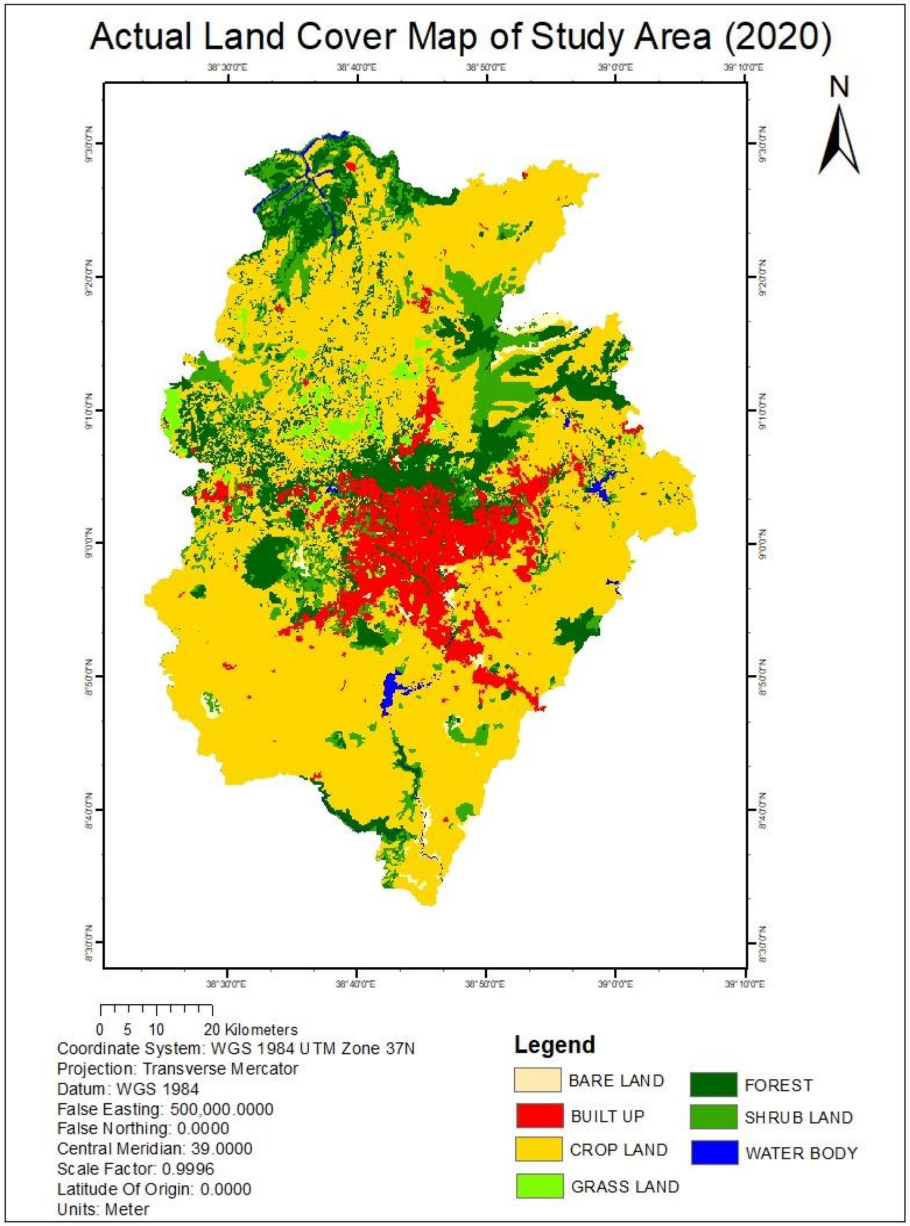


Figure 4. 7 Actual land cover of 2020 Vs. Predicted land cover of 2020

The study obtained values from validating the simulated and actual LULC map of the study area using the first method which was the comparison method of the simulated and actual land cover map was Cramer's V = 0.7833 and a Kappa total= 0.8904. The value attained from, ROC module of IDRISI Terrset AUC value of 0.79. Concerning the model validation based on the κ coefficient for quantity and location was obtained and kappa statistics show that k_{no} is 0.8763, $k_{location}$ is 0.8968, $k_{location\ strata}$ are 0.8968, and $\kappa_{standard}$ is 0.8649 (Table 4.10). Accordingly, the results of the analysis indicate that the variables employed were found to be effective and simulation result is relatively reliable in predicting the future change in LULC.

Table 4. 10 Kappa index, information allocation of simulated and actual LC map of 2020

K Indicators	
K_{no}	0.8763
$K_{location}$	0.8968
$K_{location\ Strata}$	0.8968
$K_{standard}$	0.8649



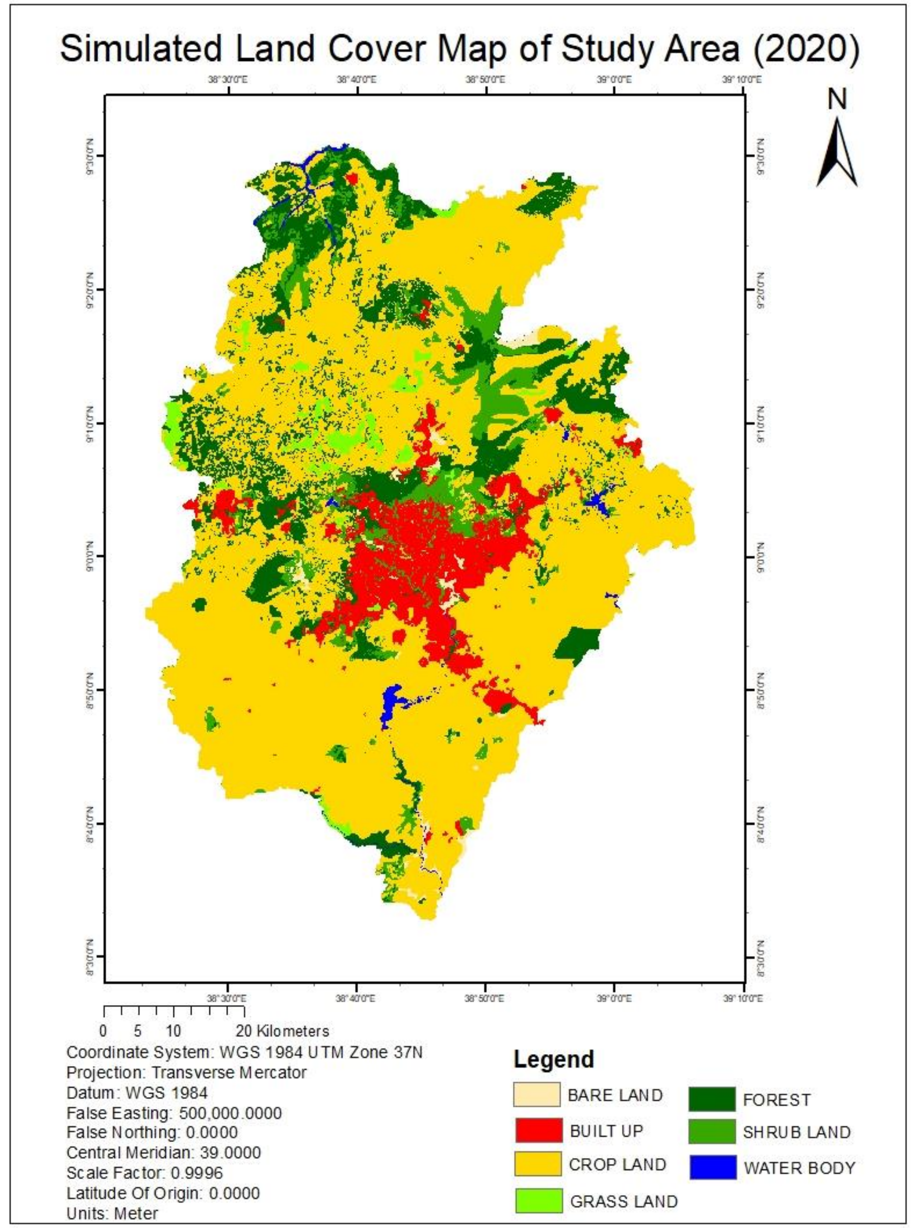


Figure 4. 9 Actual LULC Map of 2020

Figure 4. 8 Simulated LULC Map of 2020

4.7. Scenarios of Land Cover Change

4.7.1. The Business-as-usual Scenario

The result of the B-a-U scenarios in 2050 Figure 4.10 and Figure 4.11 reflects the long-term effect of the observed changes in the past. LULC change analysis between 1990 and 2020 indicates a significant loss of green area within the study area and this is expected to continue and the prediction result also reveals a notable change in the green area in the coming three decades (2020–2050). Built-up areas are predicted to exhibit the largest net increase, followed by cropland by 2050.

Whereas the area occupied by forest exhibits the largest net decrease followed by shrubland in the coming three decades. Under the B-a-U scenario, most of the deforestation and degradation is projected to occur within the study area. This is assumed due to the accessibility factors since some forest areas are located in flat and accessible locations such as built-up areas. More specifically, built-up and cropland are the most probable land use classes that will result in forest and shrubland conversion.

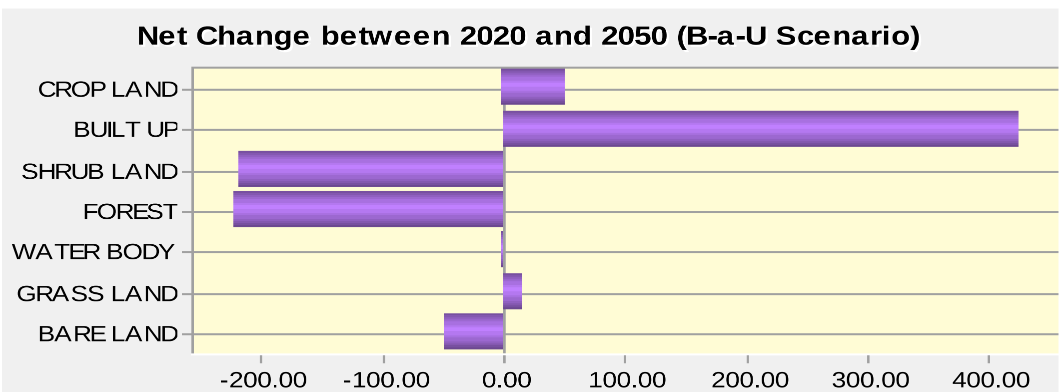


Figure 4. 10 Net Change in LULC from 2020-2050 (B-a-U)

Land conversion to built-up area is expected to happen at the cost of forest land, shrubland, bare land, and other croplands. The total area of forest is expected to notably decrease from 758 sq. km in 2020 to 534.90 sq. km in 2050 under the B-a-U scenario. Similarly, shrubland is anticipated to decrease from 406 sq. km to 221 sq. km, bare land from 305 sq. km to 8 sq. km and other croplands from 2963 sq. km to 3197 sq. km (Table 4. 11). Those areas, which are close to settlement and urban centers, will be subjected to significant loss of forest. The main reason for the conversion is due to high demand for land and it would be easy to convert them due to fewer or no restrictions. Overall, predicted transitions for 2050 seem consistent with previous trends in land use changes experienced between 1990 and 2020.

Table 4. 11 Area statistics and Percentage of the LULC units from 2020-2050

	2020		2050 (B-a-U)		2020-2050	
LULC Types	Area (km^2)	%	Area (km^2)	%	Change (Δ /km^2)	(%)
Bare Land	305.81	6%	8.49	0.17	-297.32	-97%
Grass Land	85.36	2%	100.68	2.02	15.32	18%
Water Body	36.13	1%	33.99	0.68	-2.14	-6%
Forest	729.66	15%	534.9	10.73	-194.76	-27%
Shrubland	406.35	8%	221.49	4.44	-184.86	-45%
Built Up	460.26	9%	890.19	17.85	429.93	93%
Crop Land	2963.16	59%	3196.99	64.11	233.83	8%

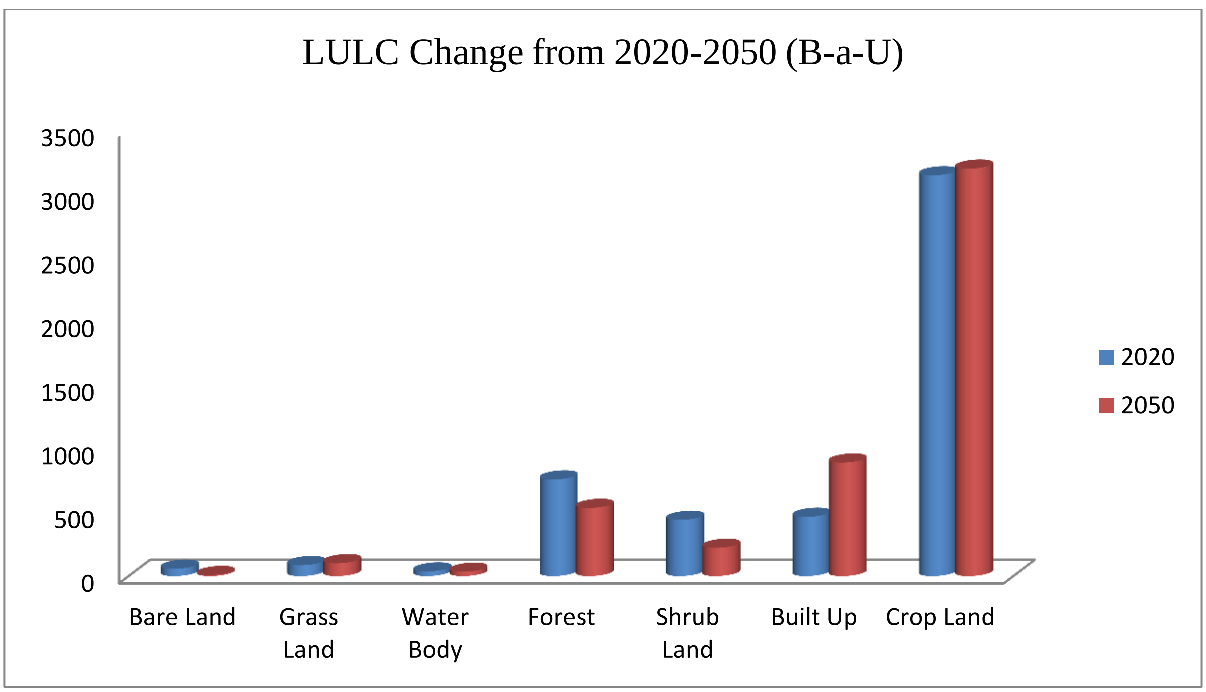


Figure 4. 11 Land use and land cover changes from 2020 to 2050 (B-a-U Scenario)

Figure 4.13 shows the predicted LULC map of study area for 2050 and by then approximately 64% of city will be covered by the cropland area with a total area of 3,197 sq km. The center of the city will be completely covered by built-up area by 2050 except for a few patches of forests due to restrictions. Table 4.12 shows Markov transition probabilities of the probability of changes in 2050. The probability of diagonal cells (Table 4.12) represents areas which remain under the same class.

Table 4. 12 Markov Probability of Changes for 2050

Markov Probability of Changes for 2050							
LULC Class	Bare Land	Grass Land	Water Body	Forest	Shrubland	Built-Up	Crop Land
Bare Land	0.2880	0.0211	0.0000	0.0153	0.0575	0.1163	0.5018
Grass Land	0.0028	0.6658	0.0000	0.0163	0.0009	0.1285	0.1857
Water Body	0.0009	0.0054	0.8160	0.0097	0.0516	0.0001	0.1163
Forest	0.0174	0.0163	0.0007	0.5937	0.1729	0.0559	0.1431
Shrubland	0.0068	0.0013	0.0000	0.0183	0.2956	0.0661	0.6119
Built Up	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Crop Land	0.0031	0.0000	0.0000	0.0236	0.0210	0.0765	0.8947

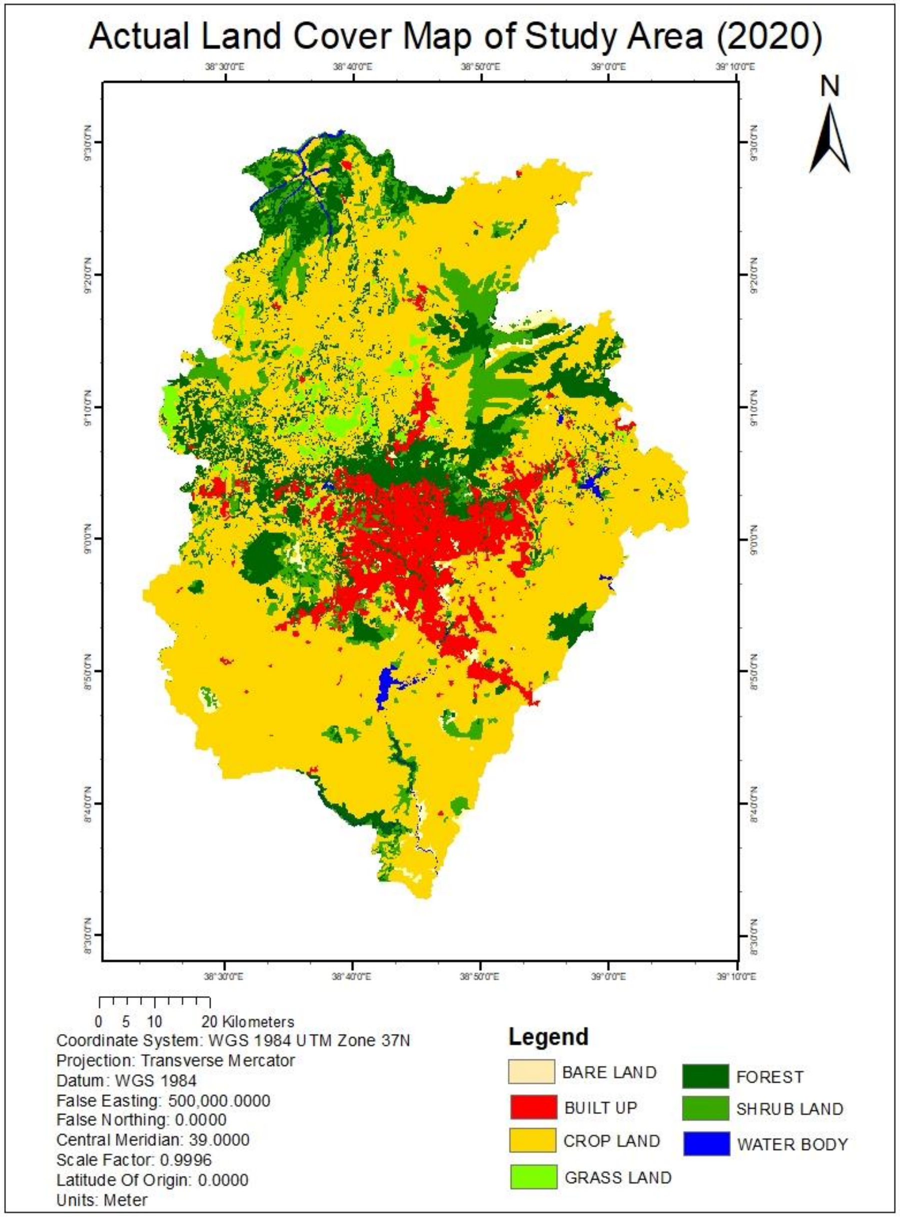


Figure 4. 12 LULC Map of 2020

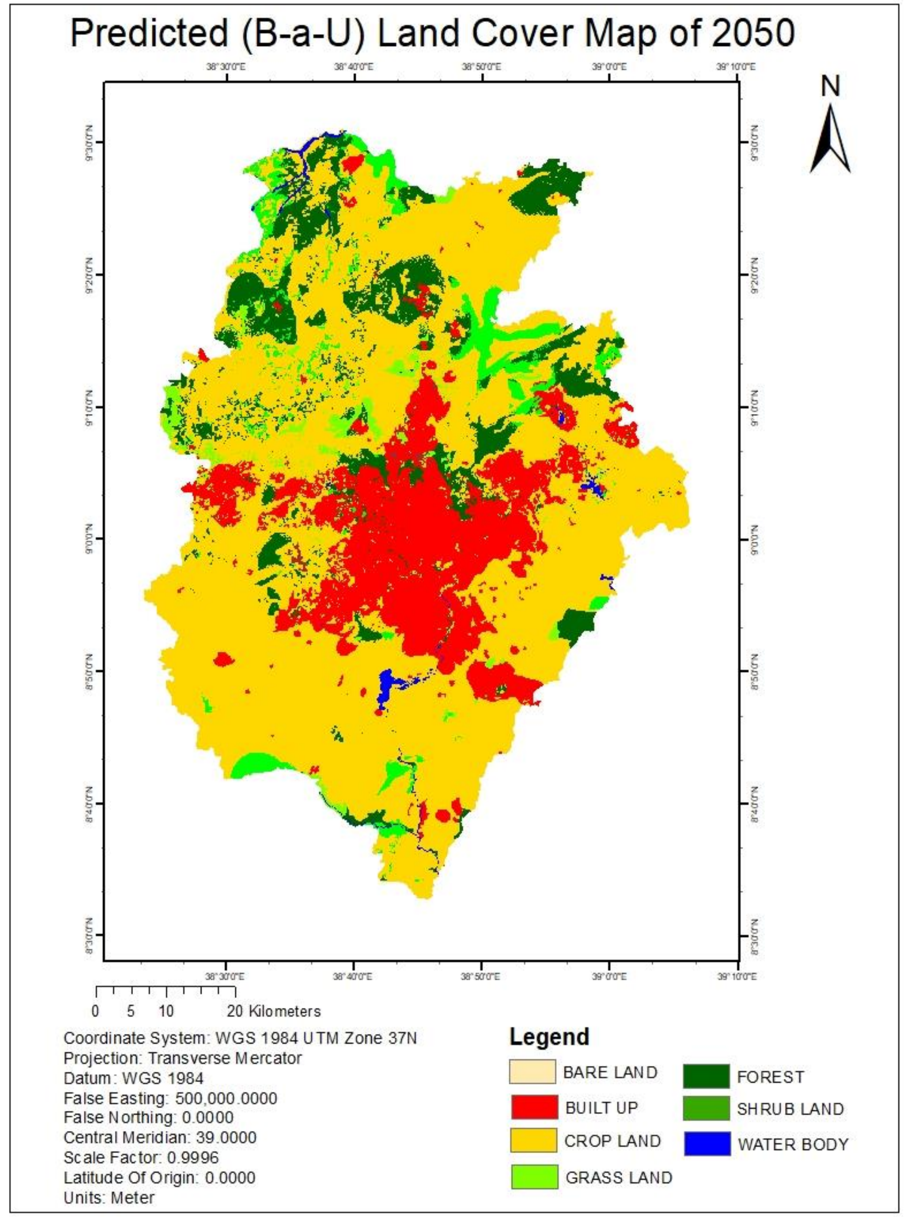


Figure 4. 13 Predicted LULC Map of 2050 (B-a-U)

4.5.2. Ecosystem Conservation (Green) Scenario

Prediction was carried out for 2027 and 2050 (Figure. 4.18 and Figure. 4.19) to understand and compare the impact of short (2027) and long (2050) term planning effects on land cover changes in forest cover. The green scenario in 2027 results in the increase of forest area as a result of the loss of permanent croplands by the end of the planning period (2027). Forest land and grassland are expected to gain 110 sq. km and 13 sq. km as a result of the planning whereas, shrubland and cropland are anticipated to decrease by 113 sq. km and 112 sq. km. (Figure 4.14) reveals that built-up area is predicted to increase markedly from 9% to 12%.

Typically, over the green scenario, the study observed an increase in forest land and modest grassland while a decrease of shrubland and cropland are observed. The green scenario favors the expansion of plantation areas, which are allowed inside current cropland and shrubland areas. This factor increases the expansion of forest land along cropland area compared to the BAU Scenario.

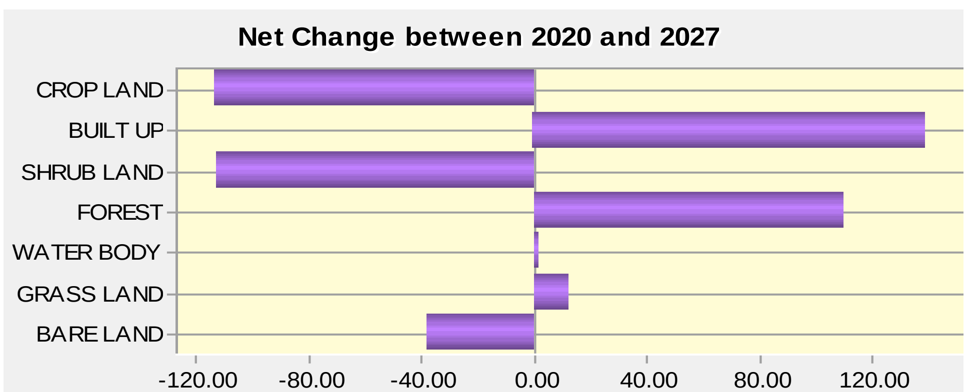


Figure 4. 14 Net Change in LULC from 2020-2027

The prediction analysis shows that the areal extent of the Forest land between 2027 and 2050 will be decreased from 868 sq. km (17%) to 741 sq. km (14%). This shows that the forest land will decline by 15% between 2027 and 2050. The predicted future LULC as shown in Figure 4.15 indicated the expansion of cropland from 61% in 2027 to 62% in 2050. Built-Up land cover classes would increase from 604 sq. km (12%) to 794 (16%) at the expense of crop land and shrubland. The results also revealed that shrubland and bare land will reveal decrement by 28% and 58 % between the same period. Grassland will experience an increasing trend from 1.9% in 2027 to 2.1% in 2050.

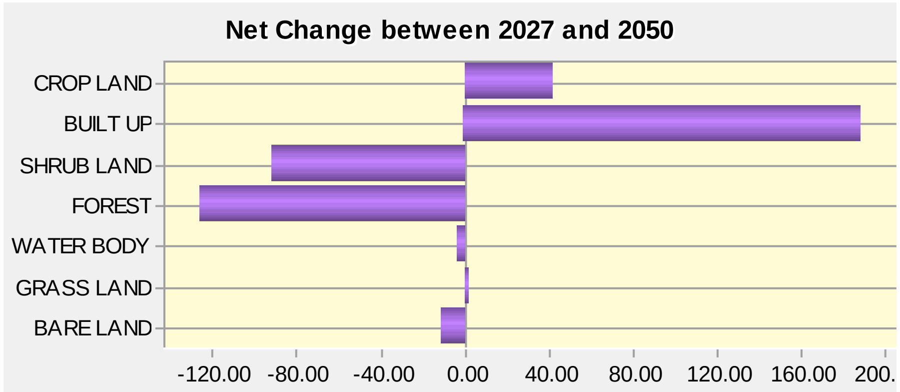


Figure 4. 15 Net Change in LULC from 2027-2050

Generally, the results of the green scenario in 2050 reflect the long-term effect of the planning within the study area. As shown in Figure 4.16 forest land, agricultural land, bare land, and shrubland are expected to decline in the coming decades (2020-2050). Shrubland and cropland will reveal decrement by 46 % and 2% by the end of 2050. Forest land is anticipated to decline by 126.34 sq km (14.6%) between 2020 and 2050 with predictions showing significant increase between 2020 and 2027, followed by a remarkable decrease from 2027 to 2050. The built-up area is predicted to continue increasing at a slightly higher rate between 2020 and 2027 and is expected to fairly increase between 2027 and 2050. However, increasing rate of built-up area in green scenario is lower compared to the B-a-U scenario. Table 4.13 and Figure 4.17 list the area statistics for both stages (2027 and 2050).

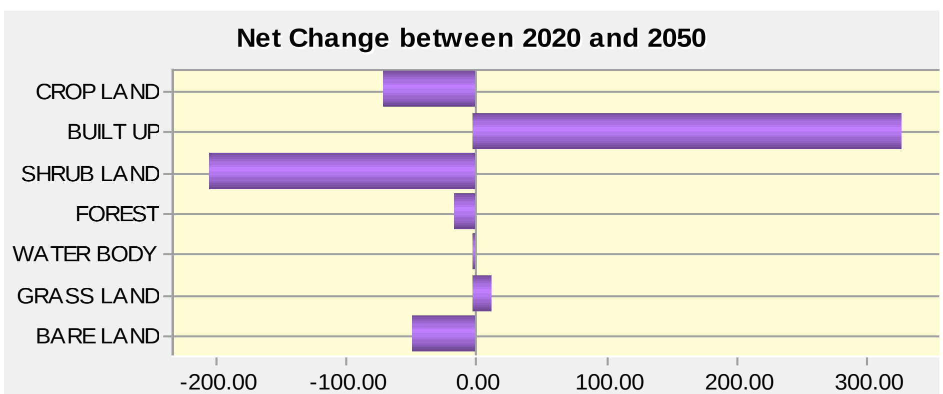


Figure 4. 16 Net Change in LULC from 2020-2050

Table 4. 13 Area statistics and Percentage of the land use/cover units from 2020-2050

LULC Types	2020		2027		2050		2020-2027		2027-2050		2020-2050	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Change (Δ /Km^2)	(%)	Change (Δ /Km^2)	(%)	Change (Δ /Km^2)	(%)
Bare Land	305.81	6	19.55	0.39	8.17	0.16	-286.26	-94	-11.38	-58.2	-297.64	-97
Grass Land	85.36	2	98.29	1.97	100.14	2.01	12.93	15	1.85	1.9	14.78	17
Water Body	36.13	1	37.68	0.76	33.8	0.68	1.55	4	-3.88	-10.3	-2.33	-6
Forest	729.66	15	868.13	17.41	741.79	14.88	138.47	19	-126.34	-14.6	12.13	2
Shrubland	406.35	8	327.92	6.58	235.82	4.73	-78.43	-19	-92.1	-28.1	-170.53	-42
Built Up	460.26	9	604.39	12.12	793.83	15.92	144.13	31	189.44	31.3	333.57	72
Crop Land	2963.16	59	3030.77	60.78	3073.19	61.63	67.61	2	42.41	1.4	110.03	4

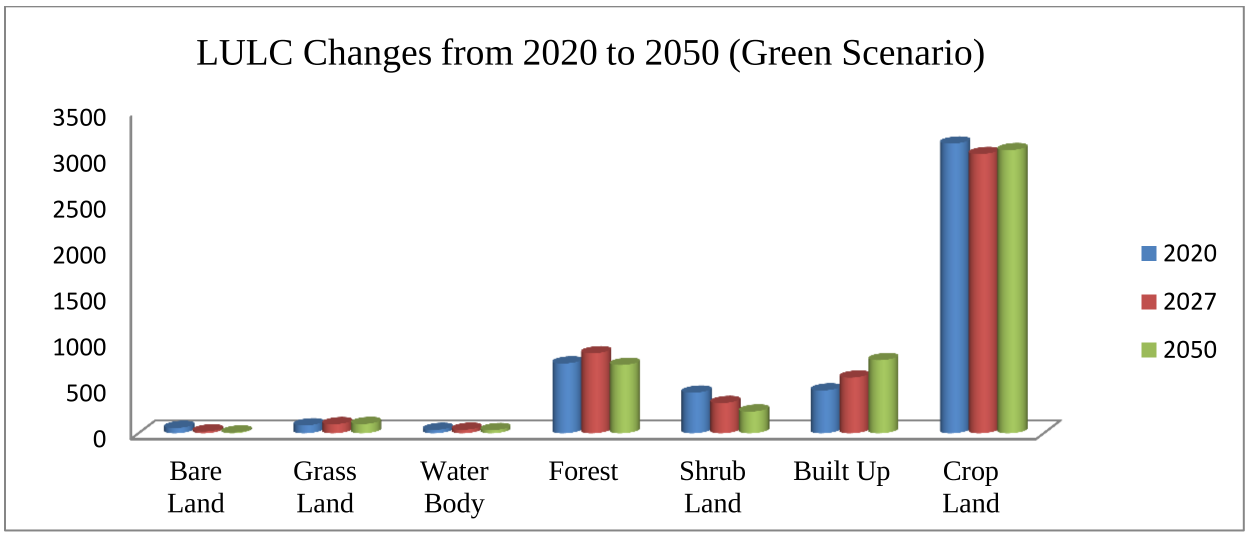


Figure 4. 17 Land use and land cover changes from 2020 to 2050 (Green Scenario)

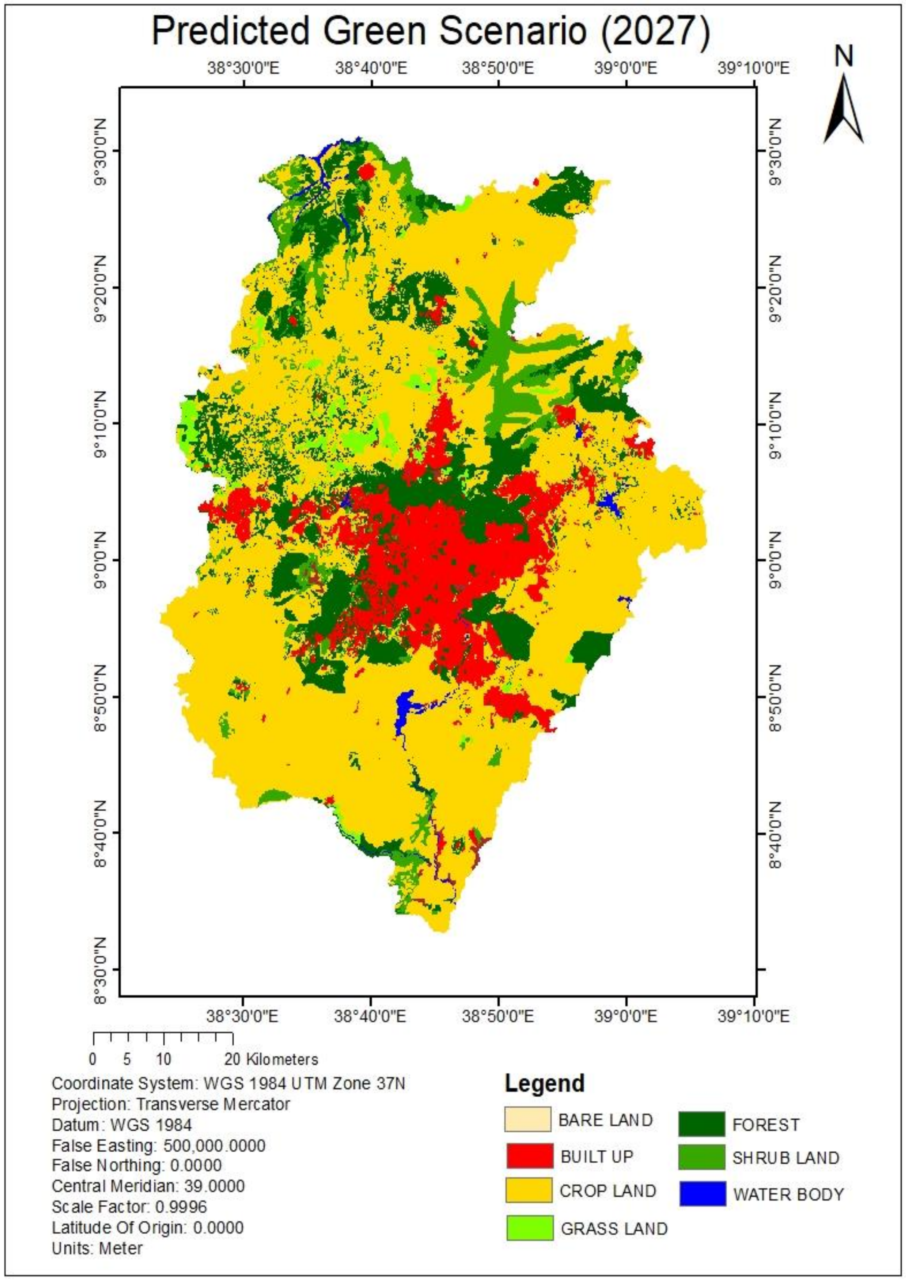


Figure 4. 18 Predicted LULC Map of 2027

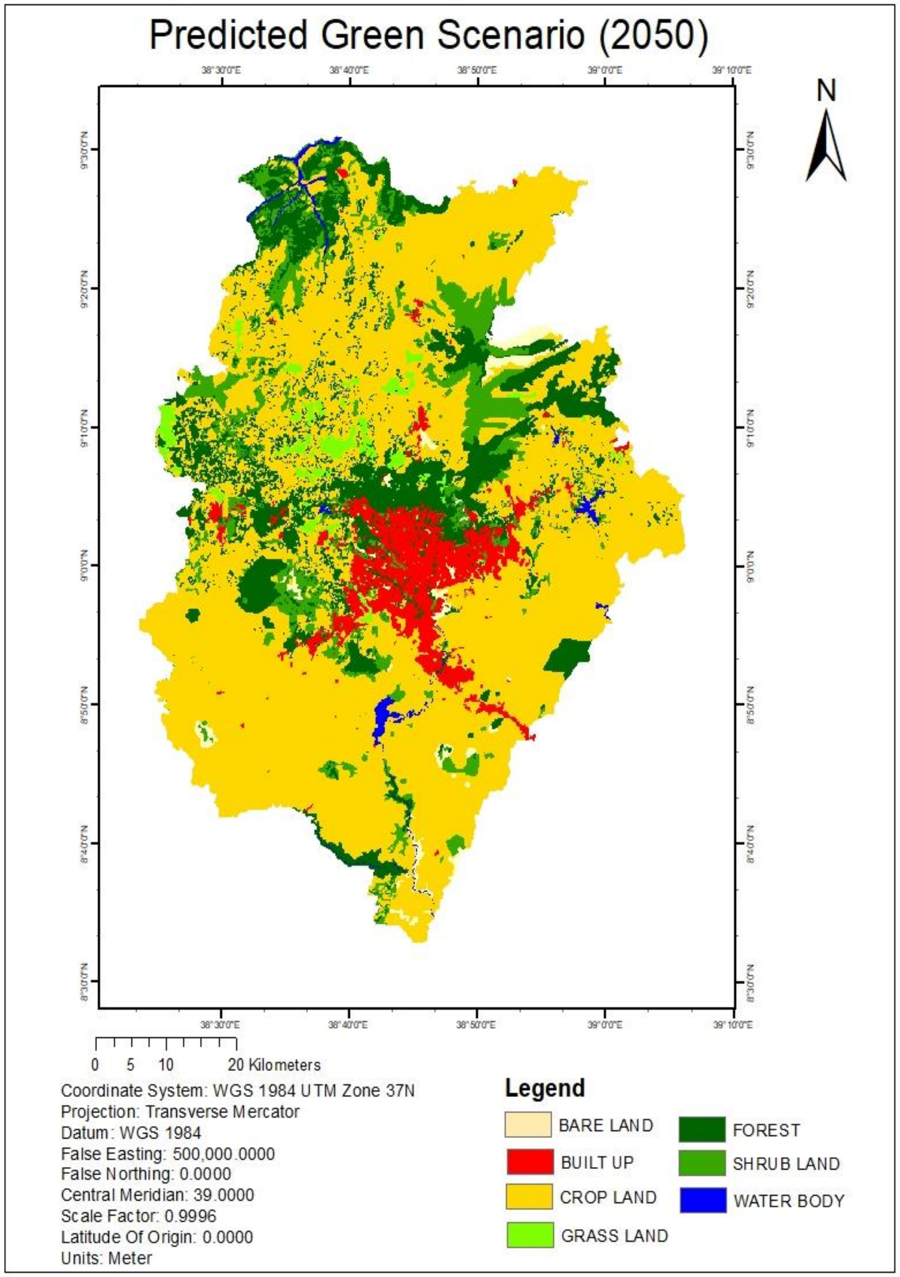


Figure 4. 19 Predicted LULC Map of 2050

4.8. Carbon Storage

Results obtained with the InVEST model revealed that the current total carbon storage in the study area is 39.1 Tg C. Based on the presented results, the largest contribution came from carbon stored in soil (48%), followed by aboveground biomass (40%), belowground biomass (10%), and the C stored as deadwood (2%). The total average carbon stock of Forest land, shrubland, grassland, cropland, bare land, and built-up resulted 152.68 Mg C ha $^{-1}$, 124.98 Mg C ha $^{-1}$, 86.81 Mg C ha^{-1}, 68.32 Mg C ha^{-1}, 51.1 Mg C ha^{-1}, 10.22 Mg C ha^{-1} respectively. Generally, forest land had higher total carbon stock followed by shrubland, grassland, cropland, and bare land and built-up in this study.

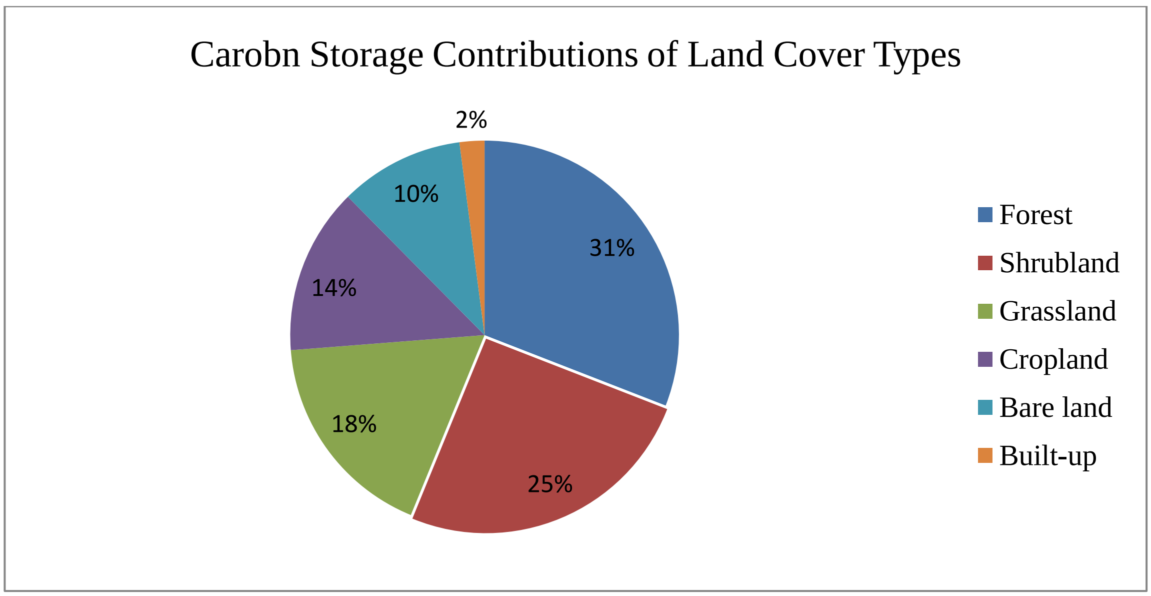


Figure 4. 20 Carbon Storage Contributions of Land Cover Types in the Study Area

Over the coming three decades, carbon storage results show that the current carbon storage of the study area (39.1 Tg C) will be decreased to 33.6 Tg C in 2050 under the B-a-U scenario. According to the green scenario, carbon storage of the study area will be increased to 40 Tg C by the end of the planning period (2027) as a result of reforestation and regeneration of forest and green area. Correspondingly, by the end of 2050 observed result depicts carbon losses (36.99 Tg C) for the whole area since the predicted land cover map represents the reduction of green area.

Carbon sequestration value calculated based on the B-a-U scenario for the time period 2020–2050 compared to the baseline 2020 depicts that the total carbon sequestered under the B-a-U scenario will be -5.5 Tg C. Under the green scenario the amount of carbon sequestered expected to grow between 2020 and 2027 due to the greenery planning is 0.9 Tg C however, the result observed from the long-term effect of the greenery planning revealed that the amount of carbon to be sequestered is -2.11 Tg C between 2020 and 2050. According to the observed results, the model shows a similar trend of carbon stock decline in the study area due to the conversion of forest land, shrubland, grassland, and cropland covers into built-up areas LULC classes.

4.9. Discussion

The current study performs the analysis of LULC change in 1990 to 2020 and predicted future land cover map that provides an answer to the research question of LULC change trend in the past three decades and where LULC changes are expected to occur in 2050 under the B-a-U scenario and Green scenario. Formerly, depending on the current and predicted land cover map the carbon storage and sequestration level of the study area were anticipated.

4.9.1. Land Use Land Cover Change Dynamics

The study area practiced downward trends in most of the LULC types during the study period whereas the two LULC types that showed a minor loss, namely, grassland and water body, while built-up is the only land cover that showed surpassing expansion along the past three decades. This implies that there has been continuous deforestation and degradation in the study area during the past three decades driven by an increment of built-up, expansion of small-scale agriculture, and overgrazing. The most common understanding of the use of change analysis is to provide relevant data on changes concerning extent, trend, location, and how the change was distributed spatially. Hence, the study is important to indicate the trend of land cover change pertaining to enhance the prediction of future land cover.

According to the spatial trend between 1990 and 2020 most deforestation and degradation of the green area were triggered by expansion of built-up area. Similar findings were reported by Deribew and Dalacho (2019), Girma et al. (2019), and Mohamed et al. (2019) and their findings revealed a substantial decline in forest, shrubland as well as that cropland expansion is also affected by the expansion of built-up areas in Addis Ababa and the surrounding Oromia Special zone, respectively. Mohamed et al. (2019) contend that built-up areas are considerably increasing at the expense of forest land and cropland. Moreover, degradation mainly occurred around forest lands because of their proximity to built-up area. Therefore, it could be considered that one of the most important reasons for the increasing of environmental degradations within the mentioned period is pressures resulting from the expansion of built-up and cropland expansion.

While predicting future land cover study implemented two different scenarios namely the business as usual (B-a-U) scenario and green scenario. The results from implementing the B-a-U imply that B-a-U scenario would benefit from being better designed: as the so-called "trend" scenario, because it is path-dependent approaches (Ballatore et al., 2020), therefore, it can be argued that it would be more efficient to build it on the basis of a more in-depth understanding of the trends.

Pertaining to the green scenario the study emphasize the need to integrate greenery planning data in predicting the future LULC considering the possibility that the coming decades will be characterized by the implementation of accessible greenery planning data. Therefore not only the spatial change trends are the case while predicting future land cover under the green scenario.

The prediction result referring to the Business as Usual (B-a-U) scenario shows a substantial change in LULC classes in the coming three decades (2020-2050). The total area of forest land and shrubland are expected to significantly decrease by -30% and -50% in 2050 under the B-a-U scenario. The green scenario indicates an increase in forest land roughly by 19% in 2027. However compared to the B-a-U scenario, the green scenario has less impact on the landscape in the long run, since the result of the green scenario in 2050 reflects the long-term effect of the planning within the study area.

4.9.2. Carbon Storage and Sequestration

Addressing the results from the analysis of carbon stock, the assessment depends greatly on the accuracy and reliability of estimates of carbon stock for a given land-use type. Although producing accurate estimates is a challenge due to several factors including seasonal fluctuation, the InVEST model uses absolute values for simplified results not considering seasonal fluctuation and feedback mechanism (Sharp et al., 2018). Nevertheless, the model result is still relevant in relative terms, as it allows comparison of biomass and soil carbon stock in different categories of land use and makes it possible to quantify losses in carbon stock.

Land cover change is of global importance because of its major implications for changes in carbon stocks. The study used a wide range of land cover types such as forest land, shrubland, grassland, cropland, bare land, and built-up. (Yohannes, 2015; Tura and Eshetu, 2013) contend that higher carbon stock is found in forest land cover, similarly, in line with current study result Belay et al. (2018) indicated that grassland, cultivated land, and bare land have a great impact on carbon storage.

The result of carbon stock in land cover types are comparable to Solomon et al. (2018) who conducted 181.78 Mg ha^{-1} for forest land, 108.77 Mg ha^{-1} for grassland, and 76.54 Mg ha^{-1} for cropland found in the Tigray region. The variation in carbon stock in land cover types across the specified researches might be due to the dissimilarity of the regions, variation in density of each land cover type and variations in climate conditions. This assertion is supported by the study conducted by Belay et al. (2018) who suggested that the region and climate condition are factors for determining carbon stock capacities.

The total carbon stock results show that the current carbon stock of the study area is 39.1 Tg C. The study observed that future land cover is expected to decrease in carbon stock since resulted negative values indicate carbon loss as a result of reduced forest land, shrubland, and grassland under the B-a-U scenario. Furthermore, since forest land plays a key role in storing abundant carbon and provides ecosystem services, future planning in 2027 was considered to forecast the green scenario that resulted an increment of 0.9Tg C carbon stock. However, since the reduction in forest area is expected in 2050 induced by the deforestation and degradation trends in the previous three decades, reduction in carbon stock is anticipated.

In agreement with the present study, earlier studies have shown that land cover change is a major factor in carbon stock changes. For example, Hernández et al. (2019) observed a net loss of -45 Tg C in Mexico from 2017 to 2050. Similarly,(C. Li et al., 2018) forecasted that only the changes from cultivated and vegetation lands to built-up land between 2015 and 2025 leads to carbon storage losses of -3.527 Tg and -0.126 Tg, accounting for 96.55% and 3.45% of the total storage loss, respectively in Xuzhou, China. Therefore, arguably the changes in LULC thus cause a significant environmental effect such as decrease in carbon storage.

CHAPTER V: CONCLUSION AND RECOMMENDATION

The current study aimed to analyze and predict the dynamics of LULC of Addis Ababa and its surrounding Oromia Special Zone with the objective of modelling the carbon storage level over different types of LULC in the area. Based on the quantitative analysis of LULC of the study area using LCM and Integrated Valuation of Environmental Services and Tradeoffs (InVEST) Model, the study of assessing the impact of land use and land cover change on carbon storage and sequestration: A Case of Addis Ababa City and Surrounding Oromia Special Zone concludes the following stopping points and recommendations on the study.

5.1. Conclusion

The current study discussed on the impact of LULC change on carbon storage and sequestration. Land use and land cover changes have a wide range of consequences at all spatial and temporal scales. As a result of these effects and influences, environmental change and the conservation of natural resources have become one of the key challenges. Thus, analyzing the dynamic relationships between changes in LULC and its drivers over time and space is a key to understand the nature, trend and extent of changes in LULC in order to predict future land cover and create alternative scenarios to reduce environmental challenges.

Based on the findings of the study considerable LULC change rates have been recorded within the study area in the past three decades as a result of the rapid expansion of the built-up area along the forest land, shrubland and croplands. If this trend is expected to continue in the coming decades, the consequences will be substantial environmental degradation unless proper measures will be taken.

LULC types within the study area have significance carbon storage capacity. Although there was variability in total carbon stocks among the land cover types in the study area, the study indicates that land cover types found in the study area other than forest land are significant to store carbon. Accordingly, this could be baseline information for planning authorities so that they promote balanced planning incorporating other land cover types since they have significant contribution to store carbon.

Generally, the results of the study confirm that changes in land cover have an effect on carbon stocks, with carbon stocks declining under the B-a-U scenario in 2050s. Similarly, the green scenario has less impact on the landscape in the long run (2050). This can be an implication for promoting further planning aimed at reducing environmental degradation practiced within the study area.

Finally, the threat these results highlight is the impact of LULC change on carbon storage. The study thus has built on earlier work (Deribew & Dalacho, 2019; Mohamed & Worku, 2019) as a first step in assessing the impact of future land cover change of carbon storage and sequestration.

5.2. Recommendations

The findings of this particular study have shown that remote sensing, GIS and land-use models are useful tools for studies of land use and land cover change. The following are also recommended as potential research recommendations, based on the results of the study:

- One of the results noticed in this study was the major LULC changes triggered by rapid expansion of built-up areas. Therefore, a proper planning should be implemented by considering green area development to overcome the challenges of land surface temperature increase, with the increase of the built-up area.
- The carbon stock in all land cover types in the present study area is significant therefore; including other land cover types different from forest land during carbon storage estimation is recommendable.
- Since observed result a decline of carbon storage in the future, potential policy measures should be taken to reduce the negative effects of land use change on carbon stocks within the study area.
- A holistic approach needs to be adopted for increasing the major carbon stocks (vegetation cover) in the urban and peri-urban areas in order to alleviate effect of the environmental degradation occasioned by rapid urban land cover change in the study area. This can be achieved through various means such as planting of more trees, especially on sidewalks in the residential areas and on public/private properties.
- Similar research needs to be conducted in areas of experiencing rapid land cover change contribute new insights on the dynamics of land cover changes and their impact on carbon storage at national level.

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APPENDICES

Appendix I Potential matrix between land covers in the studied periods (sq. km)

Table 1.1 Potential matrix between land covers from 1990 to 2020

The Periods	LULC Type	Bare Land	Built-Up	Crop Land	Forest	Grassland	Shrubland	Water Body
1990-2000	Bare Land	98	20	103	34	0	29	28
	Built Up	0	82	32	292	11	59	0
	Crop Land	26	128	418	706	20	148	27
	Forest	28	364	1117	1648	36	484	22
	Grass Land	1	70	82	94	98	15	3
	Shrubland	16	134	306	451	19	357	16
	Water Body	41	0	50	102	2	60	25
2000-2010	Bare Land	118	18	35	56	0	18	0
	Built Up	19	213	110	349	42	90	1
	Crop Land	12	208	1102	1207	47	288	12
	Forest	25	548	881	2193	54	483	17
	Grass Land	0	66	59	90	82	6	2
	Shrubland	9	164	314	560	12	724	7
	Water Body	0	2	19	40	3	32	17
2010-2020	Bare Land	153	25	25	18	3	16	4
	Built Up	12	277	206	488	41	130	1
	Crop Land	52	587	1405	758	59	251	15
	Forest	22	1013	818	2889	63	423	46
	Grass Land	1	80	71	75	132	11	1
	Shrubland	16	200	272	371	10	893	9
	Water Body	11	2	15	53	3	56	63

Appendix II Driver variables

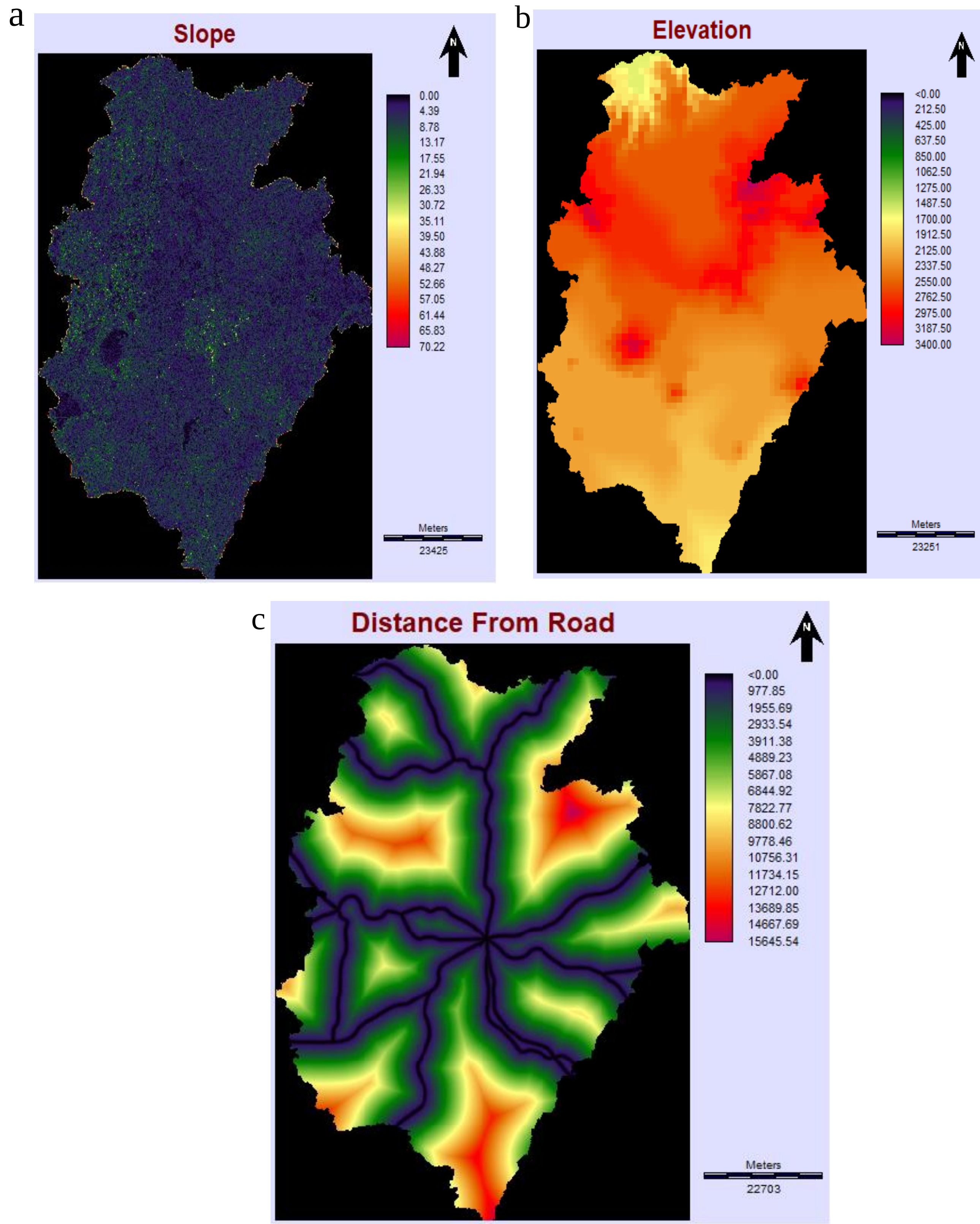


Figure 1.5.2.1 Driver Variables; (a) Slope, (b) Elevation, (c) Distance from Road

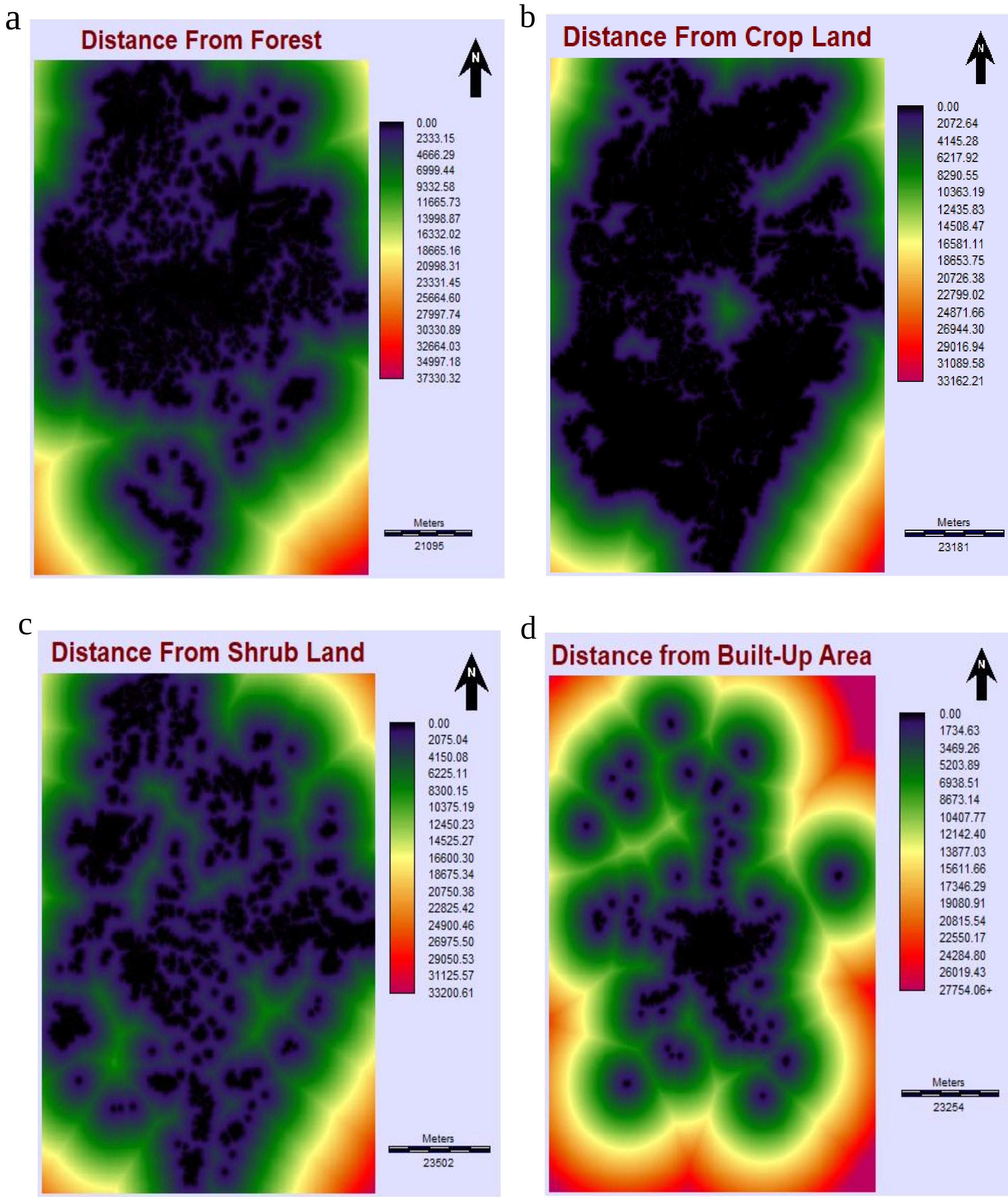
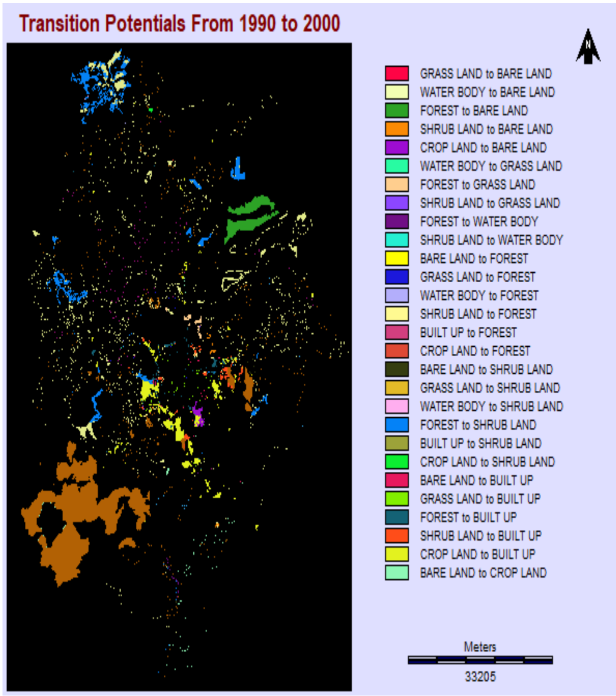


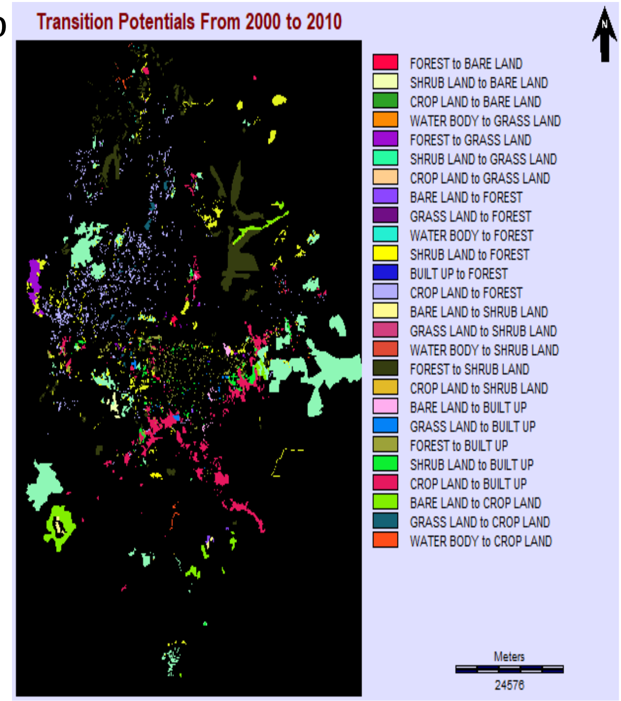
Figure 1.2 Driver Variable (a) Distance from Forest, (b) Distance from Cropland, (c) Distance from Shrub Land, (d) Distance from Built-up

Appendix III Transition Potentials

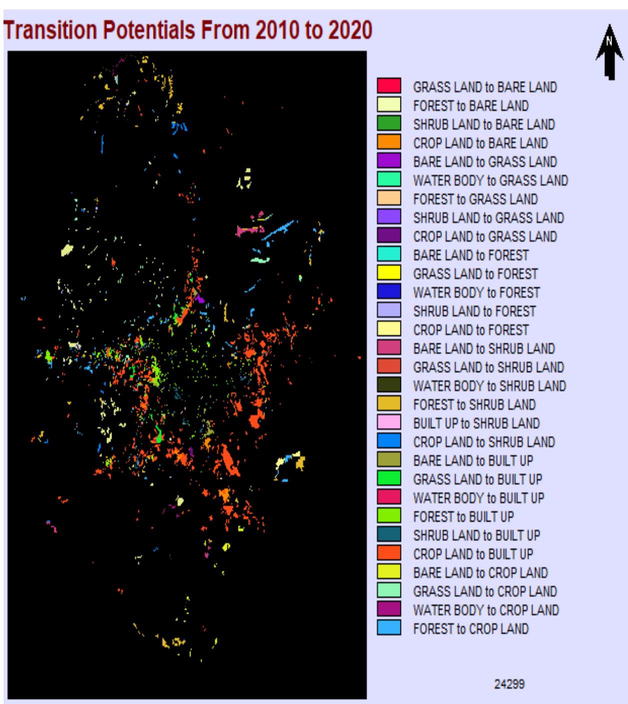
a



b



c



d

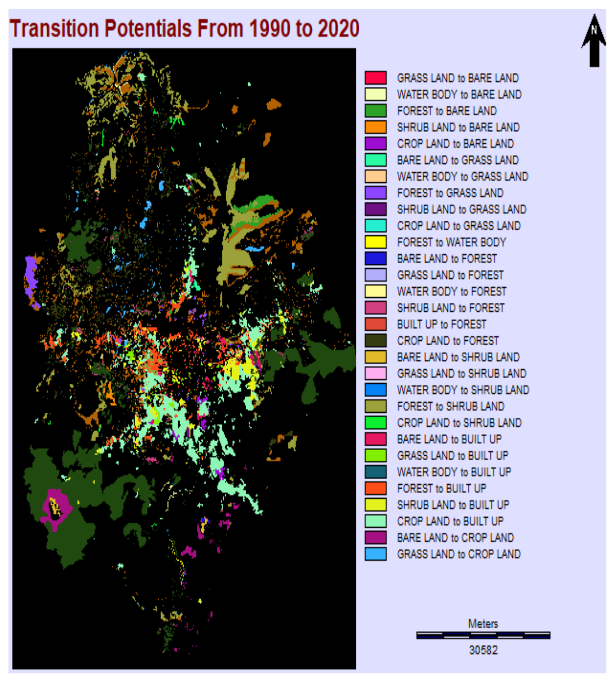


Figure 1.3 Transition Map from (a) 1990-2000, (b) 2000-2010, (c) 2010-2020, (d) 1990-2020

Appendix IV Structural plan of towns within the study area

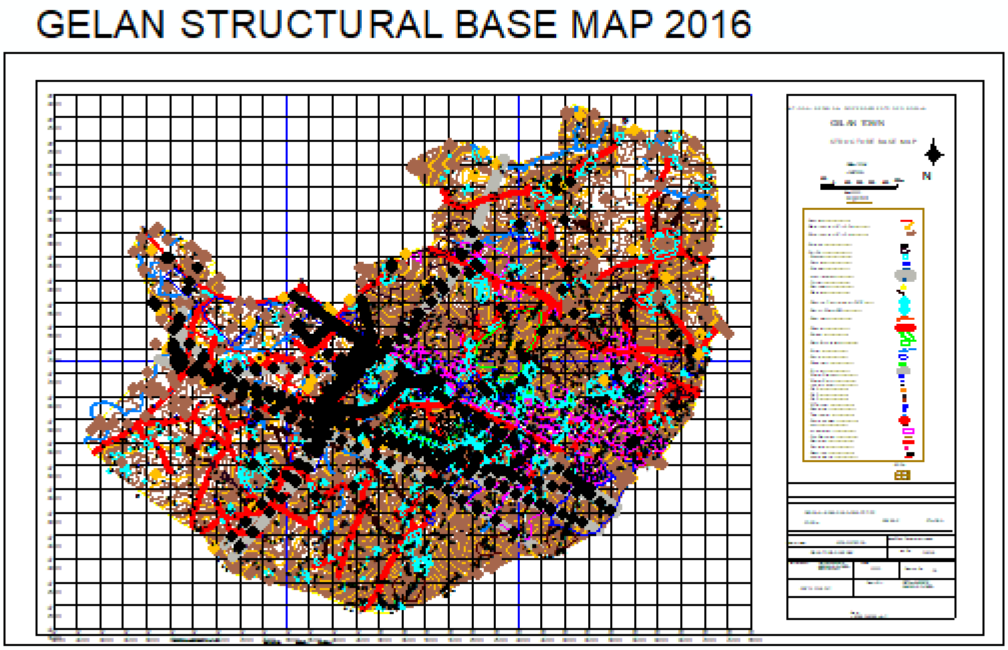


Figure 1.4 Structural Plan Map of Gelan

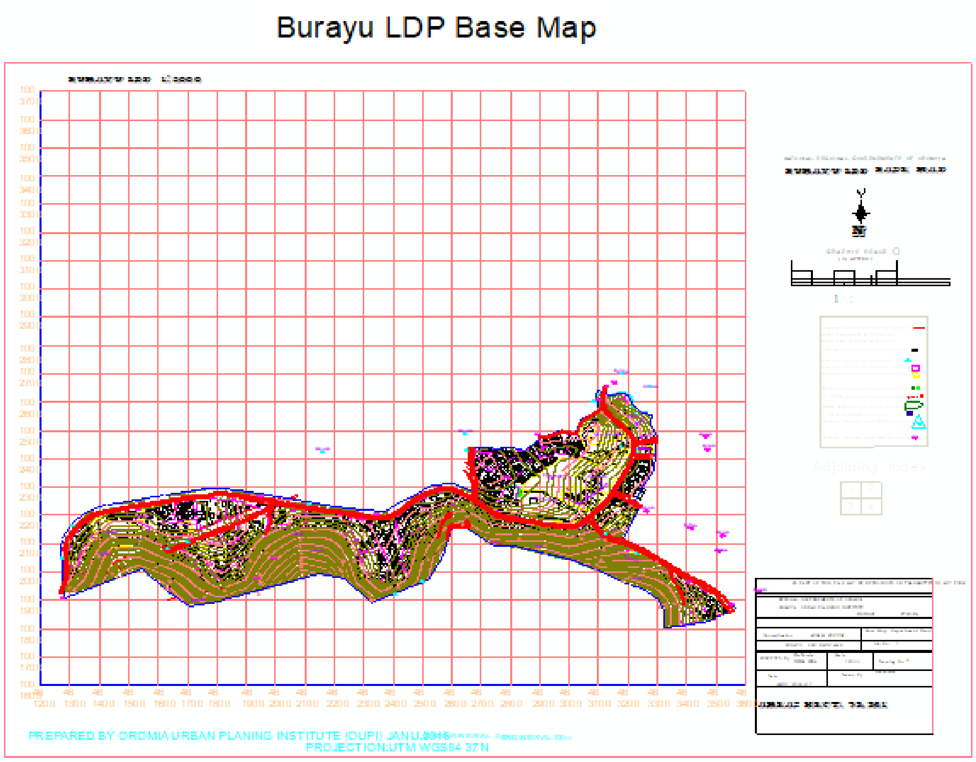


Figure 1.5 LDP Base Map of Burayu Town

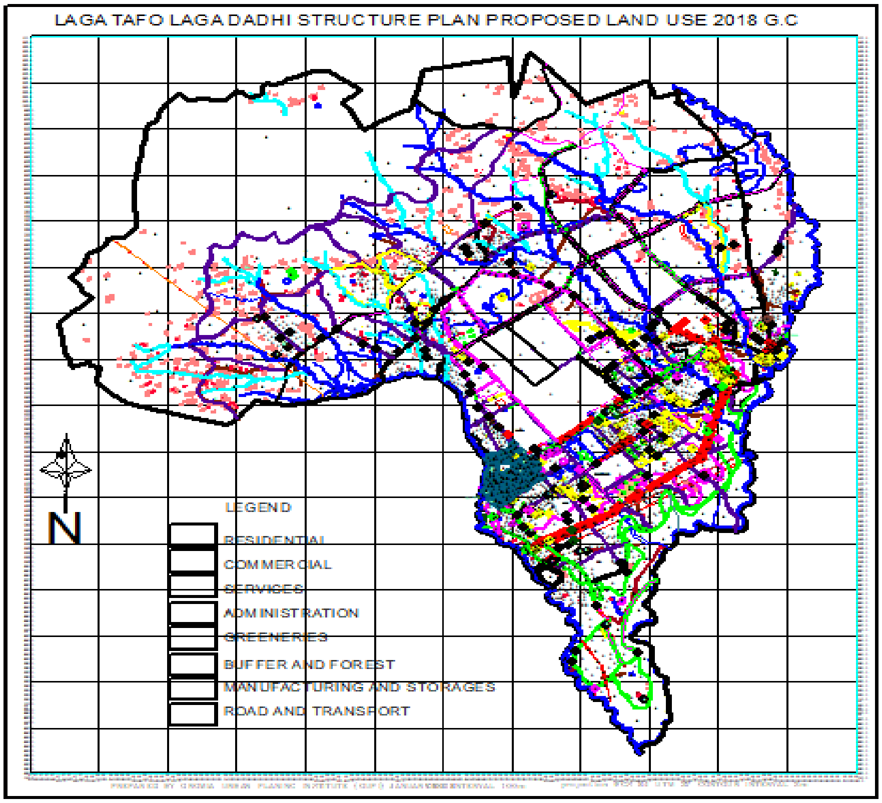


Figure 1.6 Structural Plan Map of Laga Tafo Laga Dadi

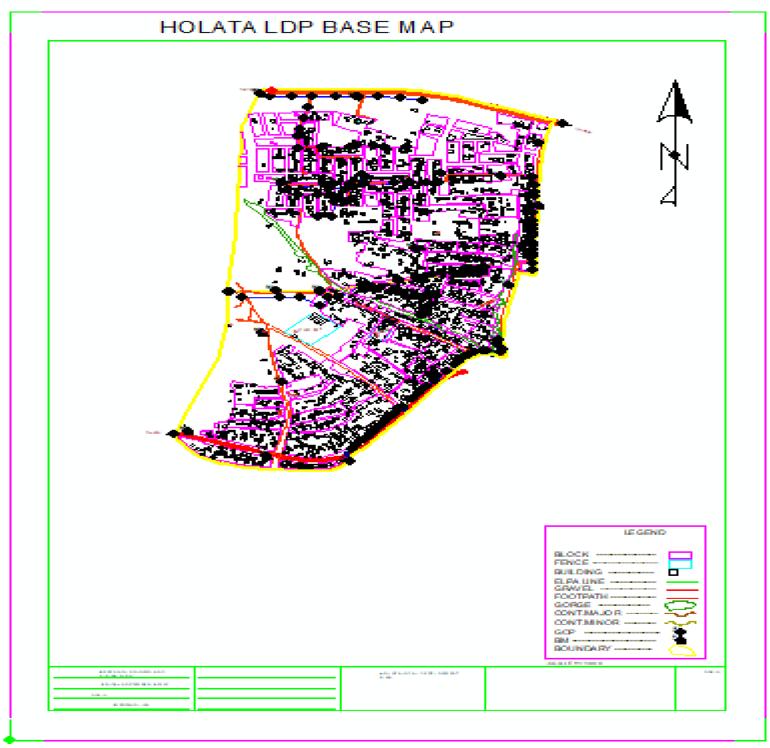


Figure 1.7 LDP Base Map of Holata Town

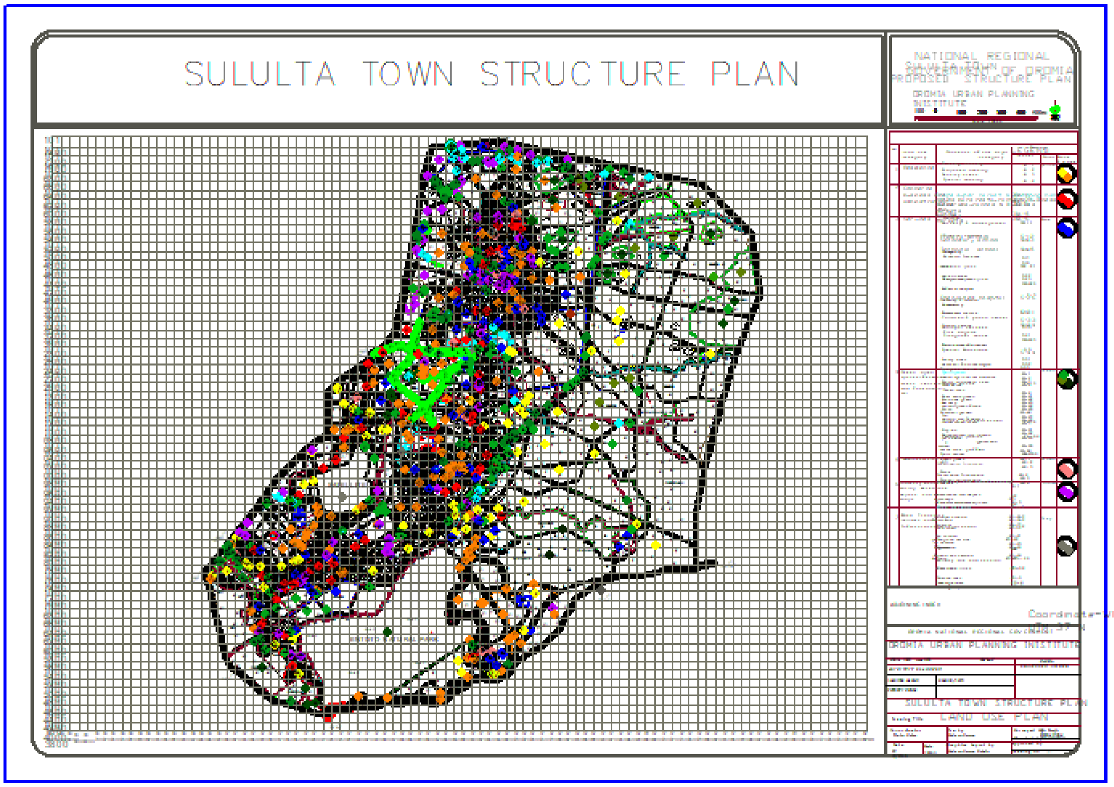


Figure 1.8 Structural Plan Map of Sululta Town

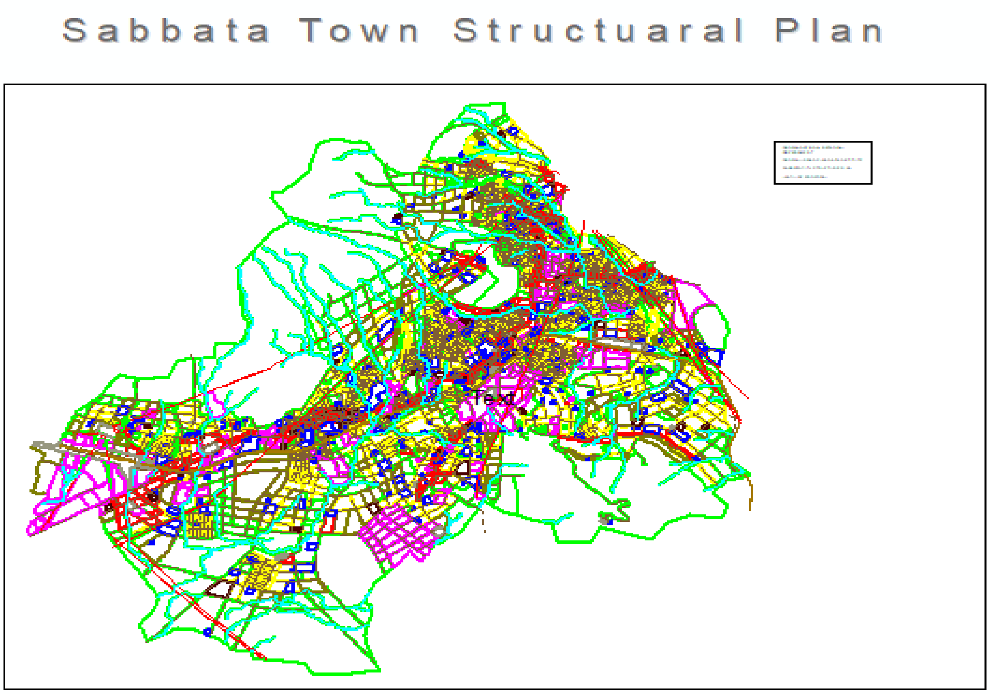


Figure 1.9 Structural Plan Map of Sabata Town

Appendix V Transition Maps

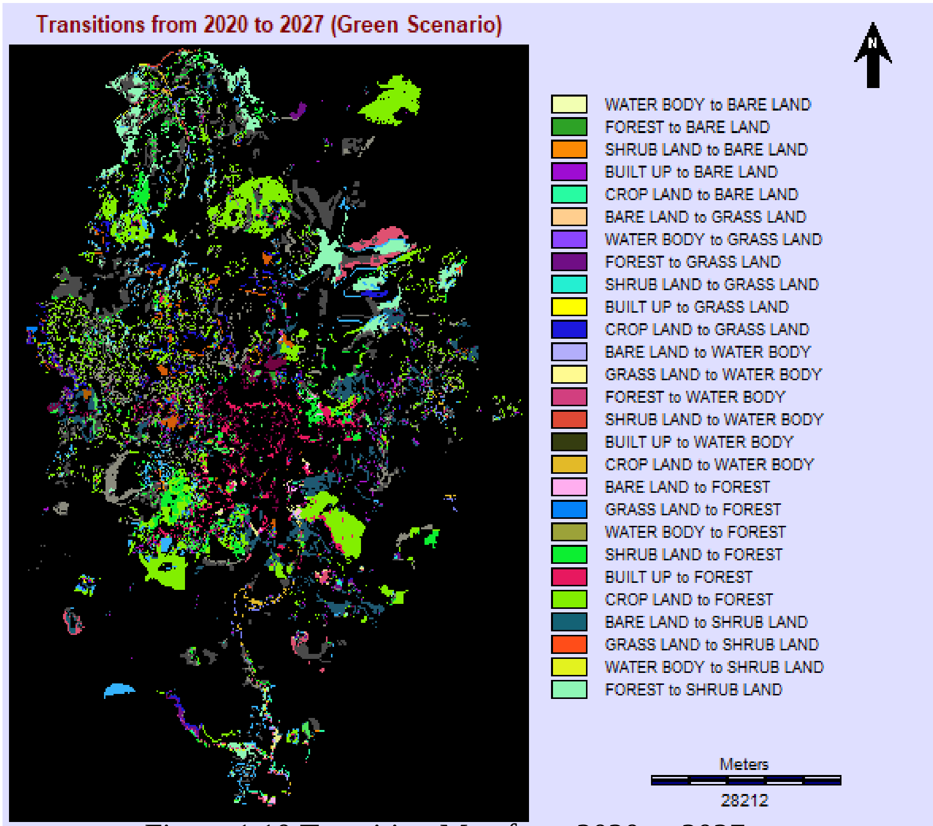


Figure 1.10 Transition Map from 2020 to 2027

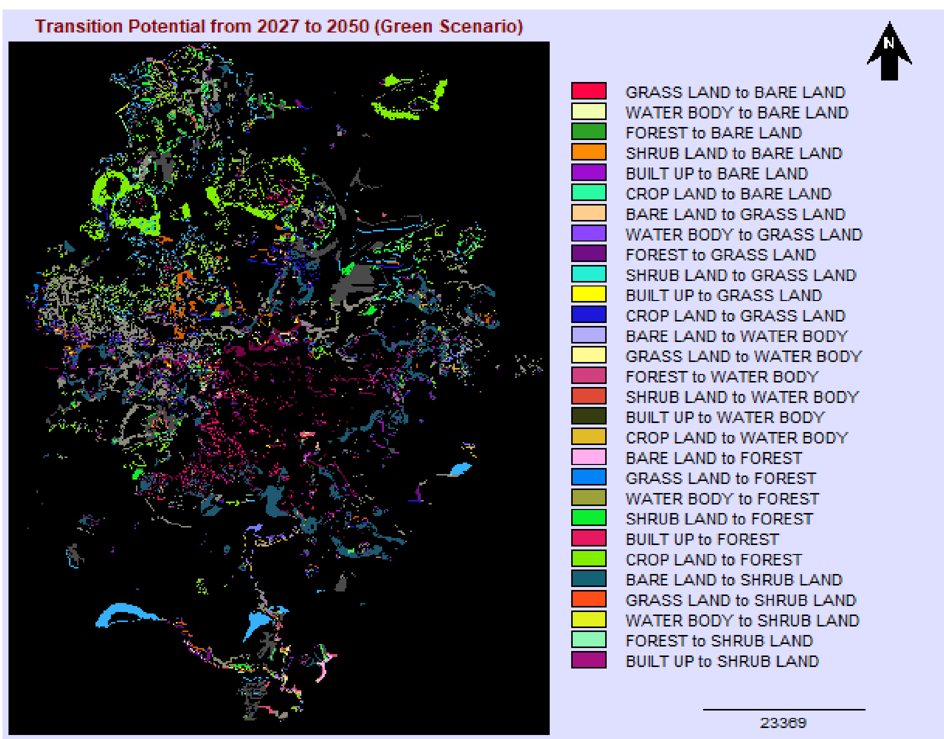


Figure 1.11 Transition Map from 2027 to 2050

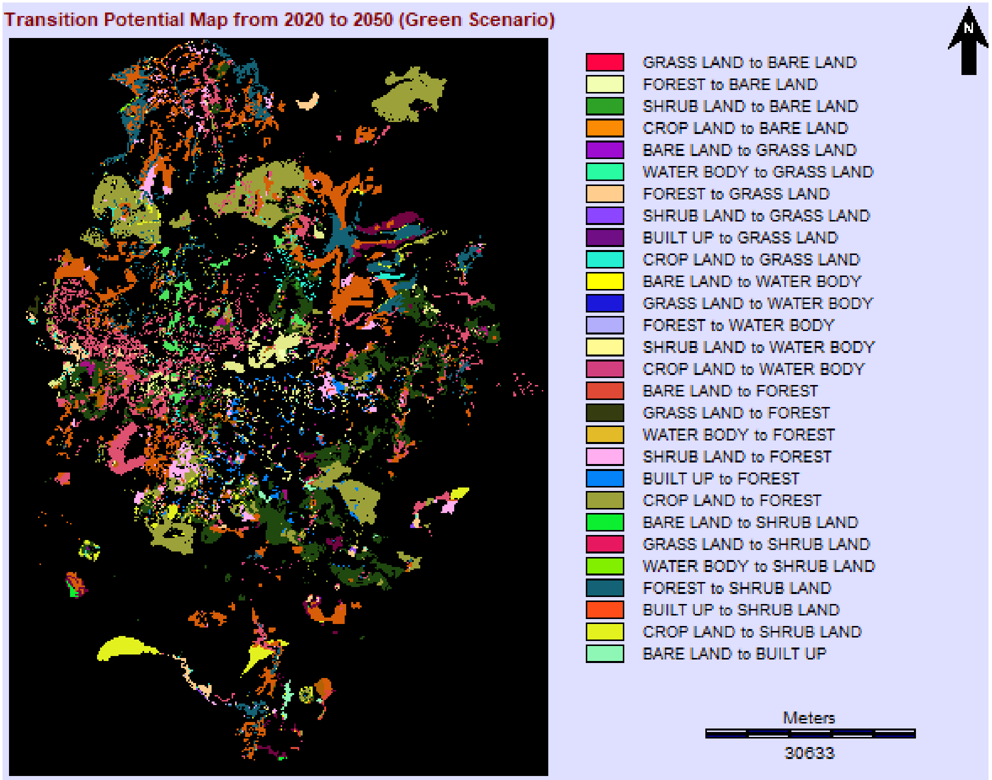


Figure 1.12 Transition Map from 2020 to 2050

Appendix VI Carbon Pool

Table 1.2 Carbon model input for soil organic carbon, aboveground biomass and belowground biomass carbon for LULC types

LULC Name	C Above	C Below	C Soil	C Dead
Bare Land	0	0	83	0
Grass Land	36	2	103	0
Water Body	0	0	0	0
Forest	236	56	125	11
Shrubland	87	25	87	4
Built Up	3	0.6	13	0
Crop Land	47	24	76	2

Source: (Yohannes, 2015; Sahle, 2011; Yilma and Derero, 2020; Solomon et al., 2018; Belay et al., 2018; F. Zhang et al., 2017)