ANALYZING AND MODELING THE SPATIO-TEMPORAL URBAN GROWTH: A CASE OF WOLAITA SODO TOWN, SOUTHERN ETHIOPIA

By: Nebiyu Eyasu Jarssa

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

Presented in Partial Fulfillment of the Requirement for the Degree of Master's of Science in Geo-Informatics

Office of Graduate Studies
Adama Science and Technology University

September, 2022
Adama, Ethiopia

ANALYZING AND MODELING THE SPATIO-TEMPORAL URBAN GROWTH: A CASE OF WOLAITA SODO TOWN, SOUTHERN ETHIOPIA

By: Nebiyu Eyasu Jarssa

Advisor: Dejene Tesema (PhD)

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

Presented in Partial Fulfillment of the Requirement for the Degree of Master's
of Science in Geo-Informatics

Office of Graduate Studies
Adama Science and Technology University

September, 2022
Adama, Ethiopia

DECLARATION

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

Name of the student	Signature	Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "Analyzing and Modeling the Spatio-Temporal Urban Growth" prepared under my guidance by Nebiyu Eyasu submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Geo-Informatics. Therefore, I recommend the submission of revised version of the thesis to the Department following the applicable procedures.

______________________	______________________	______________________
Advisor	Signature	Date

APPROVAL OF BOARD OF EXAMINERS

I, the advisors of the thesis entitled “Analyzing and Modeling the Spatio-Temporal Urban Growth” and developed by Nebiyu Eyasu, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

______________________	______________________	______________________
Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Nebiyu Eyasu have read and evaluated the thesis entitled “Analyzing and Modeling the Spatio-Temporal Urban Growth” and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geo-Informatics.

______________________	______________________	______________________
Chairperson	Signature	Date
______________________	______________________	______________________
Internal Examiner	Signature	Date
______________________	______________________	______________________
External Examiner	Signature	Date

Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

______________________	______________________	______________________
Department Head	Signature	Date
______________________	______________________	______________________
School Dean	Signature	Date
______________________	______________________	______________________
Office of Postgraduate Studies, Dean	Signature	Date

ACKNOWLEDGMENTS

Firstly, I am incredibly grateful to God for his unwavering support, love and for all kinds of wisdoms he gave me throughout this work, and I was able manage everything due to his power.

Next, I would like to express my special thanks to my research advisor; Dr. Dejene Tesema for his immense knowledge, patience, valuable comment, and constructive suggestions throughout my whole research work from title selection to the results. It was a great privilege and honor to work and study under his guidance.

Very special thanks goes to Adama Science and Technology University for sponsoring me for this study and for their financial support.

Besides my thanks also goes to my family for their support, love, prayer, and inspiration throughout my entire life and helped me to succeed in this long process of learning program. This acknowledge also goes to all my classmates as well as all Adama Science and Technology University Geomatics Engineering Department's staff members backings; who supported me in one or another way during my ups and downs of entire MSc. course and thesis work.

Finally, I would like to express my gratitude to all my friends, colleagues, and relatives who directly and indirectly made it possible for me to complete this thesis by any means of support.

TABLE OF CONTENTS

Content **Page**

LIST OF TABLES

Table Number and Title **Page**

LIST OF FIGURES

Figure Number and Title **Page**

LIST OF ACRONYMS AND ABBREVIATIONS

AOI	Area of Interest
ANN	Artificial Neural Network
ArcGIS	Aeronautical Reconnaissance Coverage Geographic Information System
CA_MARKOV	Cellular Automata and Markov Model
CSA	Central Statistical Agency
DEM	Digital Elevation Model
DN	Digital Number
ENVI	Environment for Visualizing Images
ERDAS	Earth Resources Data Analysis System
ETM	Earth Trend Modeler
FAO	Food and Agriculture Organization
GCP	Ground Control Points
GIS	Geographic Information System
GPS	Global Position System
LCM	Land Change Modeler
LULC	Land Use and Land Cover
LULCC	Land Use and Land Cover Change
MCE	Multi Criteria Evaluation
MLP	Multilayer Perceptron
NASA	National Aeronautics and Space Administration
SNNP	South Nation Nationalities and Peoples
SVM	Support Vector Machine
TM	Thematic Mapper
UN	United Nations
UN-Habitat	United Nation Human Settlement Program
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
WZFED	Wolaita Zone Finance and Development Office

ABSTRACT

Urbanization is a global trend with significant environmental effects, calling a clear policy at all levels. To develop the appropriate policies and monitoring systems for urban expansion, it is crucial to understand the urbanization-induced spatio-temporal dynamics of land use and land cover and future potential urban growth. However, little is known in the context of Ethiopian urban centers. The aim of this study, Wolaita Sodo Town, one of the rapidly growing urban centers in Southern Ethiopia, is considered to analyze its spatiotemporal growth from 1990 to 2022 and to predict its potential future expansion in the years 2030, 2040, and 2050. Through supervised image classification using the support vector machine algorithm, LULC maps of the study area in 1990, 2003, 2016, and 2022 were prepared, and the spatiotemporal changes of LULC were investigated. The dynamics of landscape structure in the study area were then investigated using FRAGSTATS and various landscape metrics at the class and landscape levels. The Multi-Layer Perceptron neural network and the Markov chain method on the land change modeler were used to forecast the growth extent of the study area for the years 2030, 2040, and 2050 using drivers representing proximity, biophysical, and socioeconomic variables. The relationship between population growth and urban built-up area expansion was explored using regression analysis. The results show that the built-up area has undergone about 27% expansion annually in the past 32 years, indicating rapid urban growth. The urban landscape of the town was more fragmented in 1990-2003, as compared to that of 2003-2016 and 2016-2022. Landscape of Sodo town was highly heterogeneous in the year 2003. Moreover, the built-up area, which presently occupies 11.37% of the study area, would increase to 13.76%, 17.03%, and 20.06% in the years 2030, 2040, and 2050, respectively. The temporal expansion of built-up area was linearly related to the growth of population. This study would support planners and stakeholders to plan a new direction before negative outcomes become irreversible. The formulation of urban planning policies should also aim to create a balance between the sustainable use of limited resources and socio-economic needs.

Keywords: *Land use/land cover; Change detection; spatio-temporal; Image classification; Spatial metrics; Land Change Modeler (LCM)*

CHAPTER I: INTRODUCTION

1.1 Background of Study

Rapid urbanization has been the main theme of urban studies in developing countries since the explosion of rates of growth in the 1960's and 1970's in very large cities (Barros, 2004). In spite of its small area coverage relative to the earth's surface, dynamic urban growth processes, particularly the expansion of urban population in a larger extent and urbanized area, have a significant impact on natural and human environment at all geographic scales (Clarke et al., 2005).

Like other anthropogenic-environment interactions, urban land cover changes respond to socioeconomic, political, cultural, demographic and environmental conditions, largely characterized by a concentration of humans (Masek et al., 2000).

A population that is urban is one in which vast numbers of people are clustered together in very small areas called towns and cities. Urbanization is a process of population concentration. It proceeds in two ways: the multiplication of points of concentration and the increase in size of points of concentration. (Oluwasola, 2007). The physical growth of urban areas can be explained demographically and functionally. While demographic definition of urbanization is restricted to factors such as population size and density, the economic functional definition refers to the territorial concentration of productive activities (industries and service) rather than population.

According to the United Nations report 2012 on World Urbanization Prospects, the world urban population is expected to increase by 72 % by 2050, from 3.6 billion in 2011 to 6.3 billion in 2050. Thus, the urban areas of the world are expected to absorb all the population growth expected over the next four decades while at the same time people are moving to rural areas by assuming that rural life is seen as simpler and less stressful. Furthermore, in the cities and towns of less developed regions the expected population growth is more concentrated than the developed regions of Europe and America (Desa, 2012).

Associated with the rapid expansion of urbanization, a lot of land has been converted from rural to urban. From the land use and land cover change point of view, expansion of urban areas is of greater importance because of its strong effect on other land cover classes, such as agricultural lands, non-built areas, forests and others. Ethiopia, having the second largest population in Africa has a total of over 80 million populations. It has a 2.3% of annual growth rate and having 4.6% average annual urban growth rate (Haregeweyn et al., 2012).

Understanding the rapid growth dynamics, developments of urban sprawl and quantifying the spatial extent of urbanization requires a geospatial tool (Araya & Cabral, 2010). Since accurate and timely information of land use and land cover change is highly necessary to many groups, remotely sensed data can be used as it provides the land cover information. It is also important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland and soil degradation and many other landscape-level phenomena (Vogelmann et al., 2001).

Urban-rural land use change is a very important phenomenon, which characterizes the urban and sub-urban areas surrounding the cities due mainly to urbanization activities, resulting from demographic and industrial development and also from immigration. Urbanization is considered to be an important issue and its impact on the agricultural lands surrounding urban areas has to be studied.

Nowadays, most of the world population lives in cities and metropolis. However, it is often the case that settlements grow irregularly under the pressure of masses coming to cities and these do not develop according to well-defined plans. Hence, it is necessary to monitor urban areas with frequent update (Desa, 2012).

Monitoring of urban expansion is, however, not easy because of the lack of information in the past. Remote sensing may provide us with an efficient tool to monitor land-cover changes in and around urban areas during past thirty years. With time series satellite data we may detect long -term changes (Tachizuka et al., 2007).

Prospect and challenges of urbanization on livelihood of rural communities, further found that an establishment of the real estate on the area affected the livelihood of farmers by reduction of farm size holding and the community participation in planning and implementation in the program was also negligible (Tadesse & Imana, 2017).

Unguided urbanization, like in most developing countries, negatively affects the natural environment and livelihoods in peri-urban areas. This could be attributed to changes occurring in land use, water resources management, waste dumping, and increasing competition between agricultural and residential use of natural resources. As a result, urbanization could bring a dramatic increase in the concentration of poverty and environmental degradation in peri-urban zones. Urban expansion in the case of Wolaita Sodo is not an exception to other Ethiopian cities. There is no information on the extent and patterns of changes that occurred in in Wolaita Sodo over time (Sodo town land administration 2021). Besides, there are no extensive studies conducted related to urban growth and its impacts. Urban planners and decision-makers should consider the potential of geospatial tools to detect, monitor, and evaluate urban land cover changes. Therefore, the need for monitoring urban development is imperative to help limit the problems of urban sprawl and LULC dynamics.

The integration of Remote Sensing and Geographic Information Systems (GIS) has been widely applied and been recognized as a powerful and elective tool in detecting urban land use and land cover change. Satellite aerial remote sensing collects multi spectral, multi resolution and multi temporal data, and turns them into information valuable for understanding and monitoring urban land processes and for building urban land covers datasets (Tachizuka et al., 2007).

1.2 Statement of the Problem

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

The rapid urban growth and an increase in urban population has led to various socio-economic demands and change for other land covers in the country. The rapid increase in population and the growth of urban areas due to urbanization has contributed massively to the change in land use land cover patterns and the conversion of farm land and vegetation to land use of different functions (Karimi et al., 2018). Because of rapid growth on the urban-rural fringe, planners and policy makers lack accurate, timely and cost-effective urban land use data which is most essential to make decision concerning land resource management. The continuous development of cities associated with more people pour into cities seeking variety of development opportunities. This has led the area of urban keep growing and area of forest, green and cultivated fields become reducing. This reality is very common in developing countries like Ethiopia where the rate of urbanization is exceeding 4.64 % annually (Samson et al, 2012). However, as it is observed in numerous developing countries, the intensified constraints, following the fast urbanization processes in the country, are unplanned and uncontrolled that resulting in scattered urban growth, loss of farmland, and environmental deterioration. Unplanned LULC shifts have a detrimental effect on the environment by raising the land surface temperature (LST), increasing relative humidity, causing erratic rainfall, and affecting the water energy balance, soil quality, biodiversity, and ecology, they also cause an increase in surface runoff. As a result, specific consideration and ongoing evaluation are needed for decision-making, monitoring, and planning urban growth.

Evidence from the past demonstrates that cities have always developed quickly because of population influx, rapid population increase, and the availability of facilities and services. They significantly contribute to improving economic conditions and boosting national finances. Unmanaged population growth, increasing social inequality, economic disproportions and poverty all increase the potential of clash. Poor urban planning and housing development lead to construction of informal settlements that lack access to basic infrastructure and provide poor living conditions. In the course of urbanization, large amount of agricultural land has been transformed into built-up area or into other urban land uses and this serious practice is intrinsically hard to control. The consequences of such kind of landscape change on the environment, resulting from urbanization are becoming more and more complex over time (Xiao et al., 2006).

Sodo Town is one of Ethiopia's urban areas that is expanding quickly. The town has attractive Potential that contributed to its accelerated growth. As a result, the town's growth is becoming unpredictable, unchecked, and frequently leads to the development of slums. Urban land use and land cover issues in Sodo Town typically rank among the most fundamental social, economic, and environmental issues that societies face (Sodo land administration 2021). In fact, there was not yet well-known research related with assessing and modelling spatio-temporal urban expansion in Wolaita Sodo. This study was bridging this gap and provide informative feedback on potential effective solutions that was taken. This study was use different urban growth indices and spatial metrics to give strong argument about urban growth. Quantifying changes in land use and land cover and modelling of it for future time is important in Wolaita Sodo, Ethiopia for monitoring and resolving the negative consequences. This study was applied GIS and remote sensing to overcome this proposed problem. This could be useful for better land use management and environmental development in the study area.

1.3 Objective

1.3.1 General Objective

The general objective of this study is to analyze and model the urbanization induced spatio-temporal dynamics of land use land cover in Wolaita Sodo.

1.3.2 Specific Objectives

Specific objectives of this study were to: -

- ✓ Analyze the changes in land use land cover in the study area from 1990 to 2022;
- ✓ Examine the dynamics of landscape structure in the study area from 1990 to 2022;
- ✓ Predict the extent and distribution of built-up area in the study area in 2030,2040 and 2050 based on past trend of urban growth;
- ✓ Explore the relationship between the trends of population growth and built-up area expansion in the study area from 1990 to 2022.

1.4 Research Questions

1. Were there any major change in the built up area within the study periods?
2. What was the landscape structure dynamics in the study area within study periods?
3. How does the built-up area in the study area changes in 2030, 2040 and 2050 under the condition of business as usual scenario?
4. There was any relationship between population growth and built-up area expansion?

1.5 Significance of the Study

Land use and land cover change is a major aspect of the pressure on the limited land resources that is driven by different biophysical and anthropogenic factors particularly population growth. Therefore, analyzing and modeling of urban land use changes provide greater importance to the research community, urban planners, stake holders as well as decision making groups in terms of understanding the impacts of land use land cover changes in Wolaita Sodo.

The results of this study could provide better information about the changes in urban land use quantified through integrated application of GIS, remote sensing, spatial metrics and land change modeler. In addition, it also provides the opportunity to understand the trends of changes in built up areas as a result of driving variables. Moreover, the findings of this study will be an initial input for future research direction for interested groups in the area.

1.6 Scope of the study

This study geographical bounded in Ethiopia SNNP region in Wolaita zone Sodo Town. The study was mainly focus on urban land use land cover change analysis from 1990-2022 and prediction of the future urban modeling at (2030,2040 and2050) using Geo-spatial technologies and giving hint about the importance of developing land use land cover change map for urban planning in Sodo town. Also, explore relationship between population growth and built-up area expansion and finally recommendations were raised based on the findings.

1.7 Structure of the Thesis

The study were presented in five different chapters. The first chapter introduces background of the study and statement of the problem, study objectives, research questions, significance and scope of the study. The next section, chapter two, focuses on theoretical literature review and related work for this study. 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 image classification and land use/land cover modeling. The results and discussions are the fourth chapter which presents the quantified results from image classification and land use change modeling. In this section, land cover maps generated using Support Vector Machine (SVM), change detection, landscape metrics and accuracy assessments of the classification are discussed in detail. Moreover, change analysis using Land Change Modeler, spatial trends and simulation of land cover maps has been performed. Validation of the simulated land cover maps has been done for comparison of model performance. The last chapter presents conclusions and recommendations. In this section, key findings and critical points that need further treatment has been forwarded as a recommendation for future related work.

CHAPTER II: LETERATURE REVIEW

2.1 Land use and Land cover Changes

The definition of land use and land cover has been used interchangeably in the land use research community because of the availability of many existing information systems. However, these two terms explain two different issues and meanings. Land cover refers to the observed biophysical cover on the earth's surface including vegetation, bare soil, hard surfaces and water bodies. Whereas land use is the utilization of land cover type by human activities for the purpose of agriculture, forestry, settlement and pasture by altering land surface processes including biogeochemistry, hydrology and biodiversity (Jansen & Gregorio, 2000).

Land use and land cover changes became prominent as a research topic on the global environmental change several decades ago with the idea of processes in the earth's surface influence climate. In early 1980's the significance impact of land use and land cover change on the global climate via carbon cycle was understood where terrestrial ecosystems acted as a source and sinks due to the changes. Following this, the forthcoming volume of the 1991 Global Change Institute of the Office of Interdisciplinary Earth Studies (OIES) dedicated to land use and land cover changes at global level by explaining the major recent trends of changes, their consequences in environment, human causes on it as well as data and modeling of changes (Meyer & Turner, 1992). Later, under the support of land use and land cover change project of the International Geosphere and Biosphere Program (IGBP) and International Human Dimensions Program on Global Environmental Change (IHDP), the research community has identified three basic issues. These were understanding the causes of land use and land cover changes, how to quantify it and how to apply models of predicting the changes (Lambin et al., 2003). Conversion and modification are the two forms of land cover changes described by (Meyer & Turner, 1992) where the former is a change from one class of land cover to another (e.g from grassland to cropland). The latter is, however, a change within a land cover category (e.g thinning of a forest or a change in composition). Land cover changes due to human activities drive land use and hence a single class of cover could support multiple uses (forest used for combinations of timbering, slash and burn agriculture, fuel wood collection and soil protection). On the other hand, a single system of land use can maintain several covers (as certain farming systems combine cultivated land, improved pasture and settlements). Changes in land use and land cover caused through direct and indirect consequences of human activities on the environment for the purpose of having better life. One of the direct impact of humans is population growth where its increase and decrease have effects on land use especially in developing world at longer time scales. According to (Lambin et al., 2003) it can also be caused by the mutual interactions between environmental and social factors at different spatial and temporal scales as land use and land cover change is a complex process. (Verburg et al., 2002) showed that causes of land use and land cover change can be categorized as direct (proximate) or indirect (underlying). The direct causes comprise human activities that could arise from the continuous use of land and directly alter land cover which reflect that human are driving forces. They are generally operated at local levels and explain how and why local land cover and ecosystem processes are modified directly by humans. On the other hand, indirect causes are fundamental forces that strengthen the more direct causes of land cover changes. These causes are resulted due to the complex interaction of social, political, economic, technological and biophysical variables.

Land use and land cover changes have significant consequences on climate change, hydrology, air pollution and biodiversity. The rise in global surface temperature is associated with deforestation through changes in land use. This in turn caused a strong warming in urban environment called urban heat island. Their study also showed water pollution occurred due to land cover changes from cultivation to settlement (urban areas). It has been reported also that loss of forest species has wide range of effects on biodiversity. Identifying the causes and impacts of land use and land cover change require understanding both how people make land-use decisions and how specific environmental and social factors interact to influence these decisions (Lambin et al., 2001). In order to understand the impacts of dynamic land use and land cover changes, the use of land use change models become an advantage since they provide information of land use trajectories by projecting for the future. This ability of models, however, important for better environmental management and land use planning (Verburg et al., 2002).

2.2 Urban Land use Changes

From a broader point of view urbanization is one of the ways in which human activities altering global land cover. Although urbanization trend is global, according to the reports of the United Nations Centre for Human Settlements (UN-HABITAT, 2016), it has showed most remarked changes in developing countries associated with the migration of rural people to cities for better opportunities. Following this there had been estimated a rapid growth of population in urban areas at an average rate of 2.3% per year between 2000-2030 (Bocquier, 2005).

Urban growth, particularly the movement of residential and commercial land use to rural areas at the periphery of metropolitan areas, has long been considered as a sign of regional economic vitality (Yuan et al., 2005). However, its importance become unbalanced with impacts on ecosystem, greater economic differences and social fragmentation. It can be defined as the rate of increase in urban population. Dynamic processes due to urban change, especially the tremendous worldwide expansion of urban population and urbanized area, affect both human and natural systems at all geographic scales (Brockerhoff, 2000).

Araya & Cabral (2010) have shown that urban growth in Setúbal and Sesimbra, Portugal has been increased significantly between 1990 and 2000 by 91.11%. Much of this growth, however, was towards the periphery of urban areas due to the coalescence of a number of smaller settlements as well as through the consumption of agricultural land. The growth was predicted to continue in the future and would have wide range of consequences on natural resources. Their study also noted that population growth was one of the major driving factors for such rapid growth in the study area.

Traditionally demographic data has been used to asses urban sprawl (Carlson & Arthur, 2000). Meanwhile the use of aerial photography become important to update land cover maps. Since land cover changes at regional level occurred increasingly due to human activity, the changes couldn't be realized in the community. Therefore, accurate and updated information is required to design strategies for sustainable development and to improve the livelihood of cities. The ability to monitor urban land cover and land use changes is highly desirable by local communities and policy decision makers. Due to the increased availability and improved quality of multi spatio-temporal data and new analytical techniques, nowadays it is possible to monitor urban land cover and land use changes and urban sprawl in a timely and cost-effective way (Yang et al., 2005). Therefore, the use of satellite data provides for regional planning and urban ecology.

2.3 Urbanization

Urbanization refers to the growth of towns and cities, often at the expense of rural areas, as people move into urban centers in search of jobs with the expectation of a better life, enabling cities and towns to grow. It can also be termed as the progressive increase in the number of people living in towns and cities. It is highly influenced by the notion that cities and towns have achieved better economic, political, and social mileages compared to the rural areas (Bhatta, 2010). Urban growth is a spatial and demographic process that refers to the increased importance of towns and cities as a concentration of people within a particular economy and society (Bhatta, 2010). There are at least three different and widely studied concepts of urban growth in the urban and regional planning literature, related to population change, economic performance, and the spatial expansion of urban areas (Reis et al., 2016). The socio-demographic dimension of urban growth focuses on demographic trends and migration.

2.3.1 World urbanization

The world is rapidly urbanizing and cities are experiencing the dynamic processes of urbanization and globalization (Monica & Moses, 2017). According to Xing Quan (2015), prior to 1950, global urbanization trends were calculated based on the transformations that took place in Organization for Economic Cooperation and Development (OECD) countries. The proportion of the world's population, which is urban, has been growing rapidly and currently a larger fraction of the total population lives within cities (UN, 2007). According to United Nations world Urbanization Prospect (UNWUP, 2014) the percentage of urban population in 1950 was 30%, which was increased to 54% in 2014, and estimated to be 66% by 2030. Contrary to this, a vast majority of the population in the third world remain residing in rural areas. By now Asia and Africa are the least urbanized, sharing 48 and 40 percent of their population urbanized, respectively.

2.3.2 Urbanization in Africa

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

2.3.3 Urbanization in Ethiopia

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

2.4 Trends of Urban Growth

The world is undergoing the largest wave of urban growth in history. According to the United Nations Population Fund (UNFPA, 2013), rapid population growth has been concentrated in towns and cities of the world. The report also projected that by the year 2030 the vast majority of this growth will be observed in the developing world of Africa and Asia where urban growth is highly concentrated. Because cities offer a lot of opportunities such as jobs and sources of income than the corresponding rural areas, they attracted a lot of people.

Following the rapid increase of population in urban areas, the growth of the world's rural population has shown a slowly decreasing pattern as indicated in figure 2.1 below.

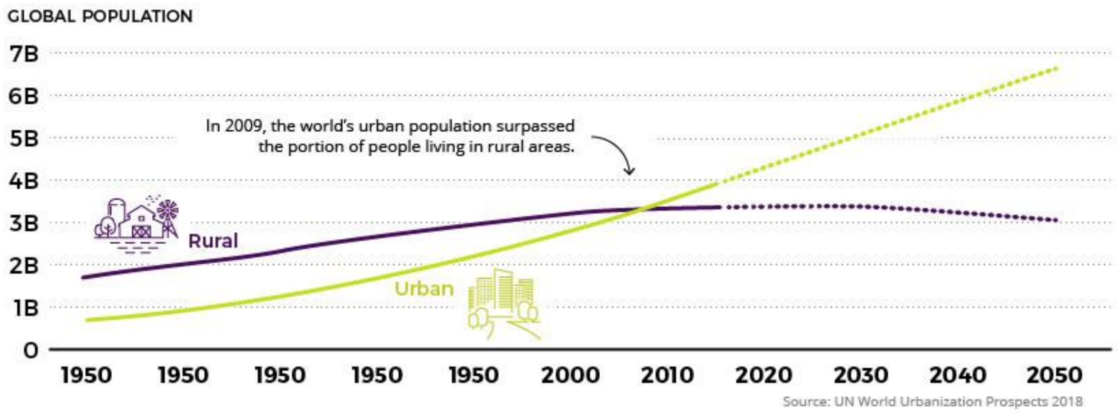


Figure 2. 1: World's urban and rural population size estimated and projected, 1950–2050, (Source: UN world urbanization prospect, 2018)

2.5 Urban Expansion

According to Adem (2010) urban expansion is the extension of the attentiveness of people or urban settlement to the surrounding area whose functions are non-agricultural activity. As with urban population growth, urbanization can contribute to the expansion of urban built over land, and some of this urban expansion is likely to cover land that would otherwise be used to farming land.

2.5.1 Forms of urban expansion

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

2.5.2 Consequences of Urban Expansion

Rapid rate of urban growth lead to rapid changes of land use and cover than ever before, particularly in developing nations, are often characterized by unrestrained urban rambling, land degradation or the transformation of agricultural land to other uses and resulting massive cost to the environment (Sankhala & Singh, 2014). Unmatched urbanization causes rapid urban expansion, which can be unhealthy without rational urban planning. Some researchers employ the term “urban sprawl” to describe unwholesome urban expansion (Angel et al., 2011). Unwholesome urban expansion, or in other words, urban sprawl, refers to an abandoned and dispersed process of urban growth regarded as by automobile dependency, low urban area density and low population density (Bhatta et al., 2010).

2.5.3 Factors of LULC change and urban expansion

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

Demographic factors

The first and foremost reason of urban growth is increase in urban population. Rapid growth of urban areas is the result of two population growth factors the first is natural increase in population, and the second is migration to urban areas (Paterson et al., 2003).

Economic factors

Economic effects include the level of economic development, difference in household incomes, exposure to globalization, the level of foreign direct investment, the degree of employment, the level finance markets, the level and effectiveness of property taxation and the presence of high inflation and acute shortage of housing (Angel et al., 2005).

Natural/environment factors:

Natural /environmental effects include those of climate, slope, mountain barriers, and the existence of drillable water aquifers. In addition, the minor causes such as Redevelopment and rebuilt up of inner cities again cause displacement of citizens (Clement, 2010).

2.6 The Role of Remote Sensing on Land use and Land cover Changes

Maktav et al (2005) showed that traditional data collection methods such as demographic data, census and sample maps were not satisfactory for the purpose of urban land use management. Accurate information of land use and land cover change is therefore highly essential to many groups. To achieve this information, remotely sensed data can be used since it provides land cover information. Remote sensing refers to the science or art of acquiring information of an object or phenomena in the earth's surface without any physical contact with it. And this can be done though sensing and recording of either reflected or emitted energy and the information being processed, analyzed and applied to a given problem (Campbell & Wynne, 2011). Remote sensing is important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland degradation and many other landscape-level phenomena. Such useful information can be then integrated into many regional to global scale models, including those that are used to develop parameters for carbon fluxes and hydrological cycles. Therefore, remote sensing data can be used as the basis for answering important ecological questions with regional to global implications (Vogelmann et al., 2001). Clarke et al (2003) also noted that one of the advantages of remote sensing is its ability to provide spatially consistent data sets covering large areas with both high detail and high temporal frequency, including historical time series. Over the past decades almost all the remote sensing researches have given more attention to natural environment than urban areas. The reason was that urban areas have complex and heterogeneous by nature (Melesse et al., 2007). However, (Clarke et al., 2003) reported that with the availability of high-resolution imagery together with suitable techniques, urban remote sensing become a rapidly gaining interest in the remote sensing community. Supported by advanced technology and satisfying social needs, urban remote sensing has become a new field of geospatial technology and applicable in all socioeconomic environments (Melesse et al., 2007). Following this, a number of applications of remote sensing for urban studies have shown the potential to map and monitor urban land use and infrastructure. Moreover, Herold et al (2001) showed urban land use information in high thematic, temporal and spatial accuracy, derived from remotely sensed data, is an important condition for decision support of city planners, economists, ecologists and resource managers. Generally, land use and land cover changes have a wide range of impacts on environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes and functions (Rimal, 2011). Therefore, the use of remote sensing data and analysis techniques provide accurate, timely and detailed information for detecting and monitoring changes in land cover and land use.

2.7 Image classification

Image classification refers to the extraction of differentiated classes or themes, usually, land cover and land use categories, from raw remotely sensed digital satellite data (Weng, 2012). Image classification using remote sensing techniques has attracted the attention of the research community as the results of classification are the backbone of environmental, social, and economic applications (Lu & Weng, 2007). Because image classification is generated using remotely sensed data, many factors cause difficulty to achieve a more accurate result. Some of the factors are the characteristics of a study area, availability of high resolution remotely sensed data, ancillary and ground reference data, Suitable classification algorithms and the analyst ‘s experience, time constraints. Image classification refers to grouping image pixels into categories or classes to produce a thematic representation. Classification is the most important aspect of image processing to GIS. Image classification operations that include image restoration, image pre-processing, enhancement, compression, spatial filtering, and pattern recognition are applied to image data. Various image classification methods can be applied to extract land cover information from remotely sensed images (Lu & Weng, 2007). However, their application depends on the methodology and type of data to be used. Some of these methods are artificial neural networks, support vector machines, fuzzy sets, and expert systems. In a more specified way, image classification approaches can be categorized as supervised and unsupervised, or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel, and per-field.

2.7.1 Supervised image classification algorithms

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

Linear Classifiers: Linear models for classification separate input vectors into classes using linear (hyperplane) decision boundaries (Elder, n. d). The goal of classification in linear classifiers in machine learning is to group items that have similar feature values, into groups. A linear classifier is often used in situations where the speed of classification is an issue since it is rated the fastest classifier (Taiwo, 2010).

Logistic regression: This is a classification function that uses a class for building and uses a single multinomial logistic regression model with a single estimator. Logistic regression usually states where the boundary between the classes exists, also states the class probabilities depend on distance from the boundary, in a specific approach. This moves towards the extremes (0 and 1) more rapidly when a data set is larger. These statements about probabilities make logistic regression more than just a classifier (Kotsiantis et al., 2007).

Naive Bayesian (NB) Networks: These are very simple Bayesian networks that are composed of directed acyclic graphs with only one parent (representing the unobserved node) and several children (corresponding to observed nodes) with a strong assumption of independence among child nodes in the context of their parent (Jiang et al., 2010). Thus, the independence model (Naive Bayes) is based on estimating, Bayes classifiers are usually less accurate than other more sophisticated learning algorithms (such as ANNs).

Multi-layer Perceptron: This is a classifier in which the weights of the network are found by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard neural network training. Other well-known algorithms are based on the notion of the perceptron. Perceptron algorithm is used for learning from a batch of training instances by running the algorithm repeatedly through the training set until it finds a prediction vector that is correct on all of the training sets. This prediction rule is then used for predicting the labels on the test set (Kotsiantis et al., 2007).

Support Vector Machines (SVMs): These are the most recent supervised machine learning technique. Support Vector Machine (SVM) models are closely related to classical multilayer perceptron neural networks. SVMs revolve around the notion of a marginal on either side of a hyperplane that separates two data classes. Maximizing the margin and thereby creating the largest possible distance between the separating hyperplane and the instances on either side of it has been proven to reduce an upper bound on the expected generalization error (Kotsiantis et al., 2007).

K-means: K means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. K-Means algorithm is be employed when labeled data is not available. The general method of converting rough rules of thumb into highly accurate prediction rules. Given a weak learning algorithm that can consistently find classifiers (rules of thumb) at least slightly better than random, say, accuracy 55%, with sufficient data, a boosting algorithm can provably construct a single classifier with very high accuracy, say, 99% (Schapire & Singer, 2000) Machine Learning Algorithms for Classification.

Decision Trees: Decision Trees (DT) are trees that classify instances by sorting them based on feature values. Each node in a decision tree represents a feature in an instance to be classified, and each branch represents a value that the node can assume. Instances are classified starting at the root node and sorted based on their feature values. Decision tree learning, used in data mining and machine learning, uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value. More descriptive names for such tree models are classification trees or regression trees (Friedman, 2001).

2.8 Land use land cover change detection

Change detection can be defined as the process of identifying differences in the state of object or phenomena by observing them at different times by using remote sensing techniques (Eastman, 2006). Essentially, it also involves the ability to quantify temporal effects using multi-temporal data sets. Because of repetitive spatial coverage at short time intervals and consistent image quality, change detection is considered as one of the major applications of remotely-sensed data obtained from Earth-orbiting satellites (Eastman, 2006). Change detection has a wide range of applications in different disciplines such as land use change analysis, forest management, vegetation phenology, seasonal changes in pasture production, risk assessment and other environmental changes (Eastman, 2006). The main objective of change detection is to compare spatial representation of two points in time frame by controlling all the variances due to differences in non-target variables and to quantify the changes due to differences in the variables of interest (Lu & Weng, 2007). A change detection research to be good, it should provide the following vital information: area change and rate of changes, spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of change detection results. Quantifying land use and land cover changes and applying suitable change detection methods highly depend on the type of changes that happened in landscapes and how those changes are noticeable in images. The changes could be continuous or categorical. Change detection in continuous land cover changes focuses on measuring the degree of changes in amount or concentration through time. However, in the case of categorical land cover changes, the goal of change detection is to identify new land cover classes and changes between classes through time (Eastman, 2006).

2.8.1 Change Detection Techniques using a Remotely Sensed Data

The selection of suitable method or algorithm for change detection is important in producing a more accurate change detection result since constraints such as spatial, spectral, thematic and temporal properties affect digital change detection. Some techniques such as image differencing can only provide change or non-change information, while some techniques such as post classification comparison can provide a complete matrix of change directions. According to Bekalo (2009), different change detection methods could produce different changes of maps depending on the algorithm they followed.

Although there are many change detection methods in remote sensing of image classification, recently researchers divided in to image ratio, image regression, image differencing and the method of change detection after classification (post classification method) (Xu et al., 2009) and (Bekalo, 2009). The classification of methods mainly depends on data transformation procedures if exists and analysis techniques applied. So, based on these conditions the current common methods of change detection are discussed below:

Image Regression Method

In image regression method of change detection, pixels from time t1 are assumed to be a linear function of the time t2 pixels. Under this assumption, it is possible to find an estimate of image obtained from t2 by using least-squares regression. Image regression technique takes in to account differences in the mean and variance between pixel values for different dates. This consideration minimizes the influence of differences in atmospheric conditions. In detecting changes of urban areas, the regression procedure has more advantage than image differencing technique.

Image Ratio Method

In image ratio method, images must be registered beforehand and rationed band by band. The results of image ratio are interpreted with a threshold of values. If the ratio of the two images is 1, it means that there is no change in the land cover classes where as a ratio value of greater or less than 1 indicates a change in land cover classes (Eastman, 2006) and (Bekalo, 2009). This method rapidly identifies areas of changes in relative terms.

Image Differencing Method

Image differencing is one of the most extensively applied change detection method. It can be applied to a wide variety of images and geographical environment. In this technique, images of the same area, obtained from times t1 and t2, are subtracted pixel wise. It is generally conducted on the basis of gray scale which used to show the spatial extent of changes in the two images. A threshold value is required for the gray of difference image in order to examine the changed and unchanged regions (Xu et al., 2009).

Post Classification Method

This method is the most simple and obvious change detection based on the comparison of independently classified images. Maps of changes can be produced by the researcher which shows a complete matrix of changes from times t1 to time t2. Based on this matrix, if the corresponding pixels have the same category label, the pixel has not been changed, or else the pixel has been changed (Xu et al., 2009). Post classification method was used in this research.

2.9 Geospatial technologies useful for urban LULC change analysis

Remote Sensing, GIS, and IDRISI are now providing new tools for advanced ecosystem management. With the advancement of technology, reduction in data cost, availability of historic spatiotemporal data and high-resolution satellite images used for urban planning, geography, earth science, transportation planning, environmental planning, disaster management, urban expansion change analysis, and modeling (Ershad & Ali, 2020).

Remote Sensing

According to Lambin et al (2003), the definition of Remote Sensing (RS) is as follows: Remote sensing is the science and art of obtaining information about the Earth's surface through the analysis of data acquired by a device which is at a distance from the surface‖. Remote sensing is an essential tool of land change science because it facilitates observations across larger extents of Earth‘s surface than is possible by ground-based observations by using of cameras, multispectral scanners.

Geographic Information System (GIS)

A Geographic Information System (GIS) is a system of computer software, hardware and data, personnel that make it possible to enter, manipulate, analyze, and present data, and the information that is tied to a location on the earth's surface (Ershad & Ali, 2020). GIS also allows the integration of these data sets for deriving meaningful information and outputting the information derivatives in map format or tabular format. GIS support any operation on geographic information: acquisition, editing, manipulation, analysis, modeling, visualization, publication, and storage. GIS has four basic subsystems: input, storage, analysis and output (Ershad & Ali, 2020).

IDRISI

IDRISI is the industry leader in raster, covering the full spectrum of GIS and remote sensing needs from database query, to spatial modeling, to image enhancement and classification. Special facilities are included for environmental monitoring and natural resource management, including land change modeling and time series analysis, multi criteria and multi-objective decision support, uncertainty and risk analysis, simulation modeling, surface interpolation and statistical characterization (IDRISI Selva Manual version 17.01).One advantage of using IDRISI for land-use change modeling is that in one software package you have: 1) the data, 2) the simulation model, and 3) the statistical techniques of goodness-of fit (Pontius & Chen, 2006).

2.10 Landscape Metrics

"Landscape metrics" refers exclusively to indices developed for categorical map patterns. Patterns are distinguished by spatial relationships among component parts in landscape metrics. A landscape pattern can be characterized by both its composition and configuration of its component parts (McGarigal, 2002). These two characteristics of a landscape can individually or in combination affect ecological processes. A variety of metrics have been developed to quantify categorical map patterns in the past studies (McGarigal, 2002). Despite the availability of plenty of metrics, offered by different literature, to describe landscape structure, they are still categorized under the two major components, namely, composition and configuration of a landscape (Mc Garigal, 2002).

Landscape metrics are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics (Nadoushan & Alebrahim, 2017).

Patch level: which defines the individual patches as the area provides metric information to characterize the spatial character and context for individual patches in the landscape. Patch metrics will serve as a reference for the calculation of landscape metrics.

Class level: which uses data of the patches that belong to the same land-use type. Class indices individually quantify the quantity and spatial configuration of each patch type and thus provide a means to quantify the level and fragmentation of each patch type in the landscape (McGarigal, 2002)

Landscape-level: defines the entire landscape, the full extent of the data. Of primary interest is the pattern of the landscape mosaic, the spatial character and distribution of patch

(McGarigal, 2002). Landscape metrics can be interpreted more broadly as landscape heterogeneity indices because they measure the overall landscape pattern.

Landscape metrics can be grouped into two general categories: those that quantify the composition of the map without reference to spatial attributes, and people that quantify the spatial configuration of the map, requiring spatial information for their calculation (McGarigal, 2002). The composition is definitely quantified and refers to features related to the variability and abundance of patch types within the landscape, but without considering the spatial character, placement, or location of patches within the mosaic. Because composition requires the integration of overall patch types, composition metrics are only applicable at the landscape-level. There are many quantitative measures of landscape composition, including the proportion of the landscape in each patch type, patch richness, patch evenness, and patch diversity (McGarigal, 2002). The landscape metrics are grouped into the levels of heterogeneity however they were further grouped to the aspect of landscape pattern.

Area and Edge metrics: This group of metrics represents a loose collection of metrics that deal with the size of patches and the amount of edge created by these patches. Although these metrics could easily be subdivided into separate groups or assigned to other already recognized groups, there is enough similarity in the basic patterns assessed by these metrics to include them under one umbrella. The area of each patch comprising a landscape mosaic is perhaps the single most important and useful piece of information contained in the landscape (McGarigal, 2002).

Shape metrics: The interaction of patch shape and size can influence a number of important ecological processes. Patch shape has been shown to influence inter-patch processes like ligneous plant colonization and may influencing animal foraging strategies (Forman And Gordon, 1986). However, the first significance of shape in determining the character of patches during a landscape seems to be associated with the 'edge effect'.

Core area metrics: Core area is defined as the area within a patch beyond some specified depth-of-edge influence (i.e., edge distance) or buffers width. Like patch shape, the first significance of the core area in determining the character and performance of patches during a landscape appears to be associated with the 'edge effect (McGarigal, 2002).

Contrast metrics: Contrast refers to the magnitude of difference between adjacent patch types with respect to one or more ecological attributes at a given scale that are relevant to the organism or process under consideration. The contrast between a patch and its neighborhood can influence a number of important ecological processes (McGarigal, 2002).

Aggregation metrics: Refers to the tendency of patch types to be spatially aggregated; that is, to occur in large, aggregated or "contagious" distributions. This property is additionally often mentioned as landscape texture. We use the term "aggregation" as an umbrella term to explain several closely related concepts: 1) dispersion, 2) interspersion, 3) subdivision and 4) isolation. Each of these concepts relates to the broader concept of aggregation, but is distinct from the others in subtle but important ways, as follows (McGarigal, 2002).

Diversity metrics: Diversity measures have been used extensively in a variety of ecological applications. They originally gained popularity as measures of plant and animal species diversity. There has been a proliferation of diversity indices and that we will make no plan to review them here. FRAGSTATS computes 3 diversity indices. These diversity measures are influenced by 2 components--richness and evenness (McGarigal, 2002).

2.11 Land use land cover change modeling

Land is utilized for multiple purposes and it is critical that land cover change be monitored and evaluated for both its negative and positive consequences. Dynamic urban land use and land cover change processes caused due to human activities have a wide range of effects on the global climate change either directly or indirectly (Clarke et al., 2005) and (Lambin et al., 2001). It also affects human and natural systems and contribute to changes in carbon exchange and climate through a range of feedbacks. Its future changes are also a function of numerous driving variables (Lambin et al., 2003) and (Veldkamp & Lambin, 2001). Some of these drivers are population change, economic activity and growth as well as biophysical conditions and are most important at a range of geographic scales. Bajwa et al (2015) noted that, the first and foremost reason for urban growth is an increase of urban population. Urban areas attained rapid growth as a result of natural increase in population. This is due to uncontrolled family planning where birth rate is greater than death rate. The second one is migration to urban areas. Where migration is defined as the movement of people from rural to urban areas within the country. Therefore, modeling of urban growth is a very essential step for further improvement of urban planning and land use management. The rising awareness and importance of land use models in the land use and land cover research community has led to the development of a wide range of land-use change models (Verburg et al., 2002).

2.11.1 LULC change prediction modeling techniques

Land Use Land Cover Change (LU/LCC) modeling is a rapidly growing scientific field because land-use change is one of the most important ways that humans influence the environment (Sankhala & Singh, 2014). Modeling means the process of creating a representation of reality; it could be a map, graph, picture, or mathematical representation. Land use land cover change modeling is defined as the process of creating maps based on the history of land use land cover, existing information, and assumptions of the future. Modeling urban growth plays a significant role to understand the impacts of the changes that occur through time. The Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler (LCM), Earth trend, Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (Eastman, 2006). It is difficult to compare the performance of the numerous models because LU/LCC models can be fundamentally different in a variety of ways. For example, some models, such as GEOMOD, simulate change between two land categories (Silva & Clarke, 2002) while others, such as CA_MARKOV, can simulate change among several categories (Pontius & Chen, 2006). However, it is difficult to compare which one gives a more accurate representation (Wu & Webster, 2000).

1. **Land Change Modeler (LCM)**

Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI SELVA that is used to the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation (Eastman, 2012). Land Change Models are important tools for environmental and geomatics research concerning LUCC (Pontius & Chen, 2006). Monitoring and analysis of changes in LULC are needed to provide information on existing land use patterns and changes for decision-makers to support sustainable development (Fan et al., 2017). LULCC models are used to improve and/or better understanding the alteration of land use that is induced by human activities (Brown et al., 2004). In LCM, tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, habitat and biodiversity impact assessment, and planning interventions (Eastman, 2012). In IRDRISI Run Transition Sub-Model panel is where the actual modeling of transition sub-models is implemented. Three methodologies are provided for modeling: a Multi-Layer Perceptron (MLP), Similarity-Weighted Instance-based Machine Learning (SimWeight), and Logistic Regression. Multi-Layer Perceptron and SimWeight procedures perform best in modeling transitions (Eastman, 2012). The MLP option can run multiple transitions, up to 9, per sub-model. But SimWeight and Logistic Regression can only run one transition per sub-model. Both MLP and SimWeight use half of the samples (change pixels) for training and the other half for validation. MLP generates predicted class memberships for each of the validation pixels at each iteration and reports the aggregate accuracy as well as a skill score. The skill score represents the difference between the calculated accuracy using the validation data and expected accuracy if one were to randomly guess at the class memberships of the validation pixels. SimWeight calculates the mean transition potential among validation pixels that changed (i.e., went through the transition) and the mean transition potential among pixels that did not change (persisted). These express the hit rate and false alarm rate respectively. The difference between them yields the Peirce Skill Score a value between 0 and 1 Logistic Regression. This model undertakes binomial Logistic Regression and prediction using the Maximum Likelihood method.

2. Earth Trend Modeler (ETM)

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

3. GEOMOD

GEOMOD is the model that has been used frequently to analyze baseline scenarios of deforestation (Pontius & Chen, 2006). It is a grid-based land-use and land-cover change model, which simulates the spatial pattern of land change forwards or backward in time. Simulates the change between exactly two land categories denoted as 1(non-developed and 2 (developed), but 1 and 2 could represent any two categories for any particular application (Pontius & Chen, 2006). The minimum input requirements are the beginning time, the ending time, an image of the beginning time for two land cover types that must be denoted by 1 and

2, and an estimate of the number of cells of each of the two categories at the ending time and Suitability map. GEOMOD is used to Predicts land selected land classes in the future using a land use/cover map. Its advantages need only a one-time land use map for calibration and its disadvantage can simulate change only in two categories (Pontius & Chen, 2006). GEOMOD has been designed such that it can take maximum advantage of data that can vary highly in availability, completeness, precision, currency, and accuracy (Silva & Clarke, 2002).

4. **Cellular Automata (CA)**

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

5. **Markov chain model**

A Markov chain is a random process having a property characterized by memory less transition from one state to another on a state space take place such that it depends only on the present state and not on the past states that the process went through. A random process could be termed as a Markov chain when in a series of events, any event that is about to occur depends only on the present state and eventually forms a kind of a chain. A Markov chain model is a stochastic process that analyses the probability that one state will change to another one – i.e., the state of a system at time t2 is predicted from the state the system is in at time t1 (Thomas and Laurence, 2006). Future prediction using Markov chain modeling is generally done by analyzing two qualitative land cover images taken on different dates (Moghadam & Helbich, 2013). The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix, stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012). Markov Model used to explain Land use change using Multi-Temporal Land Use/ cover Maps. Its strength is considered both spatial and temporal change and its weakness is no sense of Geography (Agarwal, 2002).

6. CA-Markov Model

The Markov model can quantitatively predict the dynamic changes of landscape patterns, while it is not good at dealing with the spatial pattern of landscape change. On the other hand, Cellular Automata (CA) has the ability to predict any transition among any number of categories (Sang et al., 2011). Combining the advantages of Cellular Automata theory and the space layout forecast of Markov theory, the CA- Markov model performs better in modeling land cover change in both time and spatial dimensions. CA-MARKOV Used to explain Spatio-Temporal dynamic modeling and Predicts land use/cover in the future using Multi-Temporal Land Use/ cover maps and Suitability maps. The strength of CA-MARKOV is creating the data is easy, CA add a spatial dimension to the model, and can simulate change among several categories. Its weakness is Socioeconomic factors are not considered and calibrating the model with MCE is too time-consuming compared to other methods (Adhikari & Southworth, 2012).

2.12 Review of empirical studies

Urban growth, a dynamic and demographic phenomenon, refers to the increased spatial value of urban areas, such as cities and towns, due to social and economic forces. Nowadays, urban lands are rapidly increasing, replacing non-urban lands such as agricultural, forest, water, rural, and open lands (Ajeeb et al., 2020) and (Hashem & Balakrishnan, 2015), study on Seremban Basin. Ajeeb et al (2020) was attempts to determine effectiveness of the CA-Markov chain model in modeling urban growth can clearly be seen in Seremban Basin, something is does especially well in developing countries with their varied urban environments. According to this study apply the force behind the urban growth in the predictive processes of the CA-Markov chain model, so that we may obtain a much deeper understanding of the change in urban growth patterns.

The spatial characteristics of land use features were measured using spatial metrics to explain the physical characteristics (Aithal & Ramachandra, 2016); (Pham & Yamaguchi, 2011) and (Akintunde, 2019), forms and pattern of the land use. The area under vegetation has declined from 70 % to 48 % with urbanization has increased from 1.46 % to about 18.5 % Chennai, India (Aithal & Ramachandra, 2016). The study has demonstrated that urban growth processes, patterns and structures can be quantified and monitored using a combination of remote sensing data, geo-informatics and spatial metrics through gradient approaches. The combination of remote sensing, landscape metrics and gradient analysis provides insights into the multidimensional phenomenon of urbanization and of dispersed growth– factors essential for urban planning. The spatial metrics reveal a significant increase in number of urban patches in all directions and gradients during two decades, indicating landscape fragmentation post 2000 (Aithal & Ramachandra, 2016). Patches at the city center are combining to form a single clumped dominant patch, whereas in outer gradients is more fragmented. The analysis of urban growth patterns emphasizes the need for judicious land-use transformation, as well as the formulation of urban development policy with an emphasis on the sustainable utilization of natural resources.

Depending on the availability of data and analytical techniques, studies on the changing land use and land cover in Ethiopia span a variety of geographical areas and academic fields. The majority of research, however, has been on deforestation, the expansion of farmed land to land degradation, river catchments and watersheds, natural ecosystems, and forests, as well as the resulting effects. Among these:(Amsalu et al., 2007); (Bewket & Abebe, 2013); (Tekle & Hedlund, 2000) and (Zeleke & Hurni, 2001) were found. While urban growth and its impacts are relatively studied in larger and megacities (a metropolitan area of more than ten million people) worldwide. Urban growth and modeling studies in cities of developing countries like, Ethiopia, were limited. However, few studies have been reported relatively such as: (Haregeweyn et al., 2012); (Dorosh & Schmidt, 2010); (Zeleke & Hurni, 2001); (Amsalu et al., 2007) and (Bekalo, 2009). (Zeleke & Hurni, 2001) reported an expansion of cultivated land at the expense of natural forest cover between 1957 and 1982 in Dembecha area, north-western Ethiopia. The study also investigated a series trend of land degradation resulted due to the expansion of cultivated land on steep slopes at the expense of natural forests. Amsalu et al (2007) showed a significant decline in natural vegetation cover, however, there was an increase of plantation in Beressa watershed, in the central highlands of Ethiopia between 1957 and 2000. Yeshaneh et al (2013) also showed a significant decrease of natural woody vegetation of the Koga catchment since 1950 due to deforestation in spite of an increasing trend in eucalyptus tree plantations after the 1980's. Barow et al (2019) testified built-up areas in Jigjiga town have expanded dramatically, while cropland and vegetation cover shrunk. The sprawl of Jigjiga town was largely due to the rapid expansion of built-up area towards the surrounding peri-urban neighborhoods caused by natural phenomenon of population increase, rural-urban migration, and most importantly, the changing status of the town from zonal capital to regional capital. Such a phenomenal increase in the town's population has led to a construction boom in the surrounding peri-urban areas which in turn reduced the size of cropland and vegetation cover.

Land use/land cover change (LULC) analyses are crucial for a well-informed decision-making regarding proper land uses planning policy. This study identified five LULC classes such as forestland, farmland, grassland, settlement, and waterbody in the study area, for the study periods of 1987–2017. Based on the LULC changes, farmland and settlement increased while forestland and grassland were reduced in the study period of time (1987–2017). A broad-spectrum trend was inspected as increment of farmland and settlement areas; meanwhile, shrinkage of forestland, grassland, and waterbody will continue in the near future, 2032–2047 (Tadese et al., 2021).

Bewket & Abebe (2013) reported a reduction of natural vegetation cover, but an expansion of open grassland, cultivated areas and settlements in Gish Abay watershed, north-western Ethiopia. Tegene (2002) reported a significant conversion of natural vegetation cover to cultivated land between 1957 and 1986 in Derekolli catchment of the South Welo Zone of Amhara Region, Ethiopia. (Kindu et al., 2013) investigated a significantly reduction of natural forest cover and grasslands, but an increase of croplands between 1973 and 2012 in Munessa, Shashemene landscape of the Ethiopian Highlands. A similar study by (Tekle & Hedlund, 2000) reported an increase of open areas and settlements as the expense of forests and shrub land between 1958 and 1986 in Kalu District, Southern Wello, Ethiopia.

The impacts of land use and land cover changes on the hydrological flow regime of the watershed have been reported in many studies. The impact is through altering the balance between rainfall and evaporation and the runoff response. Muluneh & Arnalds (2010) reported an increment of a direct runoff Gum-Selassa and Maileba catchments annually from 1964 to 2006 in both catchments due to long-term changes of land use and land cover. A similar study reported the drying of Lake Cheleleka and the disappeared Lake Haramaya due to these long-term impacts. It was also reported by Geremew (2013) that land use and land cover changes affected the stream flow of Gilgel Abbay watershed, Ethiopia. His study identified that there was an increase of stream flow by 16.26 m3/s during wet months and decreased by 5.41 m3/s from 1986 to 2001 as a consequence of conversion of cultivated land.

Land use and land cover changes in response to urban growth also reported by some studies that, an expansion of urban areas annually from 1957 to 2009 has been identified by (Haregeweyn et al., 2012) in the urban fringe of Bahir Dar area as a consequence of increasing population. Bekalo (2009) identified a significantly increase of urban areas from 34% in 1986 to 51% in 2000 in Addis Ababa, Ethiopia by the expense of agricultural land and vegetated areas driven by population growth. Dorosh & Schmidt (2010) also reported a significant urban growth for the last 3 decades as a result of increase in population of Ethiopian highlands. Muluneh & Arnalds (2010) cited on Haile (2004) that unsustainable growth of population contributed to environmental degradation especially in most populated areas such as in Ethiopian highlands. From most of these studies it is evident that population pressure is one of the major drivers of land use and land cover changes through destruction of forest and vegetation cover for the purpose of agricultural and urban expansion as discussed by (Zeleke & Hurni, 2001) and (Amsalu et al., 2007). Population growth coupled with migration from rural to cities leads to further expansion of urban areas at the expense of vegetation cover which is commonly practiced in western highlands of Ethiopia according to (Zeleke & Hurni, 2001) study.

The study in Wolaita Sodo Badesso (2020) identified changes in land use in relationship with growing population in Sodo and its peripheries for the period 1985 to 2016. The study showed that the area under forestland, bare land, grassland and cropland were declined while the area under built-up area was increased. Urbanization is the most irreversible and human dominated form of land use in the area. Some of the socio-demographic data are of relevance to the respondents' disposition and bearing on the peri-urban land use change patterns. Teshome M (2019) investigate land use/land cover changes over the last two decades in Wolaita Sodo town between 1999 and 2019 using remote sensing and GIS techniques. The results clearly showed that LU/LC changes were significant during the period under study. There was significant expansion of built-up area noticed. On the other hand, there is decrease in agricultural areas, open spaces and green fields.

2.12.1 Research and Knowledge gaps

Badesso (2020) and Teshome (2019), both of them were use Maximum Likelihood classification algorithm in ERDAS IMAGINE and mapped using ArcGIS in case of Wolaita Sodo town, in this study support vector machine(SVM) classification algorithm was used to generate LULC map of Wolaita Sodo town, high resolution sentinel satellite image was used for classification. Regassa (2014); Nugusa (2020) and Gemechu (2021), were use markov chain model to predict future land use/land cover, this thesis uses markov chain to predict and use population as a constraint to get future land use land cover of the study area and uses spatial metrics to examine landscape structure.

2.13 Conceptual Framework

The current geospatial information on patterns and trends in land use/land cover are already playing a significant role in understanding the evolution of different land-use systems, analyzing dramatic changes in land use/land cover at global, continental, and local levels, and further exploring the extent of future changes. Remotely sensed imageries provide an efficient

means of obtaining information on temporal trends and spatial distribution of urban areas needed for understanding, modeling, and projecting land changes (Elvidge et al., 2004). The following flowchart were conceptual frame work that was applied for the study. It demonstrates how analyze and model the spatio-temporal urban growth of Wolaita Sodo.

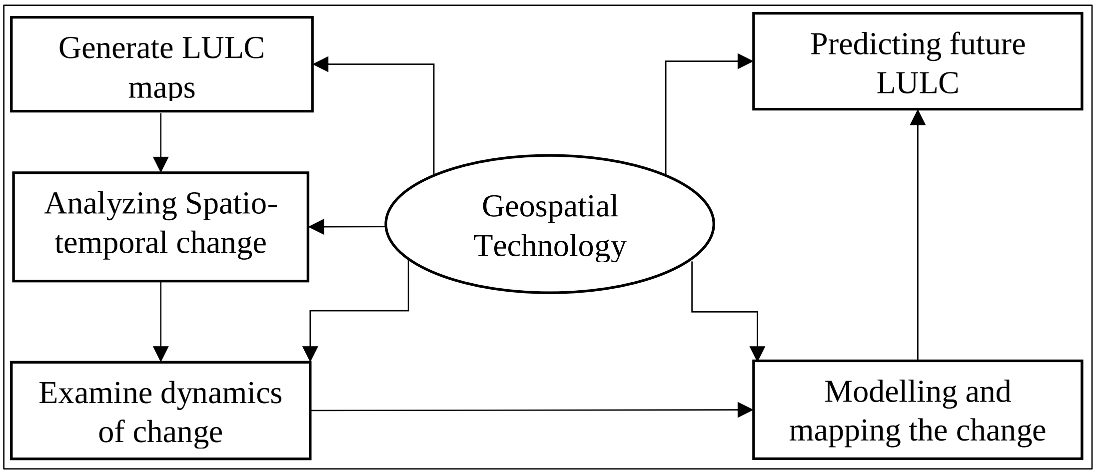


Figure 2.2: Conceptual Framework (Source: Author)

CHAPTER III: MATERIALS AND METHODS

3.1 Description of the study area

3.1.1 Geographic location

Wolaita Sodo is the administrative capital of Wolaita Zone in Southern regional State of Ethiopia, is located 328 Km South and 151 Km of South West of Addis Ababa and Hawassa, respectively. The town is located 6°51'18" N latitude and 37°46'51" E longitude. Currently, the total area of the town is about 16269ha and is divided in to seven kebeles namely Arada, Mehal, Merkato yushuwa, Fana womba, Wadu amba, Dilbegerera and Larena amba. The town connects commercially important zonal capital such as Arbaminich (capital of Gamo Zone), Sawulla (capital of Gofa Zone), Hosanna (capital of Hadiya Zone), and Shashemane town (capital of Western Arsi Zone).

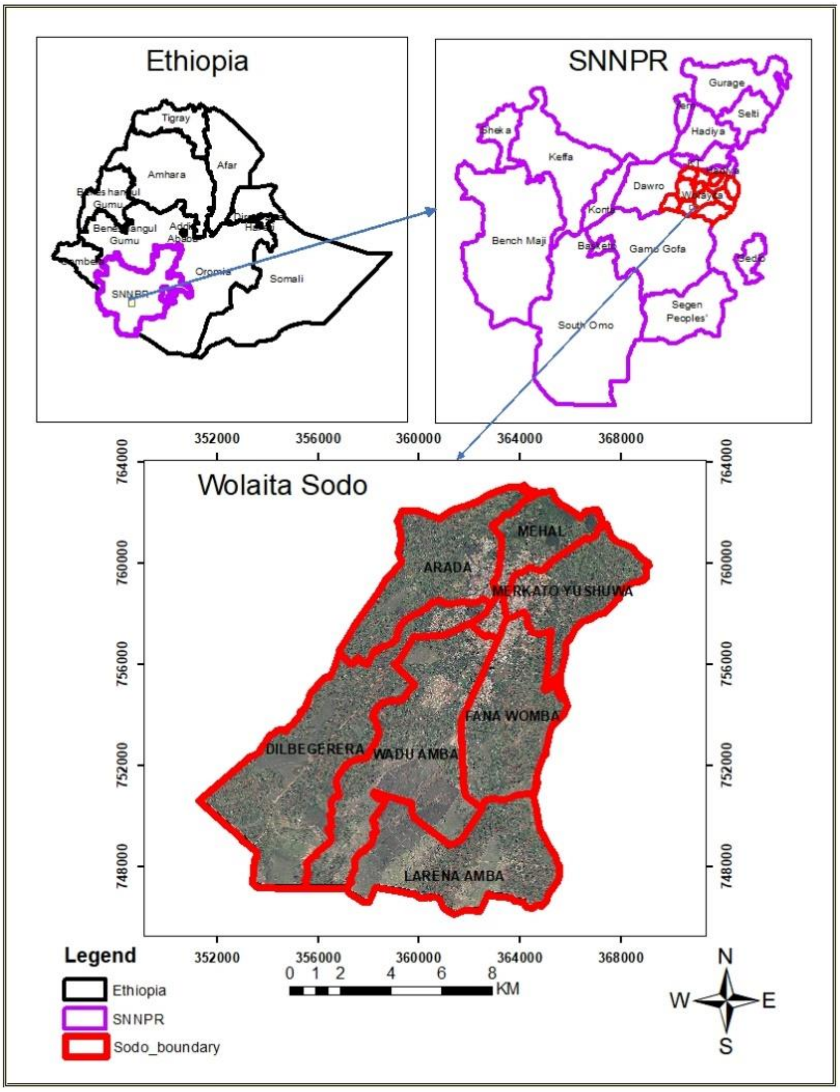


Figure 3.1: Map of the study area (Source: Author)

3.1.2 Establishment of the town

Wolaita Sodo is one of the oldest and fast-growing towns in SNNPR state. For the last 119 and more years Wolaita Sodo has been center of politics, social relations, religious practices, commercial place and symbol of the people of Wolaita. The name of the twon was derived from the prominent resident of the village called “*Mochena Borago Sodo”* (WDA Bulletin, 2008). The town was established during the conquest of *Ase* Menillik towards South of the capital, Addis Ababa. It was since this time that the town has become an important urban center following large scale formal settlement. The town has two main offices, these are the mayor offices led by the mayor and the municipal office which is led by manger that is accountable to the mayor and it is divided in to three sub town administration and eleven kebeles, now it is decreased to seven kebele administration. Currently the town serves as a capital of Wolaita zone, Sodo Town, Sodo Zuria district and it has many regional and federal government institutions.

3.1.3 Climate

Sodo is located in the tropics at high altitude Sodo possesses a well-moderated Subtropical highland climate, with a pronounced pattern of wet summers and dry winters. The climate of Wolaita Sodo town is described based on the type of rain fall and temperature. Despite being located in the Northern Hemisphere, Sodo is actually cooler in the "summer" than the "winter" due to much higher rainfall in the high-sun season, a phenomenon common to Sodo's region. The mean annual rain fall is greater than 1550mm per year. Most part of the town Sodo experiences Woina dega (warm to cool) type of climate (SNNPR, Bureau of Regional Meteorology Annual Report 2012) except the Mt. Damot environment of the town, which experiences colder climate. The south and southwest peripheries of the town experience transitional types of climate (warm to hot) (woina dega to kolla) mainly due to the effect of south east rift valley that crosses the surrounding woreda (Dellbo Wogen and Humbo Taballa) and run into the lowlands of lake Abaya and Chamo, the rift valley lakes.

3.1.4 Topography

Topography describes the surface shape and relief of the land. It refers to the various landforms (physical features) which represent the external shape of the earth. It determines the patterns and form of many other landform and land cover features. Topography of the town is predominantly characterized by mountains, steep or hilly, gorges and plain landscapes especially towards southern part of the town. Enjoying a Woyna-Dega climate, the town lies on an elevation ranging from 1717 to 2800 meters above sea level and has a sloppy topography. The town is situated at the foot of mount Damot in the north and stretching down towards south. Mt. Damot, the most prominent feature and symbolic representation of the region, is 2800 meters high.

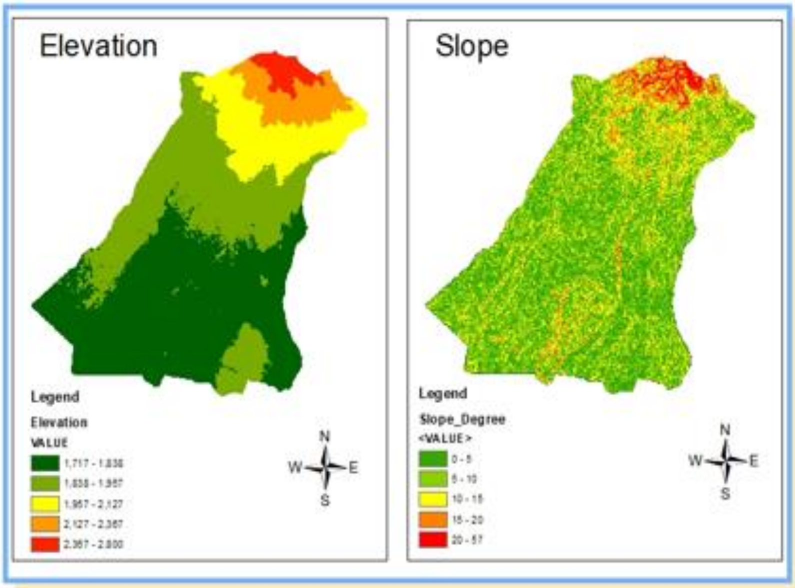


Figure 3.2: Elevation and Slope map of the study area (Source: ASTER DEM)

3.1.5 Soils of the Study Region

Soil is defined by Davidson (1980) as a natural body consisting of layers or horizons of mineral and/or organic constituents of variable thickness, which differ from the parent material in their morphological, physical, and chemical properties and their biological characteristics. According to the soil classification of FAO (1997), there are three soil types in the study area namely: chromic luvisols, chromic vertisols and dystric nitisols.

Chromic Luvisol: is the dominant type of which covering the northern parts of the study area including the north central part of the town. This part of the town has more elevated and rugged terrain. Most Luvisols have good agricultural potentialities. In soils with a heavy textured B horizon, permeability might be low, and drainage and good root distribution can be hindered.

Chromic Vertisols: This type of soil is dominant in the central area of the town. This kind of soil covered the whole areas of the central town which is highly urbanized and occupied by multi urban infrastructures. Vertisols are heavy clay soils in flat areas. During dry season they shrink and have deep cracks in a polygonal pattern, but on the contrary during the wet season the clay swells and causes pressure in the sub-soil. Chromic vertisols are brownish and better drained. But, in general, vertisols have fairly good, but limited agricultural potentialities. Land preparation is difficult, dry soils are hard and wet soils are sticky. The moisture condition of the surface layer is only during for a short period favorable to prepare land. Another difficulty is that the permeability of the subsoil is very low. Very often these soils are flooded or have stagnant water during the rainy season. The soil has high water retention, but relatively a small amount of water is available for plant growth. Rooting depth might be restricted because of the swelling and shrinking properties of the soil.

Dystric Nitisols: Nitisols are deep, clay red soils with an argillic B horizon. They have rather good potentialities for agriculture. These soils have very good physical properties. They have a uniform profile, are porous, have a stable structure and a deep rooting volume. Their moisture storage capacity is high. This soil covered the southern parts of the study area.

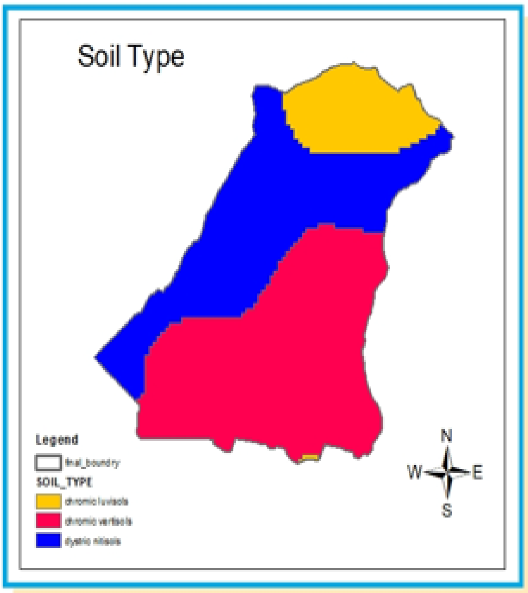


Figure 3.3: Soil type map of the study area (Source: FAO 1997)

3.1.6 Drainage

There are many streams originate from the foot of mount Damot which disseminate into the town in different parts. Among them the main ones include; *Hamassa*, *Kalte, Kokate, Bichere*, *Lintala*, *Waja* river, etc. The study region is demarcated in the west and east with two permanent rivers (*Hamassa* and *Waja* River). Most of the rivers are intermittent in nature during dry season except *Hamasa* and *Waja* rivers, which drain into Lake Abaya. As the town is situated at higher elevation, the flood hazard risks remain common and serious in damage particularly during rainy seasons.

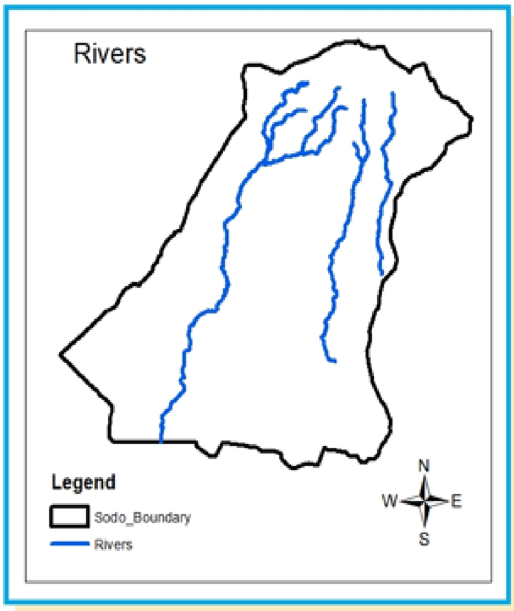


Figure 3.4: Stream map of the study area (Source: Sodo Structure Plan 2018)

3.1.7 Demography

The 1994 national census reported Sodo town had a total population of 36,287 of whom 18,863 were males and 17,424 were females. Based on the 2007 census conducted by the central statistical agency of Ethiopia (CSA) it had 76,780 and increased over the population recorded in the 1994 census, of which 40,495 were males and 36,285 were females. Based on SNNPR Finance and Economic Development Bureau (SNNPR BoFED, 2015) report, population size of Sodo town in 2015 was 197,045 of whom 99,090 are males and 97,955 are females. According to Wolaita Zone Finance and Economy Development office (WZFED, 2018) report, the town has estimated total population of 254,294, of whom 125,855 are males and 128,439 are females. The sex ratio shows slight difference between males and females. Similarly, the rate of urban population showed rapid increase with annual rate of 4.8%, which by far exceeds the regional growth rate. Population size of Wolaita Sodo in 2021 was projected based on annual growth rate, it was 290,912, of whom 143,978 are males and 146,934 area females.

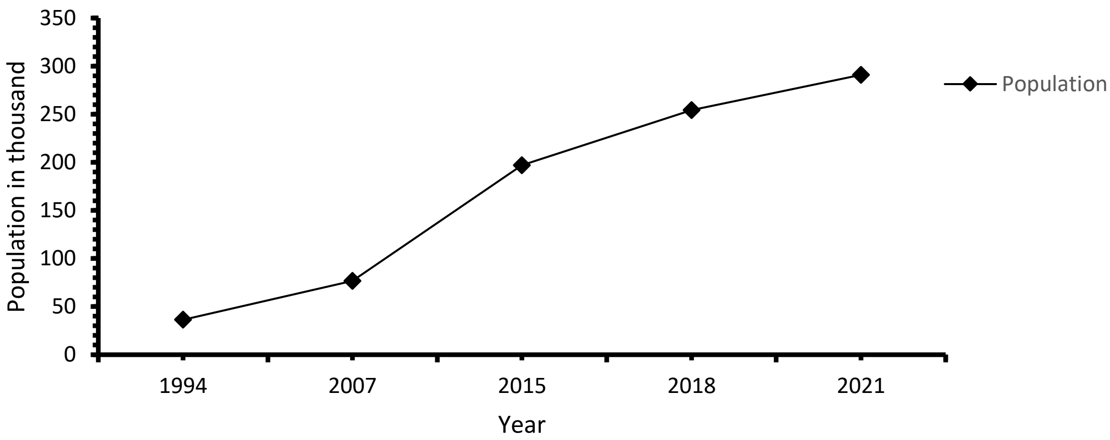


Figure 3.5: Population growth of Wolaita Sodo in the past 27 year

3.1.8 Socio-economic Characteristics

The high rate of rural to urban migration added heavy pressure on the rate of urbanization and the socio-economic condition of the town. Economically most of the dwellers are engaged in trade activities except few who are involving in the practice of different economic activities such as agricultural, handcrafts, smith and jewelry, etc. The rate of dependency is relatively low when compared with the country's share.

Sodo town is among the few towns in the region endowed with good infrastructure access, for instance, road network, hydro-electric power & cleaned pipe water supply, modern telephone, banking, educational and health facilities. The town has a graveled road network connection with its neighboring towns, fundamental for transportation access. The main highway that stretches from Addis Ababa to Arbaminch - Jinka towns passes across Sodo town.

3.2 Data Sources and Software Used

3.2.1 Data Used in this Research

The research was use Landsat and Sentinel images as the prime remote sensing data due to the availability of images for an extensive period of time as compared to other satellite types. I was use images from 1990-2022, because there are many changes in this period and for availability of the data. The interval of study period was 1990-2003, 2003-2016 and 2016-2022, in first and second study period thirteen-year gap was used and in third study period sex-year gap was used. In first study period from 1990-2003 Sodo town was changed from woreda capital to zone capital town, in second study period from 2003-2016 the socioeconomic characteristics of Sodo town was highly changed based on Wolaita Sodo mayor office report 2018, the third interval from 2016-2022 was used. The year 1990, 2003, 2016 and 2022 selection were primarily based on availability quality of Landsat and Sentinel data. Two Landsat images (1990 and 2003) and two sentinel images (2016 and 2022) is obtained from the United States Geological Survey (USGS) online data portal. Sentinel-2 is a system of two polar-orbiting satellites that contribute to the continuity and improvement of the SPOT and Landsat series of multispectral missions, and ensure the delivery of high-quality data and applications for operational land monitoring, emergency response, and security services. The satellite images were select based on the availability of data and quality. For this reason, the study was use Landsat 30m resolution and sentinel image 10m. All of the datasets use for the study were geometrically calibrated using WGS 1984_UTM zone 37 N.

Table 3.1: Characteristics and properties of the Landsat and sentinel images used

Acquisition Date	Path/Row	Landsat/Sentinel data	Senor	Spatial Resolution	Number Bands
1990-10-22	169/55	Landsat 5	TM	30 m	7
2003-02-04	169/55	Landsat 7	TM+	30 m	8
2016-11-13	169/55	Sentinel	ESA 2A	10 m	12
2022-03-07	169/55	Sentinel	ESA 2A	10m	13

Several ancillary data were also collected for this research. The ASTER Global Digital Elevation Model was retrieved from the NASA online data portal. Vector data of administrative boundaries, roads, and population data was also obtained from the Sodo land administration office. All of the datasets use for the study were geometrically calibrated using WGS 1984_UTM zone 37 N.

3.2.2 Materials and Softwares used

Software are program used for collecting, organizing, analysis, interpretation and presentation of data. In order to meet the objective of this study the software listed in table 3.2 below was used.

Table 3.2: Materials and software used

Software used	**Its functions**
ArcGIS 10.8	Visualization, map layout and accuracy assessment for classification, Post classification tabulation
ERDAS (2015)	Digital image preprocessing, layer stacking, radiometric correction, and delineation of area of interest (AOI) or subset
ENVI (5.3)	For Image classification
TerrSet2020	For change analysis, multi-criteria and multi objective decision support, simulation modeling, and prediction for the future LULC map.
Google Earth	Visualization and verification of classification and point data collection for accuracy assessment of 1990,2003 and 2016 map.
Fragstats	To calculate landscape metrics
Handle GPS	Collect Ground Controls Points (GCPs), accuracy of the handheld GPS used were 5m.

3.3 Data collection techniques

Satellite images

Two Landsat images (1990 and 2003) and two sentinel images (2016 and 2022) were obtained from the United States Geological Survey (USGS) online data portal. The satellite images were select based on the availability of data and quality. For this reason, the study was use Landsat 30m resolution and sentinel image 10m.

Vector data

Vector data of new administrative boundaries with all seven kebeles, roads, and river data was obtained from the Sodo land administration office.

Ground control point

Ground control point was collected from field by using handheld GPS by the researcher and data collectors. This ground control point was randomly taken point from field to calculate accuracy assessment of 2022 classified image.

Digital Elevation Model (DEM)

The ASTER Global Digital Elevation Model was retrieved from the NASA online data portal. This Digital Elevation Model were used to produce Elevation and Slope of the study area which were used in prediction of land use land cover map as driver variables.

Population data

The population data of Wolaita Sodo was obtained from Wolaita Zone Finance and Economy Development office. The population data for all year was projected based on the rate of population growth in the study area.

3.4 Data processing

3.4.1 Satellite image processing

The satellite image could not be used directly to interpret or delineate physical features. It needs to be process, including corrections to eliminate the errors introduced during image acquisition. The ideal or perfect remote sensing system has yet to be developed (Jensen, 2009). Remote sensing devices have constraints such as spatial, spectral, temporal, and radiometric resolution. Consequently, this has an influence on data quality during data acquisition. Therefore, it is usually necessary to pre-process the remotely sensed data before analyzing it in order to remove some of these errors. Image Pre-process including Georeferencing, mosaic construction, sub-setting of the image based on the boundary of the study area, and projection was performed for all images to be ready for use. Radiometric correction includes the process of haze reduction, removal of atmospheric noise, brightness inversion, and histogram equalization to make more representatives of the ground truth conditions based on the sensors. These activities were done to produce a corrected image as close as possible, both geometrically and radiometrically to the radiant energy characteristics of the original scene and to improve visible interpretability of the image by increasing apparent distinction between the features in the scene.

Layer staking

Layer stacking is a process for combining multiple images into a single image. In order to do that the images should have the same geometry (number of rows and number of columns), which means you will need to resample other bands which have different spatial resolution to the target resolution. In other words, all images/bands should have same spatial resolution to be able to perform layer stacking. However, combining images/bands will increase the final stacked image size, and consequently will increase the processing time later when you do your analysis. If you know that you will not use all the images/bands in your analysis, then it will be better to not stack all the images into a single image, and choose only specific images of interest. In this study the scenes of satellite image obtained from USGS were mosaicked together.

Sub-setting of study area images

The second step in image pre-processing is image extraction. Some irrelevant parts of the image can be removed and the image region of interest is focused. Taking out the project area from the whole part of the image is important to reduce the size of the image file to include only the area of interest (AOI). This does not only eliminate the extraneous data in the image. But it speeds up processing due to the smaller amount of data to process. This is important when utilizing multiband data Such as Landsat TM imagery. This reduction of data is known as Sub-setting. In this stage ERDAS IMAGINE and ArcGIS Software were important. In this process, satellite image was clipped through by the project area (Sodo town shapefile).

Image Enhancement

Image enhancement can be defined as the conversion of the image quality to a better and more understandable level for feature extraction or image interpretation (Lingereh, 2017). Although radiometric corrections (pre-processing) for illumination, atmospheric influences, and sensor characteristics were done for the suitability of visual interpretation Low sensitivity of the detectors, weak signal of the objects presents on the earth surface, similar reflectance of different objects and environmental conditions at the time of recording are the major causes of low contrast of the image. Another problem that complicates photographic display of digital image is that the human eye is poor at discriminating the slight radiometric or spectral differences that may characterize the features. The main aim of digital enhancement is to amplify these slight differences for better clarity of the image scene. This means digital enhancement increases the separability (contrast) between the interested classes or features. The digital image enhancement may be defined as some mathematical operations that are to be applied to digital remote sensing input data to improve the visual appearance of an image for better interpretability or subsequent digital analysis. It also valuable to detect and define LULC information classes since different multi temporal images have different spectral characteristics. A proper image enhancement includes multispectral transformation, false color composites and vegetation indices, which is important to achieve information of the area and spectral knowledge. Image enhancement is a method widely used to provide effective display for image interpretation (Cetin, 2009). Therefore, in this study, multispectral images were enhancement using ERDAS IMAGINE software.

3.5 Methods of data analysis

The analysis has conducted the map of urban built-up areas based on the satellite images and using other ancillary data. By delineating with the town boundaries, the spatial patterns of urban growth trends were analyzed and predicted urban growth at 2030, 2040, and 2050. Another analysis was the population figures for Sodo town for the period under investigation and investigated the relationship between built-up areas expansion and population growth for the period under investigation.

3.5.1 Analysis of land use land cover dynamics

Land use land cover mapping

- ✓ Defining classification scheme

Based on the major land use/land cover of the study area the following land class was classified from the satellite image. According to the Laotian Ministry of Agriculture and Forestry guideline (Thongphanh et al., 2006), the definition of each land class is described in the following table 3.3. In study area there are five major land use land cover classes, those are Agriculture land, Barren land, Built-up area, Forest land and Grassland.

Table 3.3: Nomenclature of land use land covers classes

Land classes	Land-cover types	Description
C1	Agriculture land	Cropland with permanent crops, farming, and fallow field
C2	Barren land	Open spaces with little or no vegetation, beaches, dunes sands, bare rocks
C3	Built-up area	Includes all developed areas, roads and transport infrastructures, buildings, housing units, commercial and residential areas, and under construction areas
C4	Forest land	Natural and manmade forests, Woodland shrubs, sparsely planted trees
C5	Grassland	Grasses, shrubs, bushes

✓ Training sample selection

Training samples for each class were collected from each image. Because highly heterogeneous land covers data (e.g., urban areas) are unlikely normally distributed; the distribution of land cover surfaces is associated with various uncertainties which prevent their description based on data distribution (Lu & Weng, 2007).

In order to reduce the sampling biases, consistency in sample selection was kept by selecting pixels that remained unchanged at different times to train the classifier. First, samples were selected from Landsat image of 1990 (first image). Subsequently, these samples were treated as training samples for the first image and used as a base for the adjacent image (2003). Second, the base samples were overlaid with the second image to check if change in class occurred. If changes were observed, new sample with more confidence was substituted from the surrounding area. Similarly, the same procedures were followed by selection of training samples for the rest of the images.

✓ Classification algorithm

Image classification is the process of sorting pixels into finite number of individual classes or categories of data, based on their DN (pixel) values. Classification of remotely sensed data is used to assign corresponding levels with respect to groups with homogeneous characteristics with the aim of discriminating multiple objects from each other within the image. The level is called class (Bhatta, 2012). Classification is the most popularly used information extraction technique in digital remote sensing

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

- ✓ Accuracy assessment

If the classification data are to be useful in detection of change analysis, it is essential to perform accuracy assessment for individual classification (Congalton & Green, 2009). Accuracy assessment is an essential and crucial part of studying image classification and thus LULCC detection is used to understand and estimate the changes accurately. It reveals the extent of correspondence between what is on the ground and the classification results. It is important to be able to derive accuracy for individual classification if the resulting data are to be useful in change detection analysis (Cagalton and Green, 2009). An overall accuracy was calculated by dividing the sum of the correctly classified sample units by the total number of sample units. Accuracy assessment is a kind of process to compare the classification with ground truth or other data. It allows evaluating a classified image file (Eastman, J. R., 2009). Usually this data is known as ground-truth data that has been collected in the field. It is not typical to ground truth each and every pixel of the classified image. Therefore, some reference pixels are generated. Reference pixels are points on the classified image. Each point of reference pixels represents specific geographic coordinate of the image. These reference pixels are randomly selected (Cagalton and Green, 2009). The randomly selected points within the classified image list two sets of class. The first set of class values represents the actual land cover type. The second set of class values are known as reference values. Reference sample data depends upon two types of sampling units, i.e., pixels (points) and polygons (patches) for this research used point sample data for accuracy assessment. Various mathematical theories develop to determine adequate sample sizes for Classification of Accuracy Assessment but no standardized consent reach yet regarding the adequate sample size determination. For the accuracy assessment overall kappa which is a statistical measure of overall agreement between two categorical items (Cohen's kappa,) and conditional kappa which includes, user's accuracy, producer's accuracy and overall accuracy were calculated. An error matrix is a square assortment of numbers defined in rows and columns that represent the number of sample units assigned to a particular category relative to the actual category as confirmed on the ground. The rows in the matrix represent the remote sensing derived land use map, while the columns represent the reference data that will be collect from fieldwork. The error matrix tables produce many statistical measures of thematic accuracy including overall classification accuracy, percentage of omission and commission error and kappa coefficient-an index that estimates in the influence of chance (Congalton & Green, 2009).

Overall accuracy

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

Overall accuracy can be calculated using below formula.

$$\boldsymbol{Over\ all\ accuracy} = \frac{\sum Xii}{n}$$

Where X number of correctly classified, N=Total number of pixel points

Omission Error

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

Commission Error

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

Producer Accuracy

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

User Accuracy

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

Kappa coefficient

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

Kappa coefficient can be calculated using below formula.

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

Where k=kappa coefficients, N=Total number of pixel points, Xii= correctly classified points (observation) in row i and column j, Xi=sum of Row points, Xj=sum of Column points.

Land use land cover change detection

One of the most important applications of spatio temporal data is to detect the changes for the same object between different seasons and different years. The process by which variation in an object at different times or changes that occur in LULC are checked and identified over a certain number of years is known as change detection (Eastman, 2006) and (Tewolde & Cabral, 2011). Land use land cover change is assessed between time 1 and time 2 between the two land cover maps. Different time steps was be used to identify changes, by making use of different multi temporal data sets of an area, which can be done with remotely sensed data.

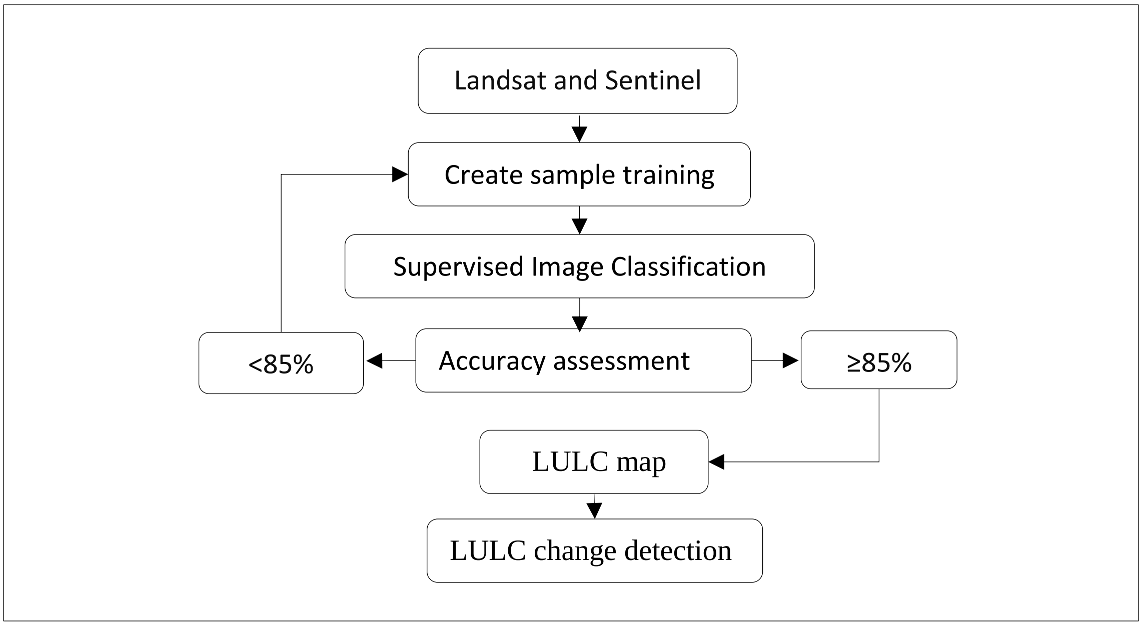


Figure 3.6: Flow chart for analysis of land use land cover change dynamics

3.5.2 Analysis of Landscape pattern and its dynamics

Selection of spatial indices

Selecting spatial indices involves a number of considerations. Firstly, the objectives of the study, spatial characteristics of the system and ecological processes under investigation determine which metrics to use (McGarigal, 2002). Secondly, landscape metrics were chosen on the basis of the literature review. A total of 14 landscape metrics both at class and landscape-level were chosen for this study. This are number of patches (NP), patch density (PD), largest patch index (LPI), landscape shape index (LSI), area-weighted mean patch fractal dimension (FRAC_AM), contagion index (CONTAG), patch cohesion index (COHESION) and Shannon's diversity index (SHDI) at landscape level, number of patches (NP), patch density (PD), class per cent of landscape (PLAND), largest patch index (LPI), patch cohesion index (COHESION) and aggregation index (AI) at class level. All of these metrics are used to quantify and examine the spatiotemporal changes of landscape compositions and configurations (Landscape structure) for the study area (McGarigal & Marks, 2002).

Computation of indices

Using the extracted classified cardinal raster image, the landscape metrics were calculated with the help of FRAGSTAT software package. The Spatio-temporal pattern of the landscape is quantitatively described in landscape level and class level.

Changes in landscape composition and configuration

Based on calculated landscape metrics both at landscape and class level, the composition and configuration change of the study area were examined. The composition and configuration of the study area was quantified and interpreted based on result that was calculated in the fragstats software package.

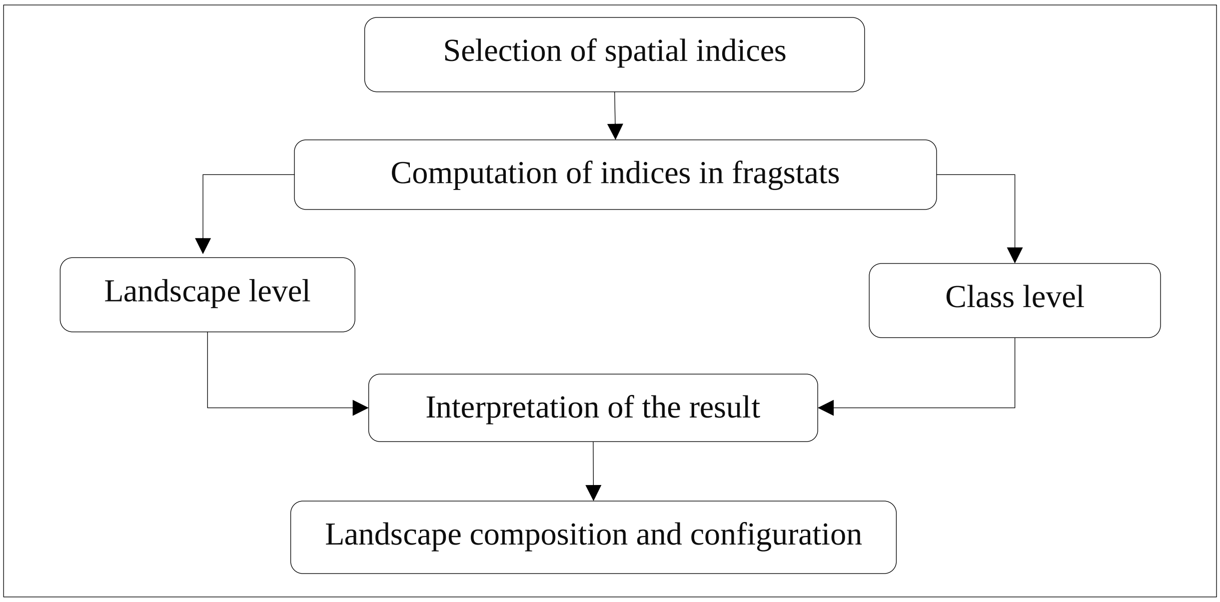


Figure 3.7: Flow chart for analysis of landscape pattern and its dynamics

3.5.3 Modelling LULC change and prediction of future growth

Modeling LULC change

Land-Use & Cover Change (LULCC) modeling is a rapidly growing scientific field because land-use change is one of the most important ways that humans influence the environment. Knowing the changes that have occurred in the past may help predict future changes. Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler (LCM), Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (Eastman, 2006). For this research Land change Modeler was used. Land change prediction in Land Change Modeler is an empirically driven process that moves in a stepwise fashion from Change Analysis to Transition Potential Modeling from Transition potential to Change Prediction.

Change Analysis

Change is assessed between time 1 and time 2 between the two land cover maps. The changes that are identified are transitions from one land cover state to another. It is likely that with many land cover classes the potential combination of transitions can be very large. What is important is to identify the dominant transitions that can be grouped and modeled, termed sub models. Each group, or sub model of transitions can be modeled separately, but ultimately each sub model will be combined with all sub models in the final change prediction. The change analysis panel provides a rapid quantitative assessment of changes, allowing the researcher to generate evaluations of gains and losses, net change, persistence and specific transitions graphical form. It also provides a means of generalizing the pattern of trend between two land cover map transitions (Eastman, 2006). Using change analysis of LCM of the Sodo Town 1990, 2003, 2016 and 2022 of LULCC in graphs of gains and losses, contributions to net change, transitions of land cover classes between different categories and spatial trend were analyzed.

Markov Chain Model Analysis

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

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

$$Pij = \begin{bmatrix} p11 & p12 & \dots & \dots\dots & p1n \\ p21 & p22 & \dots & \dots & \dots & p21 \\ pn1 & pn2 & \dots & \dots & \dots & pnn \end{bmatrix}$$

$$Including \;\; \sum_{j=1}^{n} Pij = 1$$

Where L (t) and L (t+1) represents land use status at time t and t + 1 respectively. (i, j= 1, 2… n) is the transition probability matrices that state i changes to state j and p = transition probability. The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix (Arsanjani et al., 2011), stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012).

Transition Potential Modeling

The second step in the Change Prediction process is Transition Potential Modeling, where the potential of land to transition are identified (Eastman, 2012). The collection of transition potential maps is organized within an empirically evaluated transition sub model that has the same underlying driver variables. A transition potential map for each transition is derived which is an expression of time-specific potential for change. Variables can be added to the model either as static or dynamic components. Static variables express aspects of basic suitability for the transition under consideration, and are unchanging over time. Dynamic variables are time-dependent drivers such as proximity to existing development or infrastructure and are recalculated over time during the course of a prediction. The Drivers/Factors considered are explained in detail under data analysis. Transition Potential Modeling, used to identify the potential of land to transition. A transition sub-model can consist of a single land cover transition or a group of transitions that are thought to have the same underlying driver variables. These driver variables are used to model the historical change process. Transitions Sub model are modeled using either a multi-layer perceptron (MLP) neural network, logistic regression, or similarity-weighted instance-based machine learning tool (SimWeight), but in this research MLP was used.

Multilayer Perceptron (MLP)

Artificial Neural Network is a mathematical model which is inspired from the human nervous system which interconnects the neurons for fulfills the complicated tasks in a short time. This model used for computers in order to solve the nonlinear systems. There are many types of ANN like Single Layer Perceptron, Multi-Layer Perceptron, Recurrent Network, Hopfield Network, Spiking Neural Network and many more (Neural Network, 2010). Multilayer Perceptron feed forward ANN is a network of simple neurons called the perceptron. It is composed of an input layer, output layer and hidden layers between input and output layer. It is a feed forward method which means data flows in one direction from input to output. The main algorithm of this model is computing the linear output from nonlinear inputs according to the weights by using a nonlinear activation function (Multilayer Perceptron, n.d.). Feed-forward means that data flows in one direction from input to output layer (forward). This kind of three-layer network is also known as ―Back Propagation Network‖ (IDRISI Taiga Help System, 2009).

1. Input Layer

The nodes are the elements of a feature vector. This vector might be the wavebands of a data set or the texture of an image (Berberoglu et al., 2000). This can also be ancillary data like slope, elevation, soil type, zoning etc. For this Research six inputs variable values for prediction in the network were used (LULC2016, population density, distance from Built up area 2016, distance from Road, elevation (DEM), slope map of study area).

2. Hidden Layer

The second layer is an internal or hidden layer. It does not contain output units. One hidden layer can represent any Boolean function (Berberoglu et al., 2000). The activity of each hidden unit is determined by the activities of the input units and the weights of the connections between the input and the hidden units.

3. Output Layer

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

- ✓ Number of training samples and iterations

The number of training sample also affects the training accuracy. Too few samples may not represent the pattern of each category while too many samples may cause overlap. Again, too many iterations can cause over training that may cause poor generalization of the network (IDRISI Taiga Help System, 2009). Over training can be prevented by early stopping of training (Karul et al., 2000). The acceptable error rate is evaluated based on the Root Mean Square (RMS) Error (Karul et al., 2000).

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

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

Automatic mode monitors and modifies the start and end learning rate of a dynamic learning procedure. The dynamic learning procedure starts with an initial learning rate and reduces it progressively over the iterations until the end learning rate is reached when the maximum number of iterations is reached. If significant oscillations in the RMS error are detected after the first 100 iterations, the learning rates (start and end) are reduced by half and the process is started again.

- ✓ Change prediction

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

Model Validation

After prediction the Model validation which refers to comparing the simulated and reference maps was conducted. Sometimes the simulated maps can give misleading results. In that case, it is necessary to validate the projected/simulated map with the base/reference map. Therefore, model validation is an important step in case of predictive change modeling (Eastman, J. 2009). The Validation is important stage panel that allows determining the quality of the prediction of land use/land cover map in relation to a map of reality. Validate provides a method to measure agreement between two categorical (integer or byte) images, a "comparison" map and a "reference" map. It calculates various Kappa Indices of Agreement and related statistics that indicate how well the comparison map agrees with the reference map and gives three types of results bar graph with table, trend line graph as a function of multiple resolutions, and text. Map comparison is vital in evaluating the analytical techniques for spatial data. The best way to validate a model is to compare the predicted map of time *t2* with the reference map of time *t2* (Pontius Jr & Chen, 2006). In this case for validating the output of the simulated LULC map in 2022, two maps were compared, the reference LULC map of 2022 and the simulated LULC map of 2022. The validation was based on kappa statistic and multiple-resolution. A number of variations of the Kappa statistic have been introduced by Pontius such as Kappa for no information (denoted as Kno) and Kappa for grid-cell level location (denoted as kLocation) (Pontius, 2000).

Table 3.4: Kappa statistic of Map comparison.

		Reference (Classified) 2022 Map					
		1	2	3	….	N	
Predicted 2022 map	1	P11	P12	P13	….	P1n	PP1
	2	P21	P22	P23	….	P2n	PP2
	3	P31	P32	P33	….	P3n	PP3
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	M	Pm1	Pm2	Pm3	….	Pmn	
	Total	PR1	PR2	PR3	…	1	

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

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

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

The calculation of Kappa is based on the -Contingency Table‟ or -Confusion Matrix (Hagen, 2002).

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

Where, Pnm. = the proportion of cells that is of category _n’ in map A and _m’ in map B.

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

Table 3.5: Strength of Agreement for Kappa Statistic (Landis & Koch, 1977)

Kappa Statistic	Strength of Agreement
< 0	Poor
0.00-0.20	Slight
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Substantial
0.81-1.00	Almost Perfect/Perfect

Kappa value ranges from -1 to +1. The maximum value +1 indicated, perfect agreement and the minimum value -1, indicates maximum disagreement. Kappa value 0 indicates, the observed agreement matches the agreement expected by random arranging of all cells (Hagen, 2002). Kappa can be negative. This is a sign that there is no effective agreement between the two rates (Simon, 2008).

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

Klocation: Klocation indicates the success due to the simulation‘s ability to specify location divided by the maximum possible success due to a simulation‘s ability to specify location perfectly (Pontius, 2000). It depends strictly on the spatial distribution of the categories on the map. It indicates how well the grid cells are located on the landscape (Pontius, 2000).

$$P(max) = \sum_{n=1}^{m} \min(Pn * Pm)$$

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

Where, P (max) = the maximum success rate, P (E) = the fraction of expected agreement for the whole map and P (A) = Percentage of cells in the map that are identical.

Khiston: Khisto depends on the total number of cells taken in by each category (Hagen, 2002). It is a statistic that can be calculated directly from the histograms of two maps (Hagen, 2002).

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

In order to ensure that the model is reliable in predicting a LULC for a specific project year, it must be validated using existing datasets. Therefore, the used model was validated by using two maps: the first one is the real land use and land cover of the year 2022, and the second map is a predicted (simulated) 2022 map. The latter was simulated by using the model and the same procedure that was implemented in predicting 2030,2040 and 2050 land use and land cover map, but, in this case, the 2003 and 2016 maps were used for simulating 2022 maps. The validate module in TerrSet was used for validating the model by producing several parameters: Kno, Klocation, and Kstandard that are used to identify the accuracy of the model.

Future LULC prediction

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

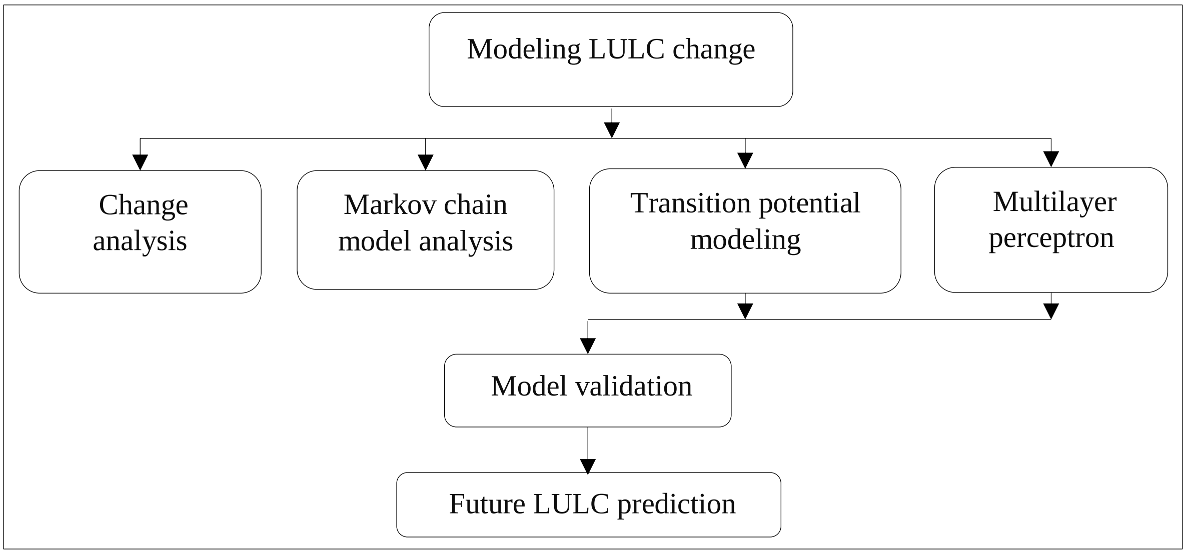


Figure 3.8: Flow chart for modeling lulc change and predicting future

3.5.4 General flow chart describes LULC change analysis and prediction

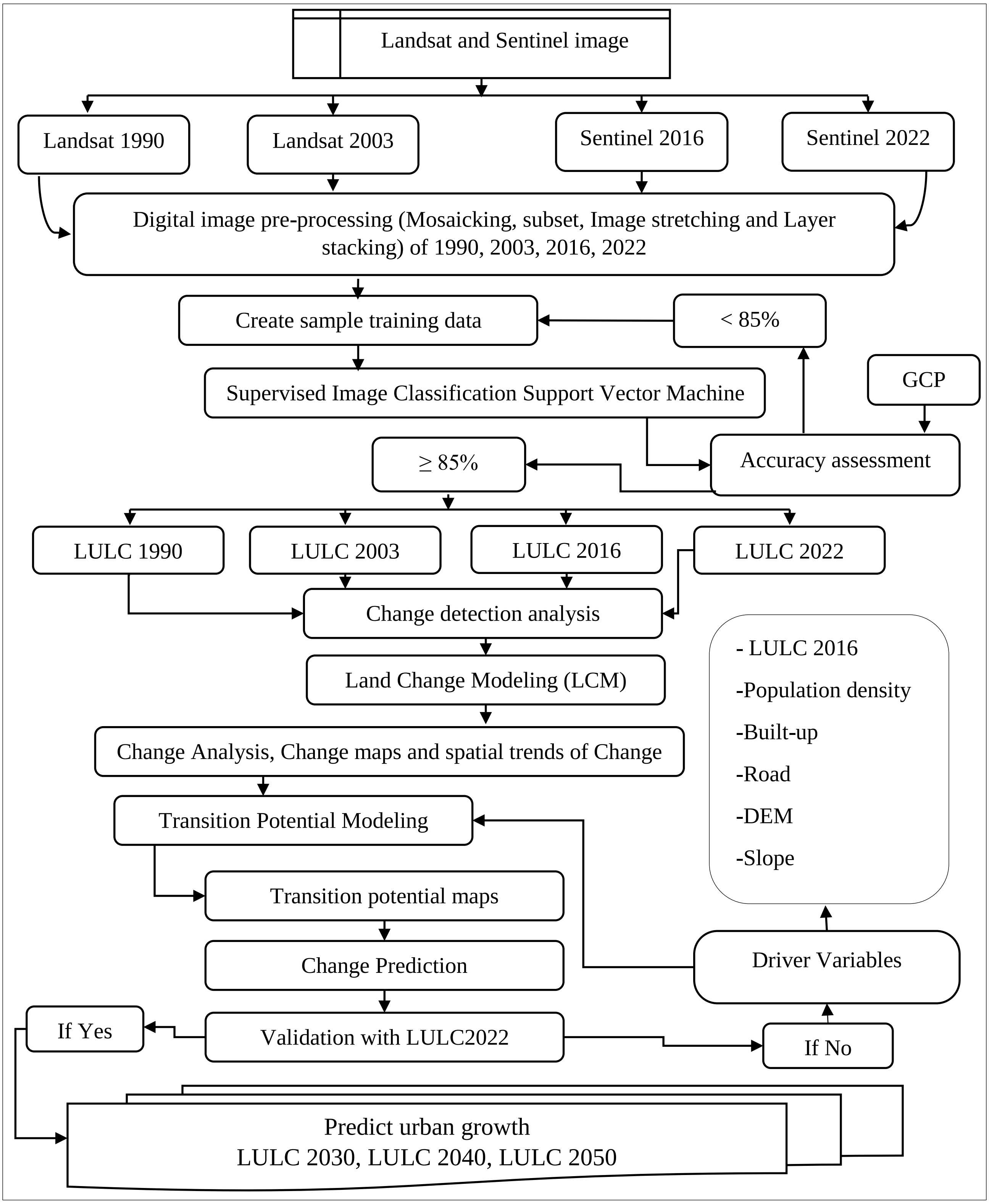


Figure 3.9: General flow chart that describe LULC change analysis and prediction

3.5.5 Regression analysis

In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome variable') and one or more independent variables (often called 'predictors, covariates', or 'features'). The most common form of regression analysis is linear regression. According to David, (2009) regression analysis can be used to infer causal relationships between the independent and dependent variables. Importantly, regressions by themselves only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset.

Correlation: is a statistical measure that determines the relationship or association of two or more variables. Correlation can be positive, negative, or no correlation. Positive correlation: when the value of one variable increase concerning another. Negative correlation: when the value of one variable decrease concerning another. No correlation: when there is no linear dependence or no relation between two variables. Correlation is utilized to assess the strength of the relationship between variables and for modeling the future relationship between them.

Relationship between Population growth and Built-up area expansion

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

Simple linear regression modeling

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

$$Y = Ax + B + e$$

Where: Y = Dependent variable, X = Independent (explanatory) variable, B = Intercept, A = Slope and e = Residual (error). The degree of correlation is perfect if the value is near ±1, then it is said to be a perfect correlation, as one variable increases, the other variable tends to also increase (if positive) or decrease (if negative). High degree if the coefficient value lies between ±0.5 and ±1, then it is said to be a strong correlation

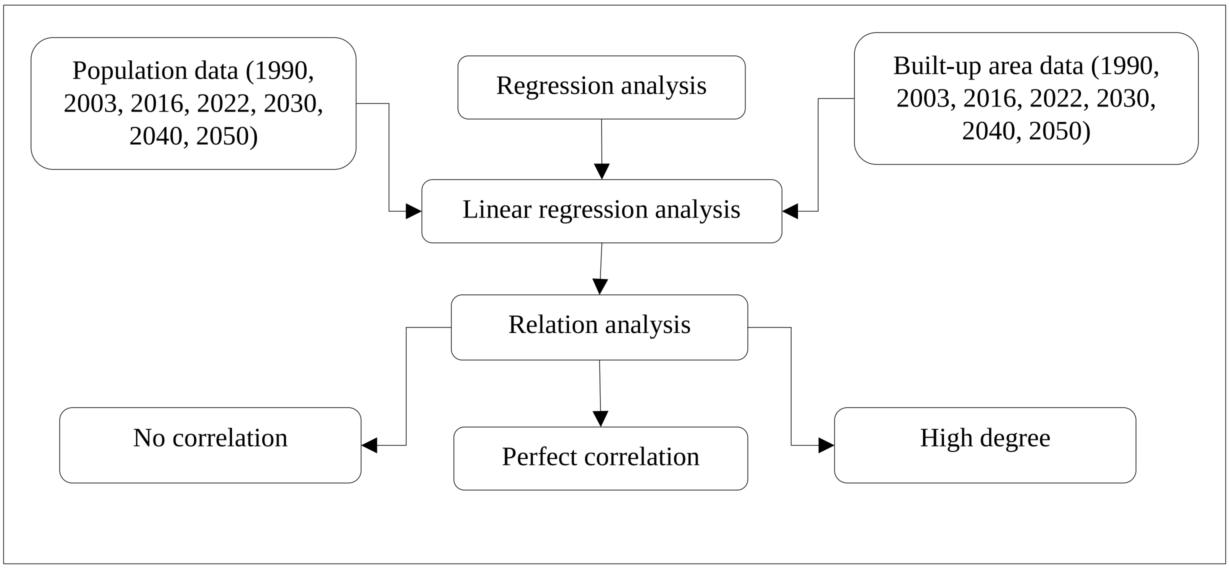


Figure 3.10: Correlation analysis between population growth and urban buildup area

CHAPTER IV: RESULTS AND DISCUSSION

In this chapter, based on the data gathered and data analysis performed output images of LULC images developed for the years 1990, 2003, 2016, and 2022 presented in the following figure and tables. An overall change in LULC in all four years is shown in Figure below. Additionally, the future Land use land cover predicted for the years 2030, 2040, and 2050 were presented in the following Figure 4.16.

4.1 Dynamics of Land use and land cover

The classified image of Landsat and sentinel image classified to five major classes (agricultural land, barren land, built-up area, forest area and grassland) based on the major class land of Sodo town. The accuracy assessment for each image were calculated and the result of all LULC are in acceptable range. The selection of the entire year was based on the availability and quality of data as the study area result in very shortage of spatial data.

4.1.1 Accuracy of image classification

LULC classification accuracy was assessed quantitatively using an error matrix which is the commonly used method in LULC classification accuracy assessment (Built, 2019). During this regard, sample pixels were selected from each of classified image. The samples were overlaid with Google earth (for 1990, 2003 and 2016) and ground truth point for 2022, supported the error matrix generated for every classified map overall accuracy, user's accuracy, producer's accuracy and overall kappa were calculated. The accuracy requirements for change detection analysis were determined supported the suggestion of Congalton and Green (2009). Accuracy assessment in this study revealed the overall accuracies of 91%, 89%, 92%, and 91% were calculated for 1990, 2003, 2016, and 2022, respectively. This implies that all classifications are in the acceptable range because the overall accuracy of each year is greater than 85% and the kappa coefficient greater than 0.80 represents strong (almost perfect) agreement (Rwanga & Ndambuki, 2017) is an indicator for a strong accuracy. The accuracy assessment value of four image were not the same because the image quality, acquisition time and resolution was not the similar. The details of the error matrix table results are shown below.

Table 4.1: Landsat 5 classification accuracy for 1990.

	Reference map 1990							
	LULC Type	Build-up	Agriculture	Forestland	Grassland	Barren land	Total	**User accuracy**
Classified LULC 1990	Build-up	20	0	0	0	1	21	**96.7%**
	Agriculture	0	82	4	4	0	90	**96.3%**
	Forestland	0	4	54	0	0	58	**94.9%**
	Grassland	0	4	3	59	0	66	**93.6%**
	Barren land	1	0	0	1	18	20	**90.0%**
	Total	21	90	61	64	19	255	
	Procedure accuracy	**95.2%**	**91.1%**	**88.5%**	**92.2%**	**94.7%**		
	Overall accuracy	**91.4%**			**Kappa coefficient (k) 0.88**			

Table 4.2: Landsat 7 classification accuracy for 2003.

	Reference map 2016							
	LULC Type	Build-up	Agriculture	Forestland	Grassland	Barren land	Total	**User accuracy**
Classified LULC 2016	Build-up	21	2	1	0	0	24	**87.5%**
	Agriculture	0	98	2	2	0	102	**96.1%**
	Forestland	0	6	35	1	0	42	**83.3%**
	Grassland	0	7	1	58	1	67	**86.6%**
	Barren land	1	0	1	2	16	20	**80.0%**
	Total	22	113	40	63	17	255	
	Procedure accuracy	**95.4%**	**86.7%**	**87.5%**	**92.1%**	**94.1%**		
	Overall accuracy	**89.4%**			**Kappa coefficient (k) 0.85**			

Table 4.3: Sentinel classification accuracy for 2016.

Classified LULC 2016	Reference map 2016						
LULC Type	Built-up	Agriculture	Forestland	Grassland	Barren land	Total	**User accuracy**
Built-up	96	3	4	0	0	103	**93.2%**
Agriculture	3	35	2	0	0	40	**87.5%**
Forestland	0	2	59	0	2	63	**93.6%**
Grassland	0	0	2	18	0	20	**90.0%**
Barren land	0	0	0	1	28	29	**96.5%**
Total	99	40	67	19	30	255	
Procedure accuracy	**96.9%**	**87.5%**	**88.1%**	**94.7%**	**93.3%**		
Overall accuracy	**92.5%**				**Kappa coefficient (k) 0.90**		

Table 4.4: Sentinel classification accuracy for 2022

Classified LULC 2022	Reference map 2022						
LULC Type	Built-up	Agriculture	Forestland	Grassland	Barren land	Total	**User accuracy**
Built-up	37	0	0	0	0	37	**100.0%**
Agriculture	4	81	8	2	0	95	**85.3%**
Forestland	1	2	39	0	0	42	**92.9%**
Grassland	0	2	0	59	0	61	**96.7%**
Barren land	0	0	0	3	17	20	**85.0%**
Total	42	85	47	64	17	255	
Procedure accuracy	**88.1%**	**95.3%**	**83.0%**	**92.2%**	**100.0%**		
Overall accuracy	**91.4%**				**Kappa coefficient (k) 0.88**		

4.1.2 Temporal land use land cover maps

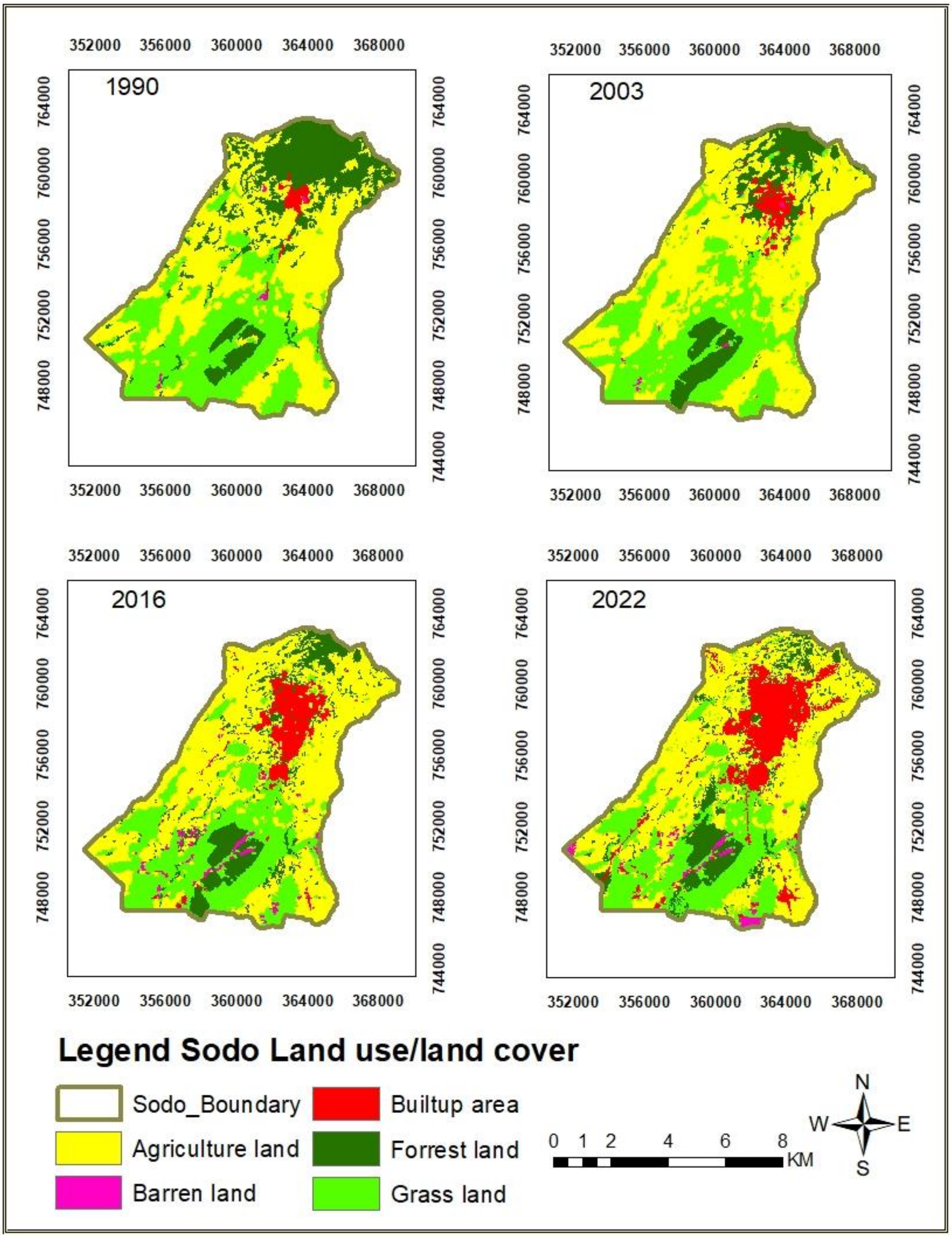


Figure 4.1: Temporal Land use/Land cover map of Sodo town 1990, 2003, 2016 and 2022.

After the preparation of temporal land use land cover maps, the changes that occurred during the studied periods in each land cover were detected. Over the past three decades, land covers in study areas such as forest area were decline and in the last six year it shows little increment, land cover type such as agriculture and barren land showed varying in pattern for past decades, the grassland land cover were continuous decline in the time period of 2003 up to 2022. The Built-up area showed continuous increment over the past 32 years. It increases for cover percent of study area from 1.16% to 11.37% in the last three decades.

The extent of change within the study area of the individual land cover categories in hectare and the percentage they occupied for 1990, 2003, 2016, and 2022 are presented in Table 4.5.

Table 4.5: Area statistics and percentage of land use land cover percentages units from 1990 – 2022

LULC	**1990**		**2003**		**2016**		**2022**	
Type	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Agriculture	7352.14	45.19	8567.87	52.66	8313.72	51.1	7625.6	46.87
Barren land	47.43	0.29	42.78	0.26	259.47	1.59	220.05	1.35
Built-up area	189.01	1.16	455.66	2.8	1161.51	7.14	1850.31	11.37
Forest area	3863.95	23.75	2285.37	14.05	2128.92	13.09	2336.9	14.36
Grass land	4816.95	29.61	4917.79	30.23	4405.84	27.08	4236.61	26.04
Total	**16269.47**	**100%**	**16269.47**	**100%**	**16269.47**	**100%**	**16269.47**	**100%**

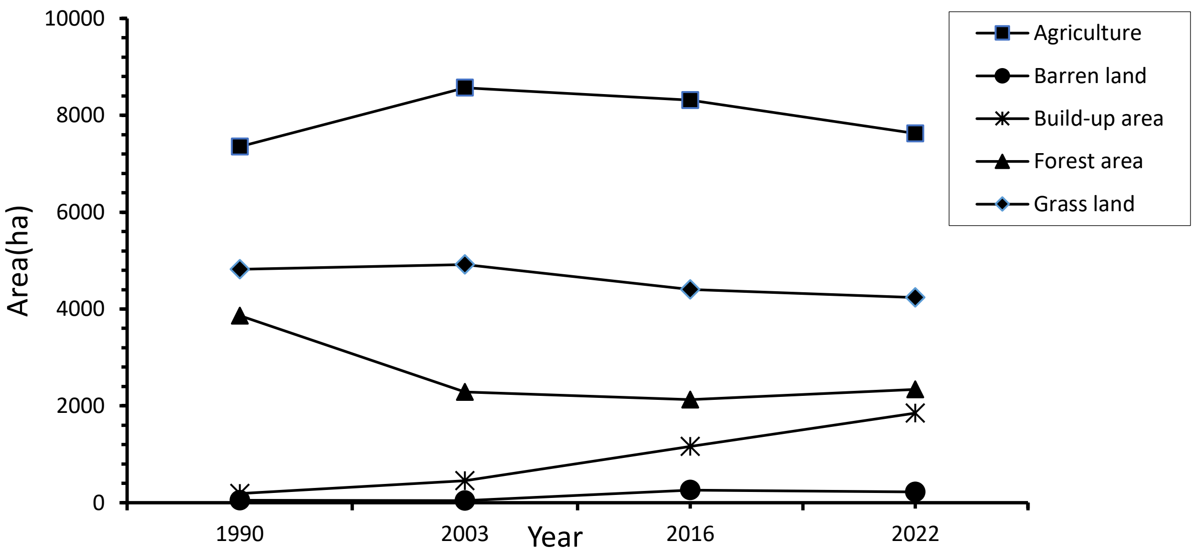


Figure 4.2: Historical change trends of LULC from 1990 – 2022 for all classes.

From the above graph agricultural area reveal increment from 1990 to 2003; then decreases from 2003 to 2016 and 2016 to 2022. Barren land was decrease in the time period between 1990 to 2003 and 2016 to 2022, it increases in the time period between 2003 to 2016. Built-up area increases throughout the entire study period. Forest area decrease in the time period between 1990 to 2003 and 2003 to 2016 and it showed by slight increment in the time period between 2016 and 2022, finally grassland was increase in the time period of 1990 to 2003 and it was continuously decline in the time period between 2003 to 2016 and 2016 to 20122.

4.1.3 Land use land cover transformation

Table 4.6: Over all amounts and percentage of land use land cover change (1990 - 2022)

LULC Type	1990-2003		2003-2016		2016-2022		1990-2022	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Agriculture	1215.73	7.47	-254.15	-1.56	-688.12	-4.23	273.46	1.68
Barren land	-4.65	-0.03	216.69	1.33	-39.42	-0.24	172.62	1.06
Built-up area	266.65	1.64	705.85	4.34	688.8	4.23	1661.3	10.21
Forest area	-1578.58	-9.7	-156.45	-0.96	207.98	1.27	-1527.05	-9.39
Grass land	100.84	0.62	-511.95	-3.15	-169.23	-1.04	-580.34	-3.57
Total	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

During the investigation Periods, distinct changes have occurred on the major land use/land cover types. From 1990 to 2003, the agriculture, built-up and grassland environment increased approximately 1215.73ha, 266.65ha and 100.84ha respectively while forest area and barren land were decreased 1578.58ha and 4.65ha respectively. During the second period between 2003 to 2016 only built-up and barren land were increase, approximately increased by 705.85ha and 216.69ha respectively while grassland, agriculture and forest land were decreased in this study period by 511.95ha, 254.15ha and 156.45ha respectively. In investigation period between 2016 and 2022 built-up area and forest area were increased approximately 688.8ha and 207.98ha respectively while agriculture, grassland and barren land were decrease by 688.12ha, 169.23ha and 39.42ha respectively. In the entire study period form 1990 up to 2022 built-up area was highly increase, it increases by 1661.3ha (10.21%), also agriculture and barren land was increase by 273.46ha (1.68%) and 172.62ha (1.06%) respectively, in this study period forest land and grassland were decline by 1527.05ha (9.39%) and 580.34ha (3.57%) respectively.

Table 4.7: Overall amount, extent, and rate of land cover change (1990 - 2022)

LULC Type	1990-2003			2003-2016			2016-2022		
	Change (ha)	Extent (%)	Rate (%)	Change (ha)	Extent (%)	Rate (%)	Change (ha)	Extent (%)	Rate (%)
Agriculture	1215.73	16.53	1.27	-254.15	-2.96	-0.23	-688.12	-8.28	-1.38
Barren land	-4.65	-10.34	-0.80	216.69	511.54	39.35	-39.42	-15.09	-2.52
Build-up area	266.65	141.38	10.88	705.85	155.00	11.92	688.80	59.24	9.87
Forest area	-1578.58	-40.84	-3.14	-156.45	-6.83	-0.53	207.98	9.70	1.62
Grass land	100.84	2.09	0.16	-511.95	-10.42	-0.80	-169.23	-3.84	-0.64

Land use/land cover change during 1990 – 2003

Table 4.8: Post classification matrix, losses, gains, persistence and net change 1990 – 2003.

	Land Use Class - 2003						
	LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**	**Total**
Land Use Class - 1990	Agriculture	6615.23	9.97	186.76	139.47	400.70	**7352.14**
	Barren land	1.44	18.45	0.46	0.88	26.20	**47.43**
	Built-up area	22.33	1.77	146.18	8.53	10.20	**189.01**
	Forest land	1702.13	0.12	122.27	1794.36	245.06	**3863.95**
	Grass land	226.21	12.46	0.00	342.44	4235.83	**4816.95**
	Total	**8567.35**	**42.78**	**455.65**	**2285.69**	**4918.00**	**16269.47**

1990 - 2003								
LULC Type	**Losses**		**Gain**		**Persistence**		**Net Change**	
	ha	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Agriculture	736.90	21.30	1952.11	56.43	6615.23	89.98	1215.21	35.13
Barren land	28.98	0.84	24.33	0.70	18.45	38.89	-4.65	-0.13
Built-up area	42.83	1.24	309.48	8.95	146.18	77.34	266.64	7.71
Forest land	2069.58	59.82	491.33	14.20	1794.36	46.44	-1578.26	-45.62
Grass land	581.12	16.80	682.17	19.72	4235.83	87.94	101.05	2.92
Total	**3459.42**	**100.00**	**3459.42**	**100.00**	**12810.05**	**340.58**	**0.00**	**0.00**

During the first period between 1990 and 2003, agricultural land cover gained 1952.11ha (56.43%) and lost 736.90ha (21.30%), having a net gain of 1215.21ha (35.13%). The built-up/urban area gained 309.48ha (8.95%) and lost 42.83ha (1.24%), witnessing a net gain of 266.64ha (2.92%). Grassland cover gained 682.17ha (19.72%) and lost 581.12ha (16.80%), having net gain of 101.05ha (2.92%). Forest land gained 491.33ha (14.20%) and lost 2069.58ha (59.82%), having a net loss of 101.05ha (45.62%). Barren land gained 24.33ha (0.70%) and lost 28.98ha (0.84%), having a net loss of 4.65ha (0.13%).

In the first period between 1990 and 2003 various LULC types were changed into other land cover types. For instance, forest land has lost its predominant position to agricultural land and agriculture land contribute 400.70ha to grassland in this study period. In this period agriculture land, built-up and grassland showed a net positive change, forest land and barren land showed a net negative change. Forrest land experienced the most significant loss during this study period. Built-up area were gained from agriculture area 186.76ha, forest land 122.27ha and barren land 0.46ha, in this period the grassland cover does not contribute any amount for built-up area. Built-up area was totally gain 309.49Ha from three land cover class.

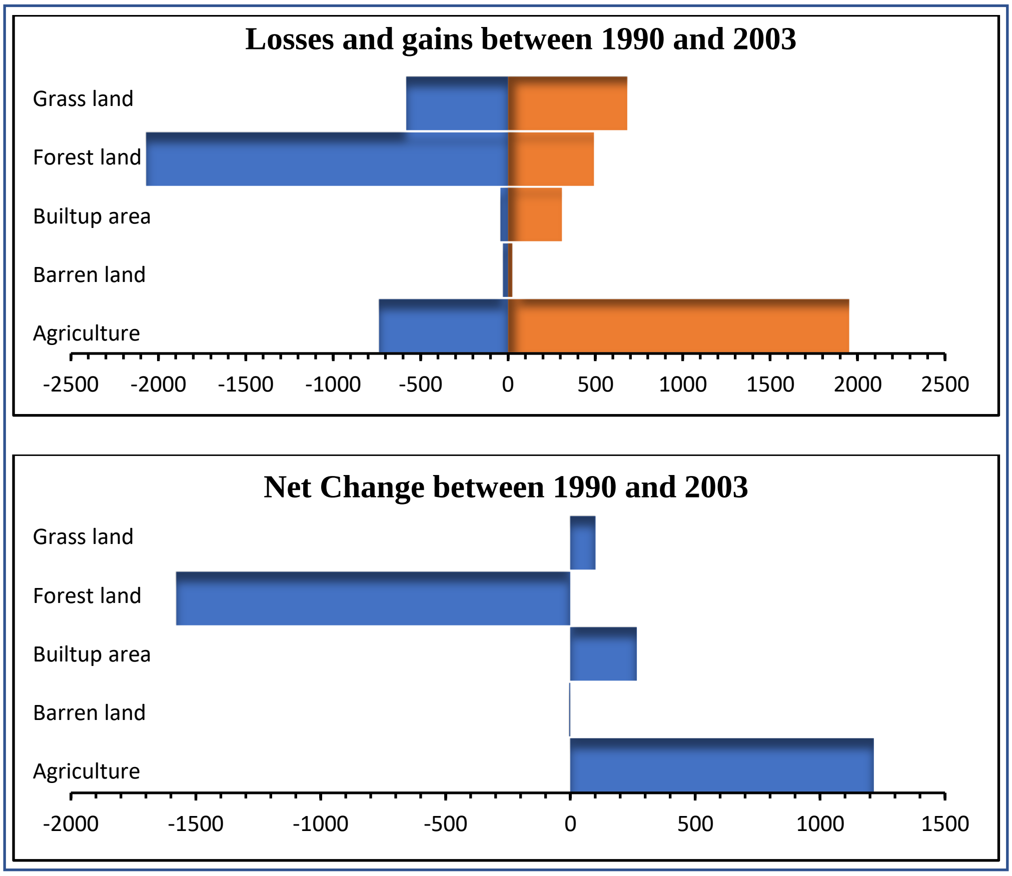


Figure 4.3: Gains, losses and net change between 1990 and 2003

Land use/land cover change during 2003 – 2016

Table 4.9: Post classification matrix, losses, gains, persistence and net change 2003 – 2016.

	Land Use Class - 2016						
Land Use Class - 2003	**LULC Type**	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**	**Total**
	Agriculture	7204.31	83.04	487.47	526.66	266.40	**8567.87**
	Barren land	2.24	25.23	7.16	0.62	7.52	**42.78**
	Built-up area	33.99	0.46	409.39	3.49	8.33	**455.66**
	Forest land	560.77	7.04	131.06	1451.04	135.45	**2285.37**
	Grass land	512.39	143.71	126.43	147.11	3988.14	**4917.79**
	Total	**8313.72**	**259.47**	**1161.51**	**2128.92**	**4405.84**	**16269. 6**

2003 - 2016								
LULC Type	**Losses**		**Gain**		**Persistence**		**Net Change**	
	ha	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Agriculture	1363.56	42.73	1109.41	34.76	7204.31	84.09	-254.16	-7.96
Barren land	17.55	0.55	234.25	7.34	25.23	58.97	216.70	6.79
Built-up area	46.27	1.45	752.12	23.57	409.39	89.84	705.85	22.12
Forest land	834.32	26.14	677.88	21.24	1451.04	63.49	-156.44	-4.90
Grass land	929.65	29.13	417.70	13.09	3988.14	81.10	-511.95	-16.04
Total	**3191.36**	**100.00**	**3191.36**	**100.00**	**13078.11**	**377.49**	**0.00**	**0.00**

During the second period between 2003 and 2016, the built-up/urban area gained 752.12ha (23.57%) and lost 46.27ha (1.45%), witnessing a net gain of 705.85ha (22.12%). Barren land gained 234.25ha (7.34%) and lost 17.55ha (0.55%), having a net gain of 216.7ha (6.76%). Grassland cover gained 417.70ha (13.09%) and lost 929.65ha (29.65%), having net loss of 511.95ha (16.04%). Agricultural land cover lost 1363.56ha (42.73%) and gain 1109.41ha (34.76%), having a net loss of 254.16ha (7.96%). Forest land gained 677.88ha (21.24%) and lost 834.32ha (26.14%), having a net loss of 156.44ha (4.90%). In the period between 2003 and 2016 grassland was lost 16.04 percent of their land cover, also agriculture land and forest land were lost their cover by 7.96 and 4.90 percent respectively. In second period barren land cover increase by 216.70ha (6.79%). Built-up area were gained from agriculture area 487.47ha, forest land 131.06ha, grassland126.43ha and barren land 7.16ha. In this period all land cover class was contribute to built-up area. Built-up area was totally gain 752.12ha from all land cover class. In second period persistence of built-up area, agriculture and grass land was high, there persistence percent is 89.84, 84.09 and 81.10 respectively, relatively the persistence of forest land and barren land was less, with the percent of 63.49 and 58.97 respectively.

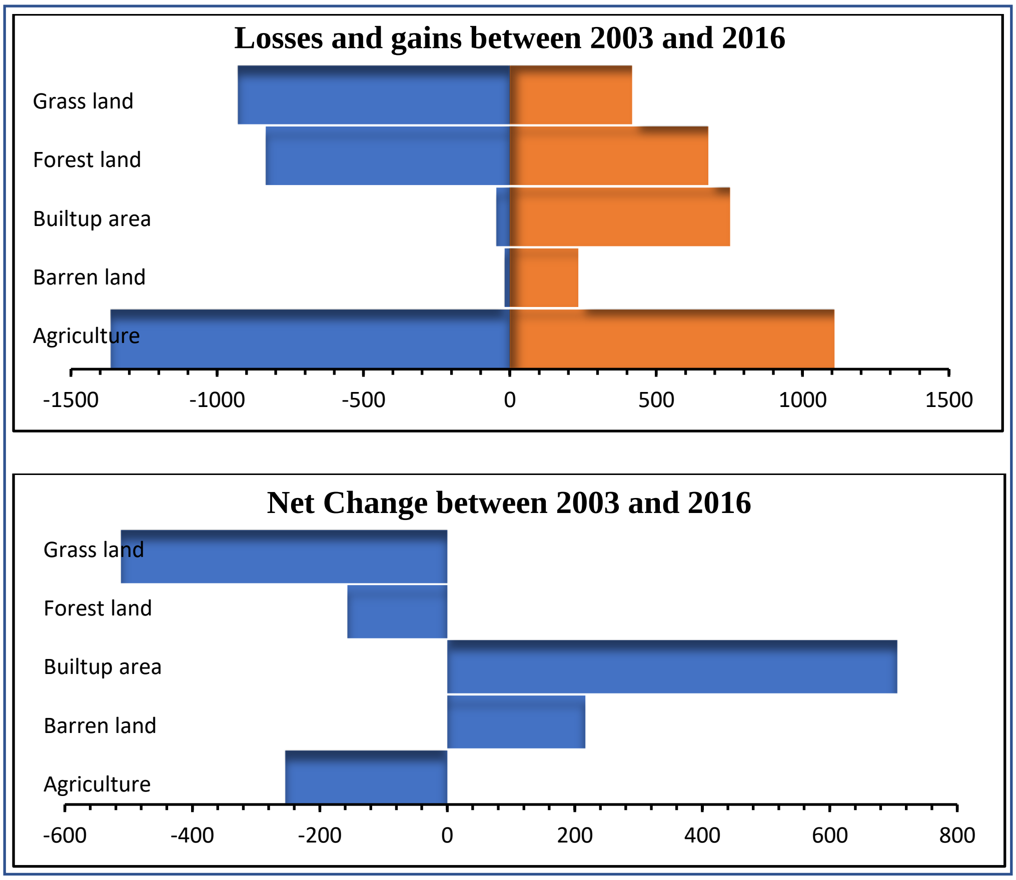


Figure 4.4: Gains, losses and net change between 2003- 2016.

Land use/land cover change during 2016 – 2022

Table 4.10: Post classification matrix, losses, gains, persistence and net change 2016-2022.

Land Use Class – 2016	Land Use Class - 2022						
	LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**	**Total**
	Agriculture	6961.67	46.6	393.24	710.6	201.61	**8313.72**
	Barren land	60.33	94.58	40	3.75	60.81	**259.47**
	Built-up area	49.68	11.2	1064.96	2.26	33.41	**1161.51**
	Forest land	423.1	14.77	88.59	1406.68	195.78	**2128.92**
	Grass land	130.82	52.89	263.52	213.61	3745	**4405.84**
	Total	**7625.60**	**220.04**	**1850.31**	**2336.90**	**4236.61**	**16269.46**

2016 - 2022								
LULC Type	**Losses**		**Gain**		**Persistence**		**Net Change**	
	ha	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Agriculture	1352.05	45.12	663.93	22.16	6961.67	83.74	-688.12	-22.96
Barren land	164.89	5.50	125.46	4.19	94.58	36.45	-39.43	-1.32
Built-up area	96.55	3.22	785.35	26.21	1064.96	91.69	688.80	22.99
Forest land	722.24	24.10	930.22	31.04	1406.68	66.07	207.98	6.94
Grass land	660.84	22.05	491.61	16.41	3745	85.00	-169.23	-5.65
Total	**2996.57**	**100.00**	**2996.57**	**100.00**	**13272.89**	**362.95**	**0.00**	**0.00**

In third study period agriculture lost 1352.05ha and gain 663.93ha, the net change was showed negative 22.96%, and still the persistence was high with the value 83.74%, also the net change of grassland and barren land showed negative 5.65% and 1.32%. The built-up area gains 785.35ha (26.21%) and lost 96.55ha (3.22%), the net change showed positive 22.99%, the persistence of built-up area was very high with the value 91.69% in this period all land class was contribute for built up area. Agriculture land donate 393.24ha for built-up area, also grassland, forest and barren land donate 263.52ha, 88.59ha and 40ha respectively. Hence for expansion of urban area/built-up had resulted in a negative change of agriculture, barren and grass land.

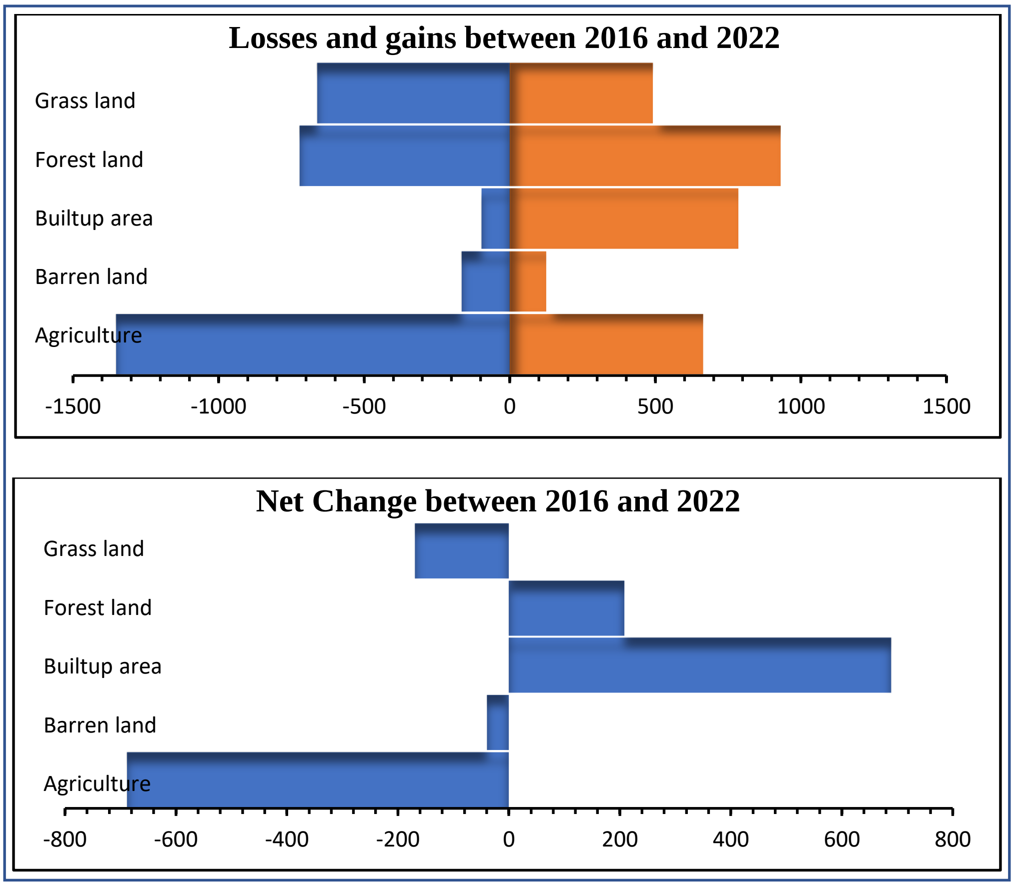


Figure 4.5: Gains, losses and net change 2016 to 2022.

Land use/land cover change during 1990– 2022

Table 4.11: Post classification matrix, losses, gains, persistence, and net change of study area from 1990 – 2022

		Land Use Class - 2022					
	LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**	**Total**
Land Use Class - 1990	Agriculture	5714.4	50.29	849.14	448.04	293.24	**7355.11**
	Barren land	2.45	0	13.5	0.09	31.4	**47.44**
	Built-up area	1.44	0	185.42	0	2.15	**189.01**
	Forest land	1716.85	13.25	556.66	1471.19	99.43	**3857.38**
	Grass land	189.42	156.5	245.52	412.92	3816.16	**4820.52**
	Total	**7624.56**	**220.04**	**1850.24**	**2332.24**	**4242.38**	**16269.46**

1990 - 2022								
LULC Type	**Losses**		**Gain**		**Persistence**		**Net Change**	
	Ha	**%**	**Ha**	**%**	**Ha**	**%**	**Ha**	**%**
Agriculture	1640.71	32.28	1910.16	37.58	5714.4	77.69	269.45	5.30
Barren land	47.44	0.93	220.04	4.33	0	0.00	172.60	3.40
Built-up area	3.59	0.07	1664.82	32.76	185.42	98.10	1661.23	32.69
Forest land	2386.19	46.95	861.05	16.94	1471.19	38.14	-1525.14	-30.01
Grass land	1004.36	19.76	426.22	8.39	3816.16	79.16	-578.14	-11.38
Total	**5082.29**	**100.00**	**5082.29**	**100.00**	**11187.17**	**293.10**	**0.00**	**0.00**

During the fourth period between 1990 and 2022 within 32-year agriculture land contribute 50.29ha, 849.14ha, 448.14ha and 293.24ha for barren land, built-up area, forest land and grass land respectively, in this period agriculture area was loss 1640.71ha(32.28%) and gain 1910.16ha(37.58%) the persistence of agriculture was 77.69% during past 32 years, net change for agriculture area was positive 269.45ha(5.30%), so in this period agriculture land cover was showed increment by 5.30 percent most of them was donated by forest land cover class. The second land cover type called barren land was contribute 2.45ha, 13.5ha, 0.09 ha and 31.4ha for land cover type agriculture land, built-up area, forest land and grass land respectively, persistence of barren land has zero in the time period of 1990-2022, the net change has positive 172.60ha (3.40%). Built-up area was showed continuous increment in the entire period (1990-2022) its loss only 3.59ha in past 32 years, built-up area was gain 1664.82ha in this time period. The persistence of built-up area was 98.10 percent, it does not loss significantly. The net change of built-up area was positive 1661.23ha (32.69%), most of this was donated by forest land and grass land in past three decades. Forest land and grass land was decline in the study period by 30.01% and 11.38% respectively. Forest land donate 1716.85ha, 13.25ha, 556.66ha, and 99.43ha for agriculture land, barren land, built-up area and grass land respectively. In this study period forest land cover was decrease extremely, also the persistence was very low it persists only 38.14 percent, the net change of forest area has negative 30.01 percent. The last land cover type namely grass land is also decline in past three decades. It were loss approximately 578.14ha in last 32 years, the class was contribute 189.42ha for agriculture, 156.5ha for barren land 245.52ha for built-up and 412.92ha for forest land cover. The persistence of grass land cover class was 79.16 percent.

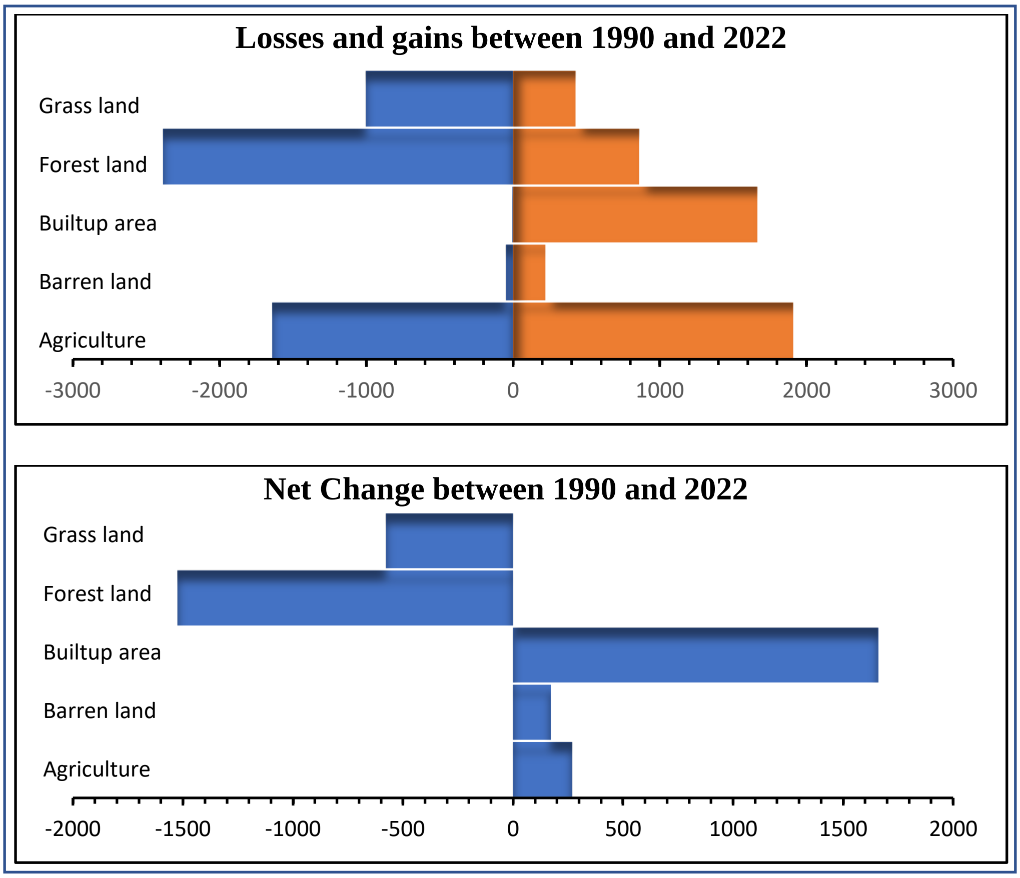


Figure 4.6: Gains, losses, and net change between 1990 and 2022.

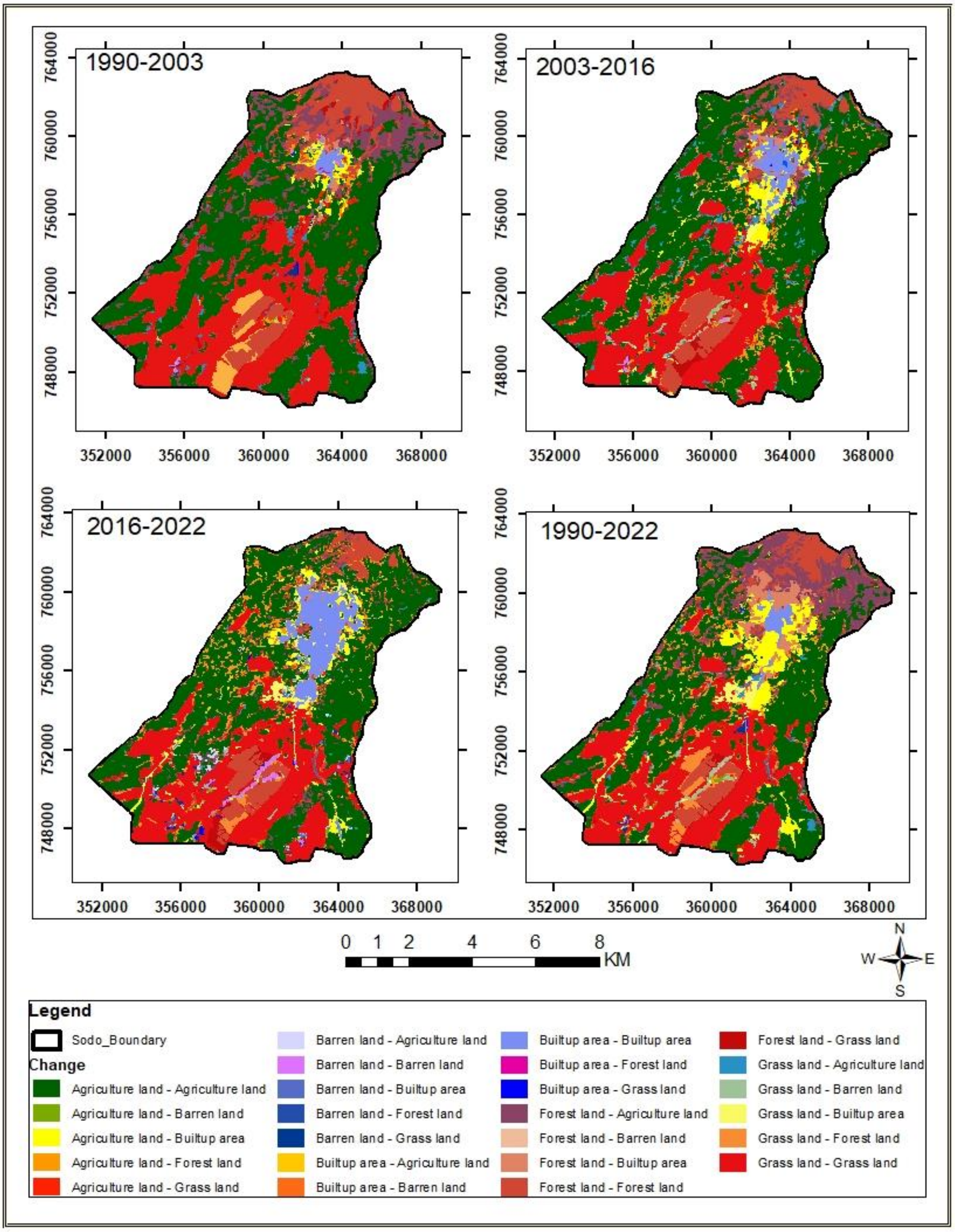


Figure 4.7: Land use/land cover change and persistence map of 1990-2003, 2003-2016, 2016-2022 and 1990 - 2022.

4.1.4 Urban Extent of the Study Area

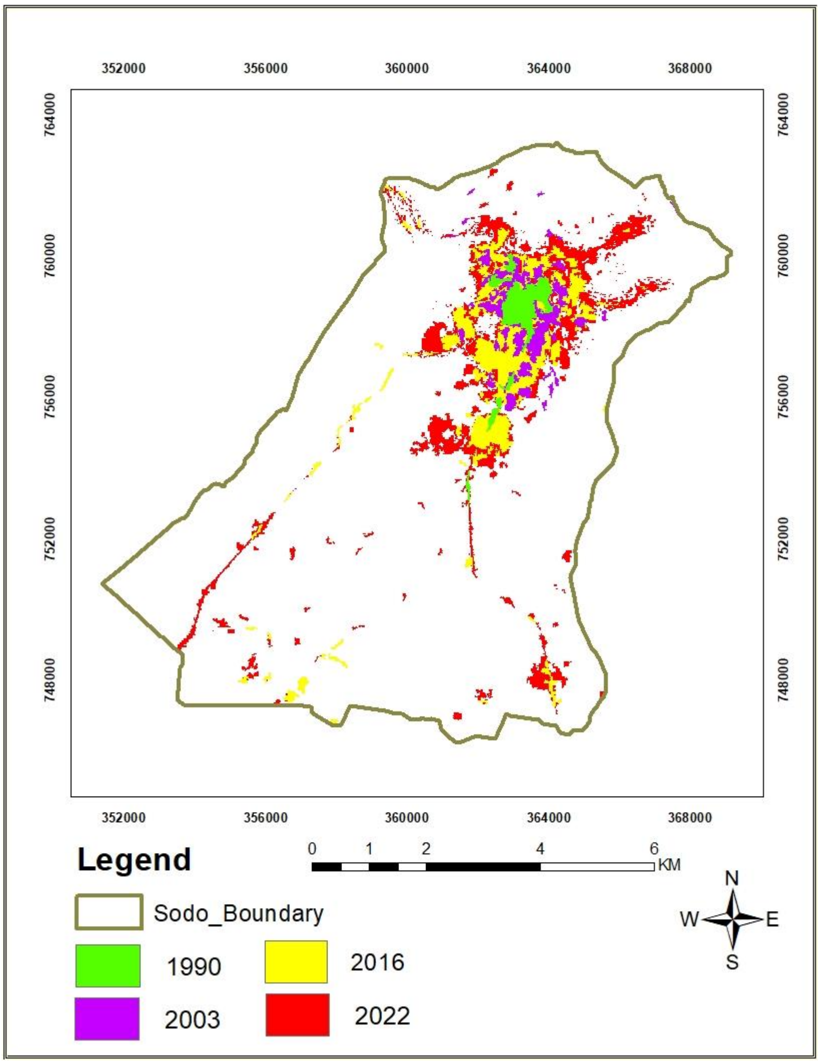


Figure 4.8: Buildup area expansion overlay analysis 1990, 2003, 2016 and 2022.

Table 4.12: Buildup area and non- built-up area 1990 – 2022.

LULC	**1990**		**2003**		**2016**		**2022**	
Type	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Buildup area	189.01	1.16	455.66	2.8	1161.51	7.14	1850.31	11.37
Non-Buildup	16080.46	98.84	15813.81	97.2	15107.96	92.86	14419.16	88.63
Total	**16269.47**	**100%**	**16269.47**	**100%**	**16269.47**	**100%**	**16269.47**	**100%**

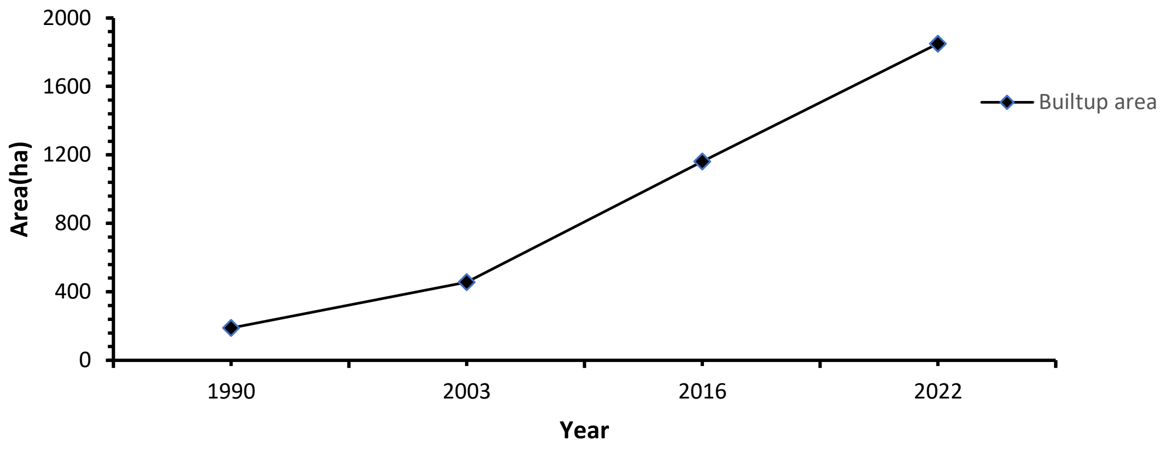


Figure 4.9: Urban expansion 1990-2022

Table 4.13: All land classes changed to build up area 1990 – 2022.

LULC Type	1990-2003		2003-2016		2016-2022		1990-2022	
	Change (ha)	Extent (%)	Change (ha)	Extent (%)	Change (ha)	Extent (%)	Change (ha)	Extent (%)
Agriculture	186.76	1.15	487.47	3.00	393.24	2.42	849.14	5.22
Barren land	0.46	0.00	7.16	0.04	40	0.25	13.5	0.08
Build-up area	146.18	0.90	409.39	2.52	1064.96	6.55	185.42	1.14
Forest area	122.27	0.75	131.06	0.81	88.59	0.54	556.66	3.42
Grass land	0.00	0.00	126.43	0.78	263.52	1.62	245.52	1.51
Total	**455.67**	**2.80**	**1161.51**	**7.14**	**1850.31**	**11.37**	**1850.24**	**11.37**

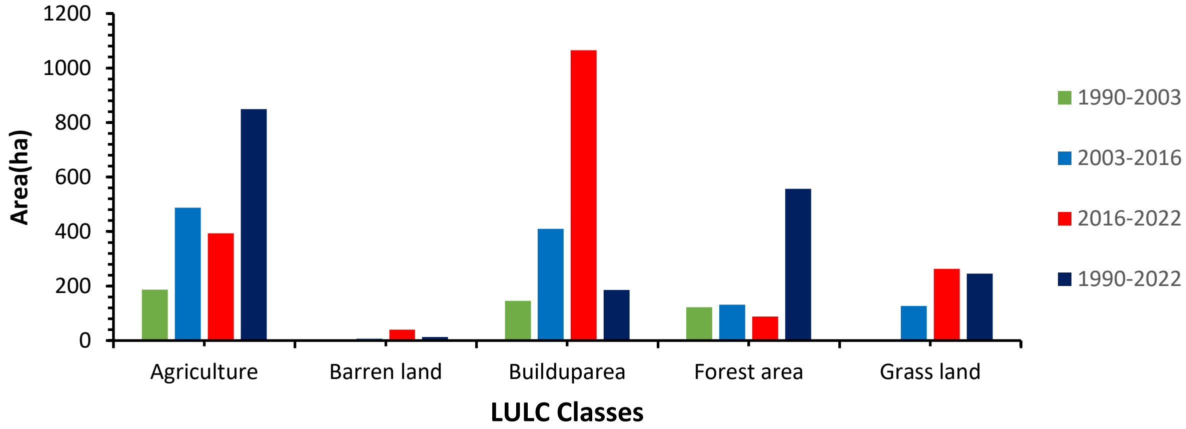


Figure 4.10: All land classes changed to the built-up area.

4.2 Dynamics of Land scape structure

Landscape pattern indicators or ‘metrics’ provide simple measures of landscape structure that can be easily calculated with readily available data and software (John A. Kupfer, 2012). Landscape metrics quantify the pattern of the landscape within the designated landscape boundary only. Consequently, the interpretation of these metrics and their ecological significance requires an acute awareness of the landscape context and the openness of the landscape relative to the phenomenon under consideration. The classified and cropped vector image were converted into raster format in ArcGIS software. Using the extracted cardinal raster image, the landscape pattern metrics were calculated with the help of FRAGSTAT software package.

4.2.1 Composition and configuration

There are many metrics that was developed to quantify the landscape composition and configuration. The Spatio-temporal pattern of the landscape is quantitatively described in the following two sections (i.e. landscape level and class levels). A total of 14 landscape metrics both at class and landscape-level were chosen for this study. These are number of patches (NP), patch density (PD), largest patch index (LPI), landscape shape index (LSI), area-weighted mean patch fractal dimension (FRAC_AM), contagion index (CONTAG), patch cohesion index (COHESION) and Shannon’s diversity index (SHDI) at landscape level, number of patches (NP), patch density (PD), class per cent of landscape (PLAND), largest patch index (LPI), patch cohesion index (COHESION) and aggregation index (AI) at class level. All of these metrics are used to quantify and examine the spatiotemporal changes of landscape compositions and configurations (Landscape structure) for the study area (Mc Garical and Marks, 2002).

Landscape Metrics at the Landscape Level

Landscape level indices represent the spatial pattern of the entire landscape mosaic, considering all patch types simultaneously. The indices can be interpreted more broadly as landscape heterogeneity indices and they measure the overall landscape pattern (McGarigal and Marks, 1995).

At the landscape level 8 landscape metrics were used (i.e. number of patches (NP), patch density (PD), largest patch index (LPI), landscape shape index (LSI), area-weighted mean patch fractal dimension (FRAC_AM), contagion index (CONTAG), patch cohesion index (COHESION) and Shannon’s diversity index (SHDI)).

Table 4. 14: Landscape metrics at a landscape level from 1990 to 2022.

Year	NP	PD	LPI	LSI	FRAC_AM	CONTAG	COHESION	SHDI
1990	670	4.1	26.9	22.1	1.25	51.5	99.3	1.2
2003	1421	8.7	39.9	20.3	1.25	58.6	99.7	1.1
2016	1383	8.5	40.1	25.3	1.26	51.2	99.5	1.2
2022	1223	7.5	34.5	26.1	1.25	48.7	99.5	1.3

Number of Patches (NP): - The number of patches increased in the first period between 1990 and 2003, it increased from 670 to 1421, the number was decreased to 1383 in the period of 2016 also it was decreased in 2022 to 1223. This number showed that, in the first period from 1990 to 2003 the urban landscape of Sodo town was fragmented, while it was less fragmented the period of 2003 to 2016 and 2016 to 2022.

Patch Density (PD): - The patch density was increased from 4.1 to 8.73 in the period of 1990 and 2003, in this period the urban landscape of Sodo was fragmented, in the second and third period the urban landscape was less fragmented specially from 2016 to 2022. Patch density increases exponentially as the irregularity of patch shape increases; yet, landscape connectivity decreases. These patterns were repeatedly supported for urbanizing landscapes throughout the world (Wu et al., 2011).

Largest Patch Index (LPI): - Largest patch index was 26.9 at the time of 1990 and it increased to 39.9 percent in 2003, it is also increased to 40.1 percent in 2016, finally largest patch index was decline to 34.4 percent, in the period of 1990 to 2003 and 2003 to 2016 the largest patch index was increase, that mean the urban land scape of Wolaita Sodo was comprised by the largest patch.

Landscape Shape Index (LSI): - Landscape shape index of study area was 22.1 in 1990, 20.3 in 2003, 25.3 in 2016 and 26.1 in 2022. Landscape shape index provides a standardized measure of total edge or edge density that adjusts for the size of the landscape.

Area-Weighted Mean Patch Fractal Dimension (FRAC_AM): - Area-weighted mean fractal dimension index (FRAC_AM) showed a very slight increase in the first (1990-2003) and second period (2016-2022) while a slight decrease in the third period (2016–2022). This indicates that shape complexity has become irregular over time and fragmentation processes have strengthened in the first and second period compared to the third period. Accelerated urbanization, including Human activities can result in landscape pattern fragmentation and more complex landscape structure.

Contagion Index (CONTAG): - The contagion index increased from 51.5% to 58.6% in first period (1990-2003), but it declines in second and third period, to 51.2% and 48.7% respectively.

Patch Cohesion Index (COHESION): - Patch cohesion index measures the physical connectedness of the corresponding patch type. Below the percolation threshold, patch cohesion is sensitive to the aggregation of the focal class. Patch cohesion increases as the patch type becomes more clumped or aggregated in its distribution; hence, more physically connected. Above the percolation threshold, patch cohesion does not appear to be sensitive to patch configuration (Gustafson 1998). Patch cohesion index of Wolaita Sodo increase in first study period (1990-2003) form 99.3 to 99.7 percent, while in second and third period it declines to 99.5 and 99.5 percent.

Shannon's Diversity Index (SHDI): - Shannon's diversity index increases as the number of different patch types (i.e., patch richness, PR) increases and the proportional distribution of area among patch types becomes more equitable. In our case SHDI was decrease from 1.2 to 1.1, in second and third period it increases to 1.2 and 1.3.

The increase in landscape pattern metrics during the study period because of the fact that fragmentation of the landscape tended to strengthen (Huang et al., 2010) and spatial variability of the landscape increased in Wolaita Sodo Town in the last three 32 years. Moreover, the landscape pattern structure became more complex, as discerned in the following landscape metric changes from 1990 to 2022. Human activities, including urban expansion and population growth can result in landscape pattern fragmentation and more complex landscape structure.

Landscape Metrics at Class level

The class-level indices have a spatial feature to represent the spatial distribution and pattern as they measure the configuration of a particular patch type. The class level indices act as fragmentation indices because class level metrics provided more comprehensive information on the comparative contributions of individual configuration of a particular patch type (Ramachandra et al., 2013). In the current study, six class level metrics was calculated using FRAGSTATAS 4.2 software. These are: the percentage of landscape (PLAND), number of patches (NP), patch density (PD), largest patch index (LPI) patch cohesion index (COHESION) and aggregation index (AI) for only built-up area class in study timeframe.

Table 4. 15: Landscape metrics at a class level from 1990 to 2022.

Year	PLAND	NP	PD	LPI	COHESION	AI
1990	1.5176	35	0.2151	0.756	93.3862	82.2218
2003	3.0889	169	1.0387	1.856	98.0678	89.5567
2016	7.2563	114	0.7007	5.5555	98.6874	92.7802
2022	11.6184	161	0.9895	9.3335	99.0807	93.1134

Results of the time series landscape metrics at class level for the study area:

Number of Patch: NP is a type of metrics that describes the growth of particular patches whether in an aggregated or fragmented growth in the region and also explains the underlying urbanization. It ranges from 0 (Clumpiness) to 100 (fragmented). In general, when the number of patches increase the level of fragmentation will also increase and vice versa. In the case of Wolaita Sodo the number of patches increase in the period of 1990 to 2003 from 35 to 169, the built-up growth in 1990 was more fragmented, then the fragmentation was decrease, while in 2016 NP was decrease to 114 the fragmentation was increase in this period and it was show increment in 2022 to 161, the pattern of built-up area was varying in the study time period.

Patch Density (PD): it is similar with NP but PD gives density about the landscape in analysis, as the number of patches increase so is the patch density.

The density of built-up area was 0.215 in 1990, then it increases to 1.038 in 2003, PD shows high increment in the first time period. In second period it decreases to 0.7007 and increases to 0.9895 in 2022. So, the PD of built-up area shows fragmentation of the study area was varied in study period.

Proportion of Land (PLAND): PLAND is fundamental measures of landscape composition; specifically, how much of the landscape is comprised of a particular patch type. The built-up proportion in the study area was 1.511 percent in 1990 and then it increases to 3.088, 7.256 and 11.618 in the period of 2003, 2016 and 2022 respectively. In study area built-up area showed continuous increment and the proportion of built-up area was increased from 1.511 percent to 11.618 percent in past 32 years.

Largest Patch Index (LPI): The largest patch index (LPI): at class level computes the percentage of the total landscape are involved inside the largest patch. Independently, it is a straightforward to estimate for dominance (McGarigal and Marks, 2002). LPI equals the percentage of the landscape comprised by the largest patch. The largest patch index of built-up area was continuously increase in the whole study period. The value of LPI of built-up area was 0.756, 1.856, 5.555 and 9.333 in 1990, 2003, 2016 and 2022. Consequently, the dominance of built-up area was increase in past 32 years.

The patch cohesion index (COHESION): measures the physical connectedness of the corresponding patch, and has a close relationship with habitat fragmentation. Patch cohesion increases as the patch type becomes more clumped or aggregated in its distribution; hence, it is more physically connected (Zhang et al., 2004). The cohesion of built-up area was also showing continuous increment, the connectedness of the built-up area in Sodo was increase in the study period. The values of cohesion index were 93.38, 98.06, 98.68 and 99.08 in the period of 1990, 2003, 2016 and 2022.

Aggregation Index (AI): gives the similar indication as Clumpiness i.e., it measures the aggregation of the urban patches, ranges from 0 to 100. Values closer to zero indicate disaggregation and values closer to 100 indicate aggregated growth of the urban areas.

The aggregation index of built-up area was increased from 82.22 to 93.11 in 1990 to 2022, while the value of AI was 89.55 in 2003 and 92.78 in 2016. The growth of built-up area was more aggregated in Wolaita Sodo.

4.3 Future Prediction and Modeling land use/land cover

Without using real data to validate the model, land use and land cover modeling cannot be completed. Therefore, it is necessary to compare the outcomes of the land use/land cover simulation regions to the actual area. In order to make sure the chosen variable was relevant to the change in land use and land cover in the model, the simulated 2022 land use and land cover areas were compared to the actual areas deduced from the 2022 land satellite image. The results were then tested using kappa, klocation, and khiston.

4.3.1 Markov Chain

The Markov Chain mathematical model, developed by Andrei Andreyevich Markov in 1906, is a stochastic process with discrete space that is based mostly on probabilities rather than certainties. The Markov Chain is a random process based on Markov property which means the next state depends only on current state not the sequence (Markov Chain, n.d.). In the 1950s, socioeconomic researchers were the first to utilize this model; but, after the 1960s, urban studies also began to employ it, and for LULC modeling it had been used in the late 1970s (Iacono and Levinson et al., 2012). The first usage of this model was on parcel level, later by Bell in 1974 it has been used for remote sensing sources as well (pixel-based) (Bell, 1974).

Implementation of Markov chain

The relation between variables and the various land use/land cover classes is depicted by Cramer's coefficient, was calculated and the value for reclassified LULC 2016, reclassified population density, distance from buildup, distance from the main road, elevation, and slop are all in an acceptable range greater than 0.15. In this study, LULC 2003 and 2016 were used to make a prediction for the year 2022. The relationship between 2003 and 2016 has been studied using the MARKOV model to be used in the 2022 simulation. The results of the MARKOV model are; *A transition matrix:* This contains the probability of each land use/cover category which can change to every other category (Eastman, 2012). The probability of each class can be observed in table 4. 16.

Table 4.16: Markov conditional probability of changing among LULC type.

LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**
Agriculture	0.919	0.005	0.027	0.032	0.015
Barren land	0.020	0.792	0.084	0.007	0.095
Built-up area	0.037	0	0.951	0	0
Forest land	0.127	0	0.028	0.814	0.029
Grass land	0.053	0.015	0.011	0.014	0.905

Multilayer perceptron and Markov chain

The model, which combined Markov Chain and Artificial Neural Network-based techniques, was used to predict future LULC in the research area. In this model, ANN is used to specify how the simulated LULC categories are distributed spatially, in other work, transition potential development and Markov Chain prediction are both done using transition potentials. The second step of the method is transition modeling, the MLP approach can be used to build the transition maps from each LULC category to urban areas. The third step involved change modeling and model validation using an accuracy assessment. The theory of the ANN and MLP must be grasped before the model can be put into practice, so it was described in methodology part.

Combination of Multilayer Perceptron and Markov Chain Methods

Development of the transition potential using the MLP approach constitutes the first stage of this combined methods. Sub model development, testing the variables, and transition potential development are the three substages that make up this stage. Second stage of the model is simulation with the MARKOV method by using transition potentials and model validation.

Transition Sub Model Development

Changes from other categories to urban were employed as a transition sub model because the impact of the urban area served as the primary indicator for this study. The primary factors that influence changes must be identified in order to simulate the changes. These variables are reclassified LULC map of 2016, population density, distance to urban centers, distance from road, elevation and slope of the study area.

Transition Potential Development

The MLP approach, which has been shown effective in resolving complicated systems, was utilized to compute and map these potentials. The simulation's outcome is more or less identical to the current situation, as shown in the figures below, although this needs to be verified through accuracy assessment.

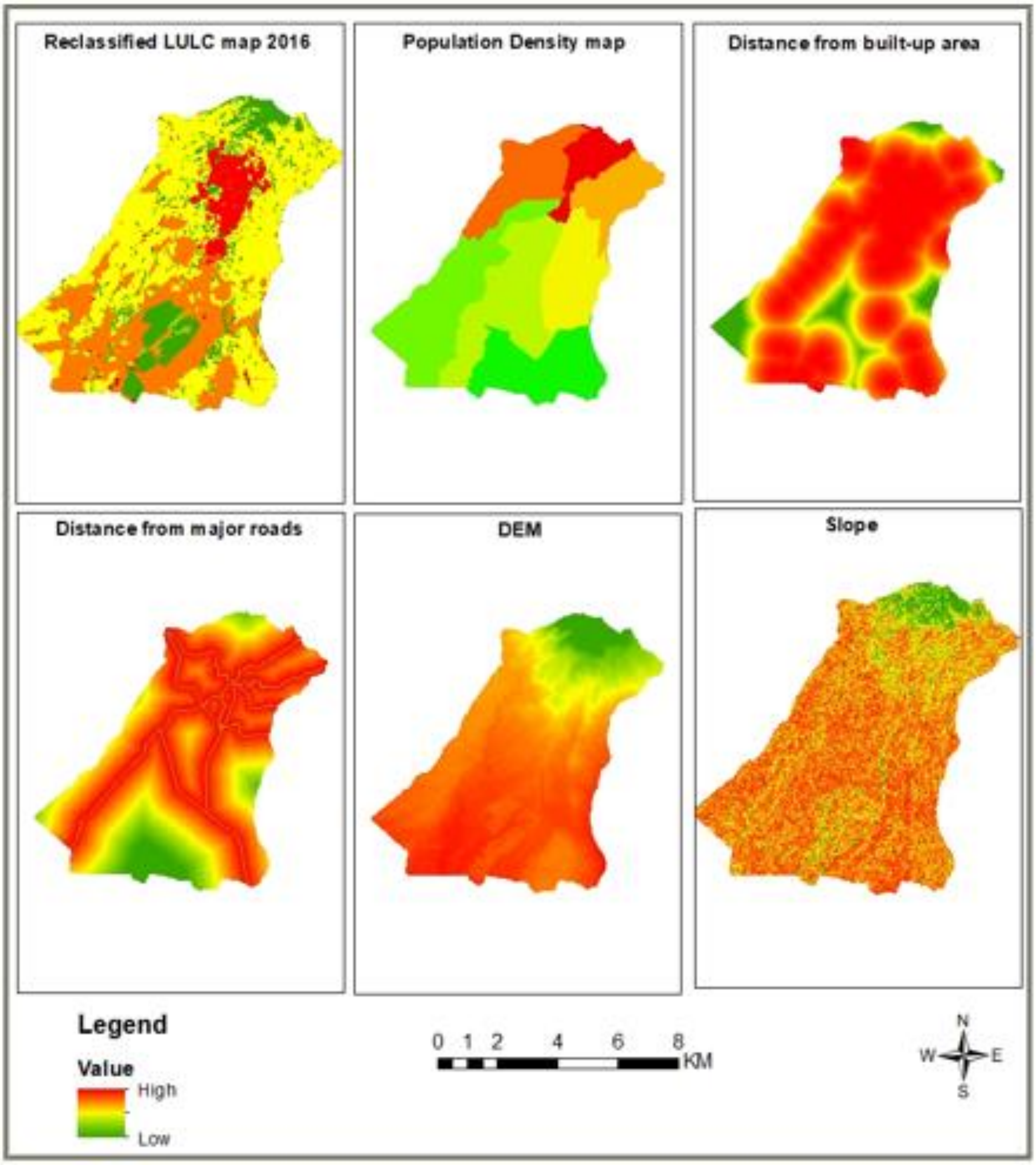


Figure 4.11: Driver variables used for future prediction.

4.3.2 Influence of driver variable on urban growth

According to the sensitivity analysis, LULC 2016 was the most influential driver variable. Population density, distance from the built-up area, distance from the road, DEM, and slope score came in second, third, fourth, fifth, and sixth, respectively. The investigation revealed that the slope had the least impact on the model of all the driver variables.

Table 4.17: Relative significance of driver variables generated by forcing independent variables to be constant.

Model	Accuracy (%)	Skill measure	Influence order
With all variables	98.39	0.97	N/A
LULC of 2016	77.28	0.19	1(most influential)
Population density	90.13	0.24	2
Distance from buildup	96	0.29	3
Distance from Road	100	1	4
DEM	100	1	5
Slop	100	1	6 (least influential)

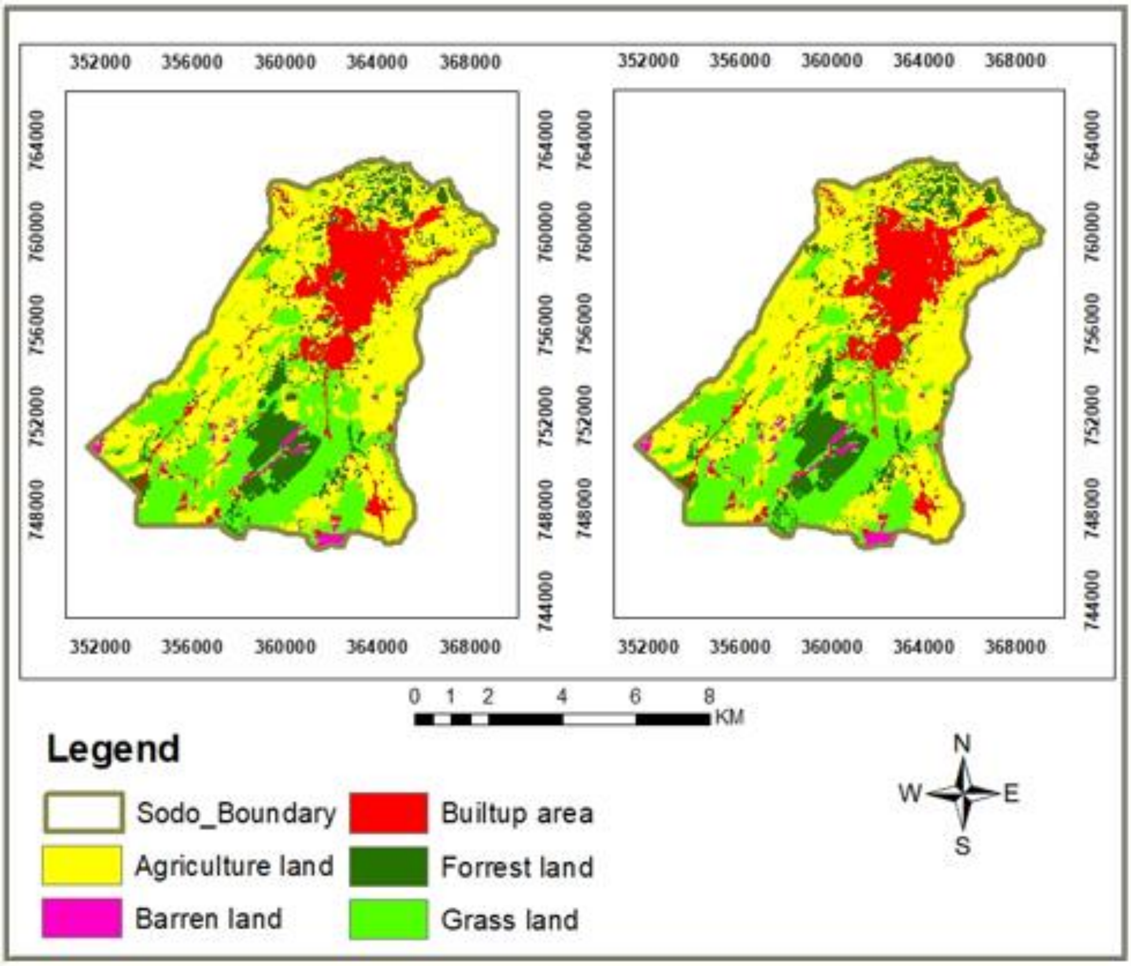


Figure 4.12: Actual land use land cover and projected 2022 (MLP and MARKOV)

4.4 Accuracy Assessment (model validation)

The accuracy assessment of image classification and simulation results is slightly different, because in the latter case the accuracy assessed by using the maps not the specific points which are indicating the real category information (Rossiter, 2004). In many studies' kappa statistical measurements have been used for the accuracy assessment Pontius & Millones (2011). The purpose was to observe the main changes between 2022 classified and then comparing the results with the predicted map, in order to understand if the overall changes have been predicted correctly or not. The technique used for the accuracy assessment, calculating kappa values related to the location and the quantity to observe the accuracy in each class. These are Klocation and Khisto which demonstrate the source of error, whether it is location or quantity. Klocation shows the similarity in the spatial distribution of classes but does not differentiate between classes that are close or distant and it is independent of the total number of cells per class (Pontius, 2000). Khisto measures quantitative similarity between two maps, in other words, it checks the similarity in the amount of the cells in the testing map and reference map (Serna, 2011). The accuracy assessment result for the model can be observed in table 4.18 from this table it can be observed that the overall kappa is 0.92.

Table 4.18: Kappa index, information allocation of simulated and actual LULC map of 2022.

k indicators	
Klocation	0.91
Kno	0.93
Klocation strata	0.93
Kstandard	0.91
Overall accuracy	**0.92**

As result of accuracy assessment, since the overall kappa is 92%, Strength of Agreement for Kappa Statistic is almost perfect (Landis, J., 1977), and the crammer's value was tested for each driver or factors and it reveals greater than 0.15 and above 0.4 crammers' value, so the model is acceptable and it can be used for the future simulation 2030, 2040 and 2050.

Table 4.19: Strength of Agreement for Kappa Statistic (Landis, J., 1977)

Kappa Statistic	Strength of Agreement
< 0	Poor
0.00-0.20	Slight
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Substantial
0.81-1.00	**Almost Perfect/Perfect**

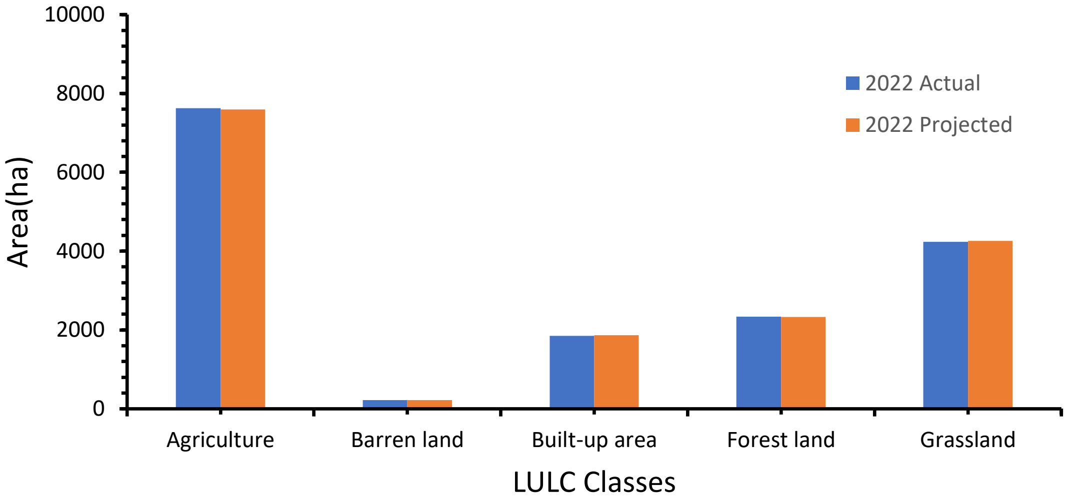


Figure 4.13: Comparison of actual and projected land use/land cover.

Table 4.20: Markov conditional probability of changing among LULC type 2030, 2040 and 2050.

LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**
Agriculture	0.829	0.010	0.061	0.065	0.034
Barren land	0.052	0.573	0.170	0.016	0.188
Built-up area	0.080	1	0.891	0.007	0.020
Forest land	0.256	0.003	0.062	0.618	0.061
Grass land	0.114	0.030	0.028	0.030	0.796

LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**
Agriculture	0.742	0.014	0.098	0.089	0.055
Barren land	0.094	0.389	0.239	0.026	0.249
Built-up area	0.126	0	0.825	0.014	0.032
Forest land	0.355	0.007	0.098	0.451	0.088
Grass land	0.176	0.041	0.051	0.046	0.684

LULC Type	**Agriculture**	**Barren land**	**Built-up area**	**Forest land**	**Grass land**
Agriculture	0.676	0.017	0.131	0.103	0.073
Barren land	0.137	0.268	0.282	0.035	0.276
Built-up area	0.165	0	0.766	0.021	0.043
Forest land	0.412	0.011	0.129	0.339	0.107
Grass land	0.226	0.046	0.076	0.058	0.594

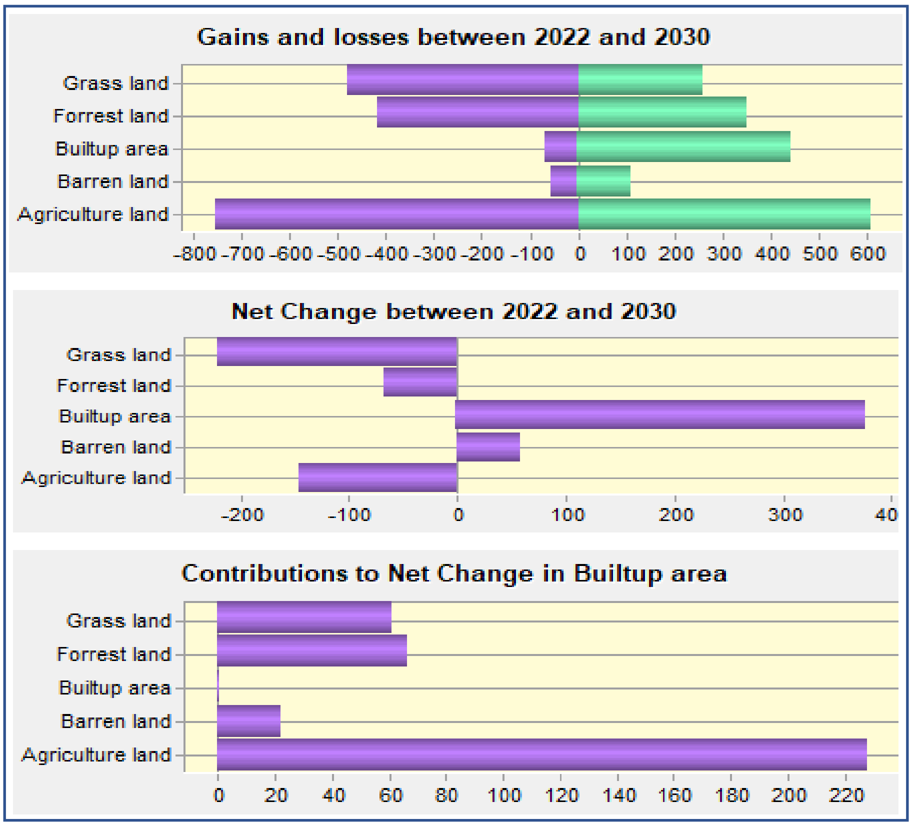


Figure 4.14: Gains, losses, net change, and contributions to built-up area between 2022-2030.

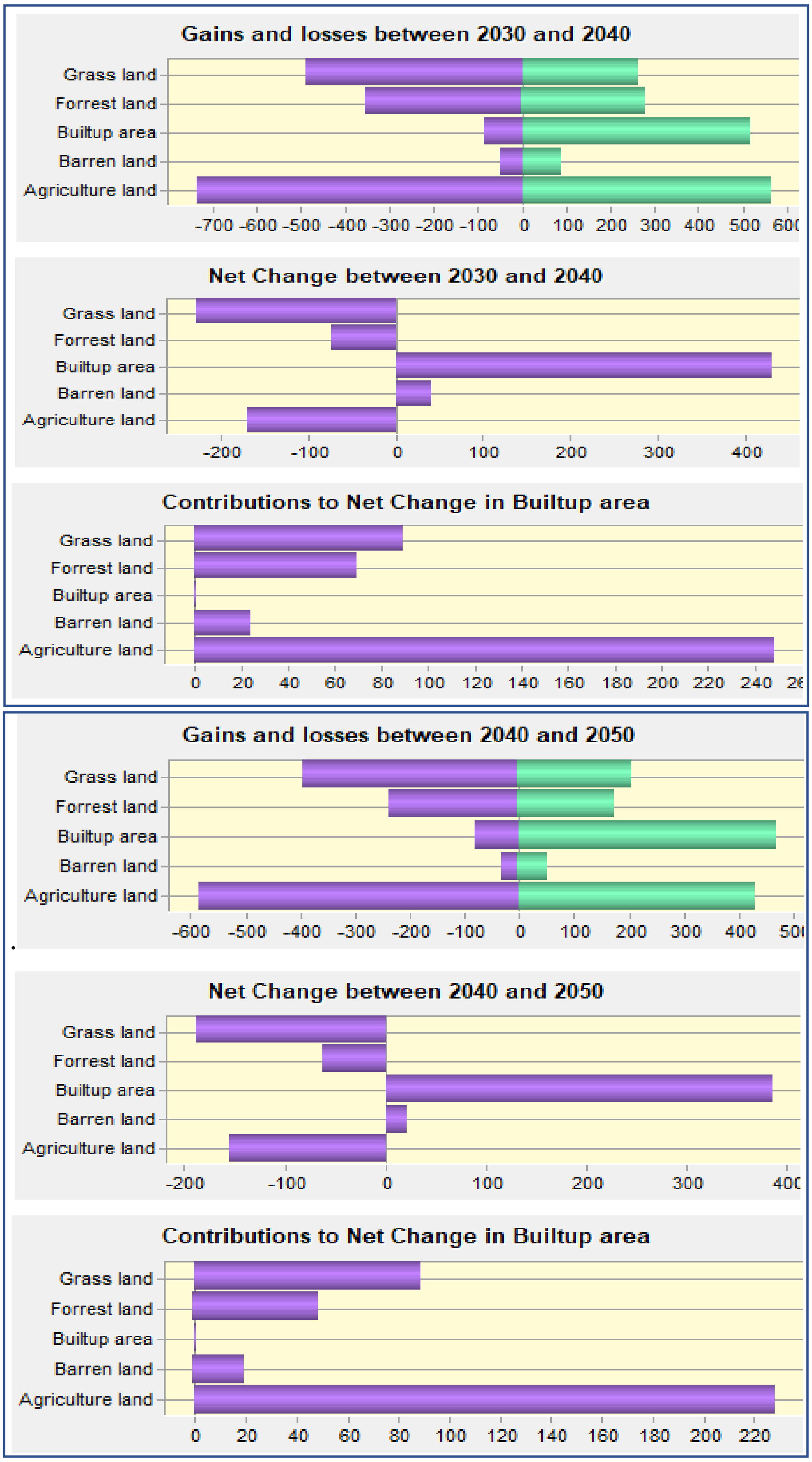


Figure 4.15: Gains, losses, net change, and contributions to built-up area between 2030 - 2040 and 2040 - 2050.

According to the above-mentioned data, Wolaita Sodo's built-up area is continuously growing, and all types of land use including agriculture, barren land, forests, and grasslands have a significant impact on urban growth in the study region.

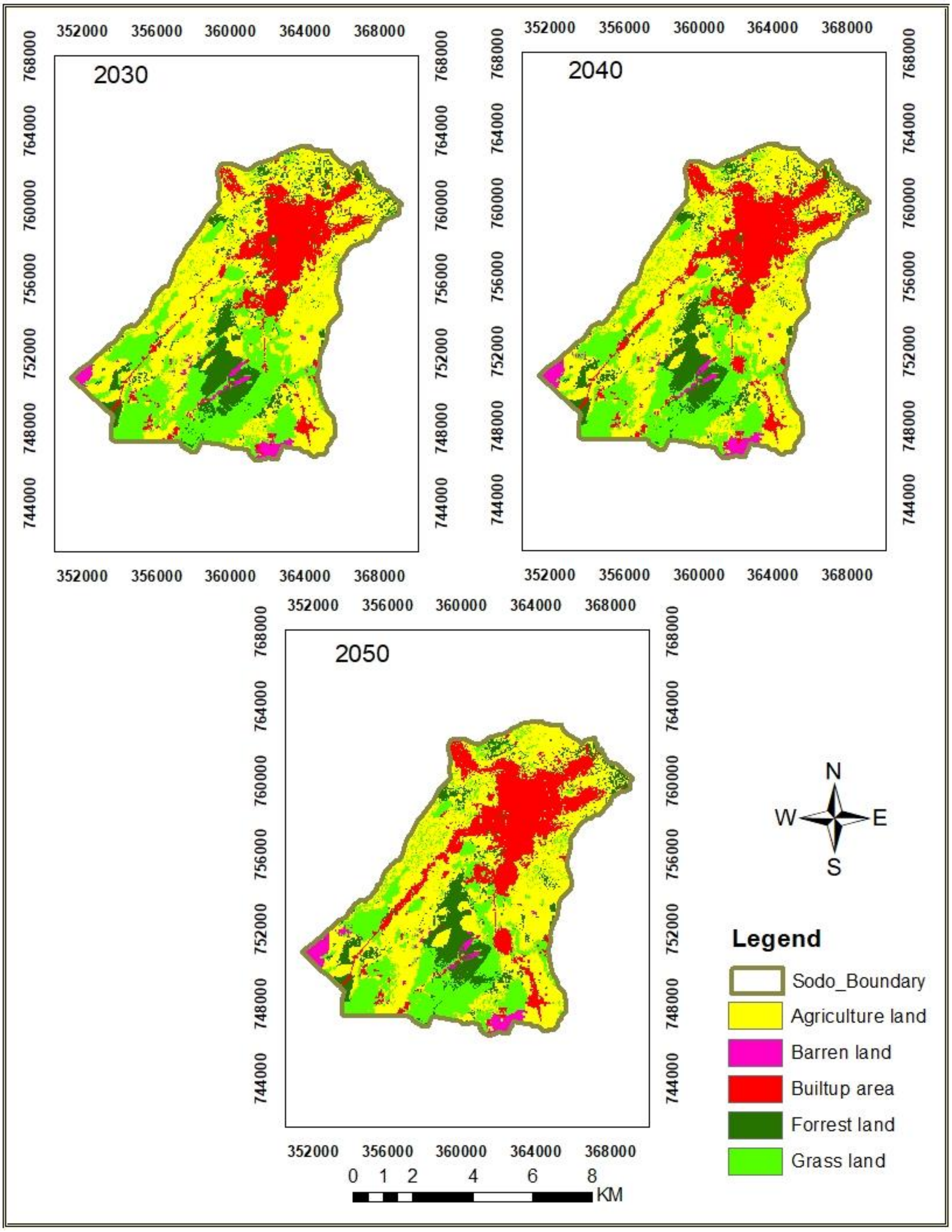


Figure 4.16: Projected land use land cover map of 2030, 2040 and 2050.

Table 4.21: Buildup area in hectares 1990 – 2050

LULC Type	1990	2003	2016	2022	2030	2040	2050
Buildup area	189.01	455.66	1161.51	1850.31	2240.04	2770.72	3264.6

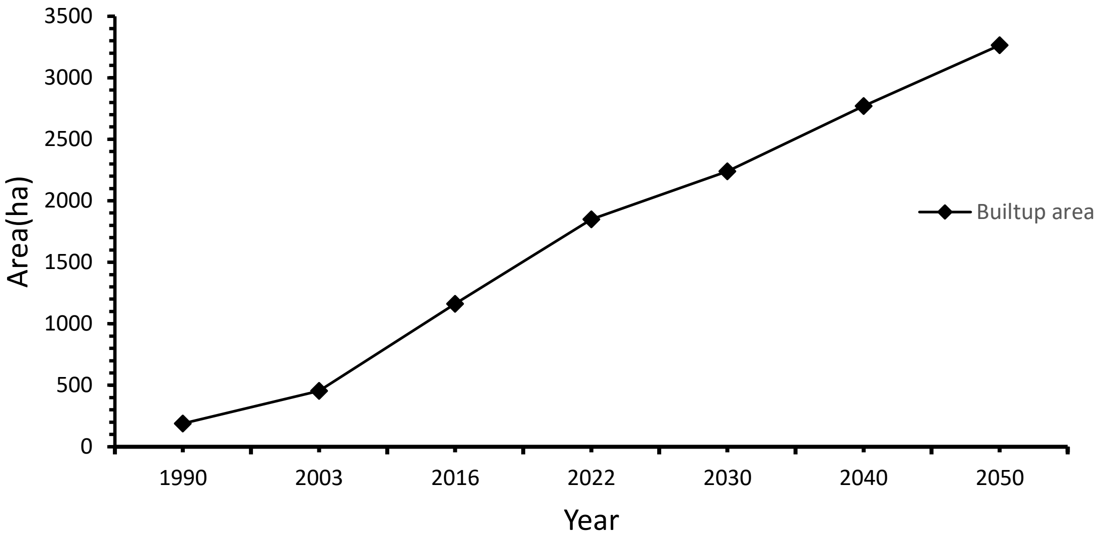


Figure 4.17: Existing and Future expected trend of buildup area expansion 1990 - 2050

4.5 Relationship Between Buildup Area expansion and Population Growth

The analysis between population growth and buildup area expansion was carried out using simple linear regression modeling which assesses the relationship between dependent and independent variables. The population growth in 1990, 2003, 2016, 2022, 2030, 2040 and 2050 was projected from existing census population data. In order to determine urbanization is the increase of urban population and built up area expansion we can evaluate relationship between population growth and urban expansion in the study area using Simple linear regression, is a model that assesses the relationship between a dependent variable and an independent variable.

Table 4.22: Population and built-up area between 1990 and 2022

Years	Population	Built-up area
1990	29871	189.01
2003	62038	455.66
2016	211290	1161.51
2022	296756	1850.31
2030	410710	2240.44
2040	607850	2770.72
2050	899618	3264.6

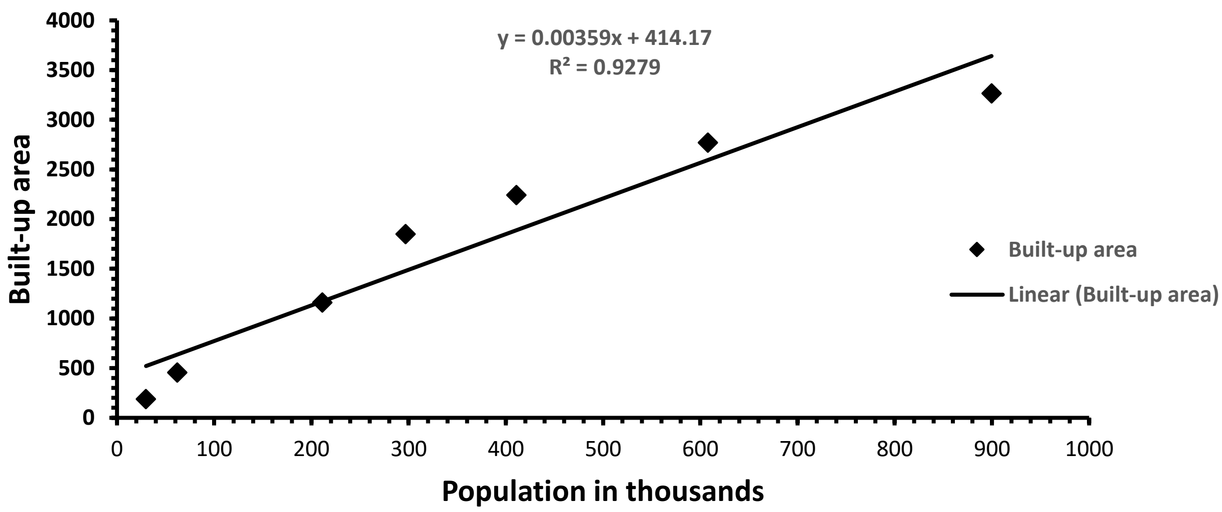


Figure 4.18: Regression line that indicates Correlation between Built-up area expansions and population growth.

The relationship between population growth and built-up area expansion have positive correlation due to positive slope and one variable increases with respect to another variable and the two variables have linear relationship.

$$\boldsymbol{B = 0.00359P + 396.02}$$

Whereas B = Total built-up area and P = Total population growth**.** Degree of correlation is high degree because the value of the coefficient is lies between ±0.5 to ±1 which indicates strength of relationship between two variables; therefore, there is high degree correlation. Built-up area increases by 0.36% for each 1 increment in population growth and the other parameters obtained was, $R^2 = 0.9279$ which indicates the accuracy of the regression model.

4.6 Discussion

The classified image proves overall accuracies of classification was 91%, 89%, 92% and 91% for the year 1990, 2003, 2016 and 2022 respectively. The values of kappa statistics for all classified image was greater than 0.8, it indicates strong agreement between the classified land use land cover class and ground truth, hence the maps satisfied accuracy criteria for land use land cover change detection analysis. The information summarized in the table 4.7 shows the spatial extents; percentage change over time as well as the annual average growth of the five-land use land cover classes (Agriculture land, Barren land Built-up area, Forest land and Grassland) in Wolaita Sodo town between 1990 and 2022.

Besides figure 4.1 proves the spatio-temporal variations of the proportions of each class occurred over the span of 32 years. Overall, the results show the extensive LULC changes in Sodo town over the study period. Agriculture, forest and grass land was dominant class at the beginning of the study period, but forest and grass land declined with the continuous increase of urban land area. It can be seen that the rate of annual urban expansion of built-up area greater by far in second and third study period, from the rest land use classes, in first period from 1990 to 2003 the agriculture land increase by 7.74 percent. The coverage of forest land was 23.75% of the total area at the beginning of the study timeframe. In the following 26 years, it decreased to about 13.09 percent and it show moderate increment in 2022 to 14.36 percent. The agriculture land in Sodo shows increment in past 32 years by 1.68 percent. The proportion of urban class was 1.16% in 1990, this figure rose to just over 11.37% in 2022, showing an increase of more than approximately tenfold of its initial spatial share. From 1990 to 2003, the built-up area increased approximately 266.65ha (141.38%) by the annual increment of 10.88%, while forest area decreased 1578.58ha (40.84%) also the barren land decreased 4.65ha (10.34%), agriculture and grass land increased 1215.73ha (16.53%) and 100.84ha (2.09%) respectively. During the second period between 2003 to 2016, the built-up environment increased by 705.85 ha (155.0%) while grassland area decreased 511.95 ha (10.42%), forest area continuously converted and decreased by 156.45 ha (6.83%) agriculture land showed by moderate change it decreased by 254.15ha (2.96%), barren land increased drastically in second period by 216.69ha (506.52%) During the third period, 2016 to 2022 all LULC decreased except the buildup area and forest area. Buildup area and forest land increased by 688.8 ha (59.24%) and 207.98ha (9.70%) respectively, while agricultural land, barren land and grassland decreased by 8.28%, 2.52%, and 3.84% respectively. Minimum net change was observed in built-up area was between 2016 and 2022, the annual increment of urban area in this study period was 9.87 percent. Hence, the expansion of built-up areas had resulted in a negative change of forest and grass land. A very recent case study on Wolaita Sodo (Badesso, 2020), accounted that the spatial coverage of built-up area coverage increased from 8.9% in 1985 to 32% in 2016 and increased by 216.8% (8.4ha/year) between 1985 and 2016. Another study on urban growth and land-use change detection in Daqahlia governorate, Egypt, by Rizk & Rashed (2015) reported that built-up area increased from 2800ha to 25500ha and agricultural land reduced by 33% between 1985 and 2010. In first period from 1990 to 2003 the urban landscape of Sodo town was more fragmented, while it was less fragmented in the period of 2003 to 2016 and 2016 to 2022, the heterogeneity was high in the year of 2003 and 2016, also the urban area of Sodo town was highly fragmented in 2003 and 2022.

Based on LCM model by using markov chain, urban growth was projected based on the past trends for 2030, 2040, and 2050, it reveals that the built-up area will be 2240.04ha, 2770.72ha, and 3264.6ha respectively. The regression analysis was also performed for built-up area expansion and population growth to determine the strength of the relationship between them and to define what urbanization is in the study area, so simple linear regression was selected to analyze the relationship between one independent and one dependent variable so, analyze reveals that they have a positive linear relationship and degree of correlation was high degree.

CHAPTER V: CONCLUSION AND RECOMMENDATION

5.1 Conclusions

Land use and land cover changes have wide range of consequences at all spatial and temporal scales. Because of these effects and influences it has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and its drivers over space and time is important to predict future developments, set decision making mechanisms and construct alternative scenarios. This study has been conducted by integrating GIS, remote sensing, Spatial metrics and spatial modeling tools. In order to detect and analyze changes in land cover classes, these techniques were implemented.

In the first section, satellite data for the study periods of 1990, 2003, 2016, and 2022 and remote sensing techniques were applied to generate land cover maps through a support vector machine (SVM) supervised image classification algorithm. The accuracy assessment and change detection processes has also been done. The overall accuracy of land use and land cover maps generated in this study had got an acceptable value of above the minimum threshold. The information from image classification accuracy became important to the modeling procedure. The dynamics of landscape structure in the study area were examined by different landscape metrics at patch level and landscape level. Then land use modeling was applied to analyze dynamic changes in built up areas as a result of different driving factors. In the last section the relationship between population growth and urban built-up area expansion were analyzed using regression analysis.

From the remote sensing of image classification result, the study showed that the proportion of built up areas were increased. There was a rapidly changing of built up areas from 1.16% in 1990 to 2.8% in 2003 to 7.14 in 2016 and 11.37% in 2022. The built-up area had an increasing positive trend of change in its areal extent while forest lands decreased continuously in first and second periods. There has been also an observable increasing and decreasing trend of change in the other land cover classes of agriculture, barren and grass land. In Wolaita Sodo agricultural land cover increased by 273.46ha (1.68%) in past 32 years. The average annual rate of change in built-up area as determined from the Landsat change statistics was 10.88 % from 1990 to 2003, 11.92 % from 2003 to 2016 and 9.87 % from 2016 to 2022, 27.5% for the entire period of 1990 to 2022. For increment of urban area in Sodo forest land contribute high proportion, followed by grassland. Barren land also showed moderate increment in past 32 years by 172.46ha (1.06%) gained from forest area and grassland. In first period from 1990 to 2003 the urban landscape of Sodo town was more fragmented, while it was less fragmented in the period of 2003 to 2016 and 2016 to 2022, the heterogeneity was high in the year of 2003 and 2016, also the urban area of Sodo town was highly fragmented in 2003 and 2022.

The resulting 2030, 2040 and 2050 projected land-use map revealed that the urban areas will continue to massively expand, encapsulating several parts of the study area. According to the projection, it is expected that by 2030, 2040 and 2050, about 2240.04ha, 2770.72ha, and 3264.6ha of land in Sodo Town will be covered to built-up area respectively, which covers roughly 13.76%, 17.03% and 20.06% of the town. This means that, between 2022 to 2030,2030 to 2040 and 2040 to 2050, the total areas that are covered by built-up area will increase by 21.06%, 23.69% and 17.82% respectively.

The study concludes that there is a significant increase in urban area that has reached from 189.01 hectare in 1990 to 1850.31 hectare in 2022. This happened due to rapid increase in population which reached from 29871 in 1990 to 296756 in 2022. According to the study the relationship between population growth and built-up area expansion was a positive correlation.

At the moment, town is expanding in almost all directions with a significantly faster rate than ever before. Population is increasing and developments are taking place within and outside the town limits in the form of roads (constructing and widening), residential built up, commercial rise and industrial expansion. Urban expansion is taking place in almost all directions particularly along the roads. The town within last 32 years that have consumed several thousand hectare of forest land. New residential structures are increasing and de-shaping the morphological pattern of the town. This reflects the saturation of town in terms of built up area and currently it has reached at the stage of urban sprawl as newly emerged urban areas. Resultantly, the services provided by local government and municipal authorities are now facing many challenges. Particularly the services related to solid waste and waste water management, water supply distribution, intra-town transportation management etc. are under a serious stress. This reflects alarming situation for local government and urban planners. Effective planning and proper management of the town systems is essential need of the time otherwise urban problems may aggravate further in near future.

5.2 Recommendation

The thesis addressed the potential of geospatial tools particularly GIS, remote sensing and spatial metrics tools for analyzed urban growth. The application of satellite images especially high-resolution images with combined with spatial metrics techniques widely being used to understand the pattern of land use/land cover change, to quantify and analyze the change, and modeling future land use/land cover. Therefore, based on the above findings the following provisional recommendations are given.

- Utilization of high spatial resolution in future able to map finer level of details more accurately by improving the classification accuracy which allow the analysis of more changes in urban land use changes and for accuracy assessment validation especially for the past year classified satellite images preparation of ortho photo map or aerial photo for each town is better for researcher to do further detail analysis with high quality. In study area there was many river streams but the size is very small, in future by using high resolution image and photo take river as a land cover class. Classification of recent images done by using ground truth data collection with the use of GPS technology, but for the past classification if historical images, and aerial photo does not exist google earth is the only solution.
- The rate of built-up area increased has played a major role for decreasing forest land and affecting land-use/land-cover changes. Therefore, the government should be revised the house provision policy, housing modality and housing land provision system.
- Urban planning authorities and town planners should think about the future growth of the town and should understand the consequence of unbalanced physical urban growth.
- The outcome of this study can be used as a base information for Urban planner, Researcher, Land administration and Management office, Environmental protection office, to investigate impacts of land use land cover change and urban expansion to natural resources and ecological service systems, as well as an effect to people's livelihood for natural and land resources management in the future.

REFERENCES

Adem, K. (2010). Urban Expansion and the Neighbourhoods: The Case of Bishoftu Town, East Shewa Zone, Oromia Regional State, Public Administration and Development Management.

Adhikari, S., & Southworth, J. (2012). Simulating Forest Cover Changes of Bannerghatta National Park Based on a CA-Markov Model: A Remote Sensing Approach. Remote Sensing, 4(10), 3215–3243.

Agarwal, C. (2002). A review and assessment of land-use change models: dynamics of space, time, and human choice.

Aithal, B. H., & Ramachandra, T. V. (2016). Visualization of Urban Growth Pattern in Chennai Using Geoinformatics and Spatial Metrics. Journal of the Indian Society of Remote Sensing, 44(4), 617–633.

Ajeeb, R., Aburas, M. M., Baba, F., Ali, A., & Alazaiza, M. Y. D. (2020). The Prediction of Urban Growth Trends and Patterns using Spatio-temporal CA-MC Model in Seremban Basin. IOP Conference Series: Earth and Environmental Science, 540(1).

Akintunde, J. A. (2019). Spatial pattern of urban growth using remote sensing and landscape metrics. Journal of Geomatics, 13(1), 53–60.

Amsalu, A., Stroosnijder, L., & Graaff, J. de. (2007). Long-term dynamics in land resource use and the driving forces in the Beressa watershed, highlands of Ethiopia. Journal of Environmental Management, 83(4), 448–459.

Angel, S., J, P., D. L, C., Blei, A., & Potere., D. (2011). The dimensions of global 2. urban expansion: estimates and projections for all countries, 2000-2050. Progress in Planning, 2, 53–107. June.

Angel, S., Sheppard, S. C., & Civco, D. L. (2005). The Dynamics of Global Urban Expansion. The World Bank, September, 205.

Araya, Y. H., & Cabral, P. (2010). Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal. Remote Sensing, 2(6), 1549–1563.

Arsanjani, J. J., Kainz, W., & Mousivand, A. J. (2011). Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran.

International Journal of Image and Data Fusion, 2(4), 329–345.

Badesso, B. B. (2020). An Exploration into LULC Dynamics and Level of Urbanization: The Case of Wolaita Sodo City and its Peripheries. International Journal of Environmental Sciences & Natural Resources, 25(3).

Bajwa, I., AHMAD, I., Engineering, Z. K.-J. of P., 2000, undefined, Zha, Y., Gao, J., Ni, S., Almas, A. S., Rahim, C. A., Butt, M. A. M. J. J., Shah, T. I., Kumagai, K., Li, H., Liu, Q., Shirazi, S. A., Kazmi, S. J. H. S., De Jong, S. M., Van der Meer, F. D., He, C., … Baig, S. (2015). Assessing the Impact of Urban Expansion on Land Surface Temperature in Lahore Using Remote Sensing Techniques. In Egyptian Journal of Remote Sensing and Space Science (Vol. 4, Issue 4).

Barow, I., Megenta, M., & Megento, T. (2019). Spatiotemporal analysis of urban expansion using GIS and remote sensing in Jigjiga town of Ethiopia. Applied Geomatics, 11(2), 121–127.

Barros, J. X. (2004). Urban growth in Latin American cities: exploring urban dynamics through agent-based simulation. October, 1 v.; 31 cm.

Behera, M. D., Borate, S. N., Panda, S. N., Behera, P. R., & Roy, P. S. (2012). Modelling and analyzing the watershed dynamics using Cellular Automata (CA)-Markov model - A geo-information based approach. Journal of Earth System Science, 121(4), 1011–1024.

Bekalo, M. T. (2009). Spatial metrics and landsat data for urban landuse change detection in Addis Ababa, Ethiopia. 89.

Berberoglu, S., Lloyd, C. D., Atkinson, P. M., & Curran, P. J. (2000). The integration of spectral and textural information using neural networks for land cover mapping in the Mediterranean. Computers & Geosciences, 26(4), 385–396.

Bewket, W., & Abebe, S. (2013). Land-use and land-cover change and its environmental implications in a tropical highland watershed, Ethiopia. International Journal of Environmental Studies, 70(1), 126–139.

Bhatta, B. (2010). Causes and Consequences of Urban Growth and Sprawl. In Analysis of Urban Growth and Sprawl from Remote Sensing Data (pp. 17–36).

Bhatta, B. (2012). Urban growth analysis and remote sensing: a case study of Kolkata, India

1980– 2010. Springer Science & Business Media.

Bocquier, P. (2005). World urbanization prospects: An alternative to the UN model of projection compatible with the mobility transition theory. Demographic Research, 12, 197–236.

Brockerhoff, M. P. (2000). An urbanizing world. Population Bulletin, 55(3), 3–43.

Brown, D. G., Walker, R., Manson, S. and, & Seto, K. (2004). Modeling land use and land cover change. In Land Change Science (pp. 395–409). Springer.

Bulti, D. T., & Sori, N. D. (2017). Evaluating land-use plan using conformance-based approach in Adama city, Ethiopia. Spatial Information Research, 25(4), 605–613.

Campbell, J. B., & Wynne, R. H. (2011). Introduction to remote sensing. Guilford Press.

Carlson, T., & Arthur, S. (2000). The impact of land use - Land cover changes due to urbanization on surface microclimate and hydrology: A satellite perspective. Global and Planetary Change, 25, 49–65.

Clarke, K. C., Couclelis, H., & Clarke, K. C. (2005). The role of spatial metrics in the analysis and modeling of urban land use change. Computers, Environment and Urban Systems, 29(4), 369–399.

Clarke, K. C., Herold, M., & Goldstein, N. C. (2003). The spatiotemporal form of urban growth: Measurement, analysis and modeling. Remote Sensing of Environment, 86(3), 286–302.

Clement, M. T. (2010). Urbanization and the Natural Environment: An Environmental Sociological Review and Synthesis. Organization & Environment, 23(3), 291–314.

Congalton, R. G., & Green, K. (2009). Assessing the Accuracy of Remotely Sensed Data.

Desa, U. N. (2012). World urbanization prospects, the 2011 revision. Final Rep. with Annex Tables. New York, NY United Nations Dep. Econ. Soc. Aff.

Dorosh, P., & Schmidt, E. (2010). The Rural-Urban Transformation in Ethiopia. ESSP Working Papers.

Eastman, J. R. (2006). IDRISI Andes tutorial. Clark Labs, Worcester, MA.

Eastman, J. R. (2012). Idrisi Selva Tutorial’. Idrisi Production, Clark Labs-Clark University, 45.

Elvidge, C. D., Sutton, P. C., & Wagner, T. W. (2004). .Urbanization. In: G.Gutman, A.Janetos, Justice C., et al (Eds.), Land change science: Observing, monitoring, and understanding trajectories of change on the earth's surface (pp.315-328). Dordrecht,Netherlands: Kluwer Academic publishers.

Ershad, M., & Ali, E. (2020). Geographic Information System (GIS): Definition, Development, Applications & Components.

Fan, H., Wu, H., & Wu, S. (2017). Exploring Spatiotemporal Patterns of Long-Distance Taxi Rides in Shanghai.

Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. The Annals of Statistics, 29(5), 1189–1232.

Gemechu, A. E. (2021). Modeling spatial and temporal urban growth patterns and trends by using geospatial technologies, the case of ambo town, oromia, ethiopia. Unpublished, Msc Thesis Submitted to Adama Science and Technology University.

Geremew, A. A. (2013). Assessing The Impacts Of Land Use And Land Cover Change On Hydrology Of Watershed : Assessing The Impacts Of Land Use And Land Cover Change On Hydrology Of Watershed : A Case Study On Gilgel – Abbay Watershed , Lake Tana. 82.

Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. Applied Geography, 63, 101–112.

Haregeweyn, N., Fikadu, G., Tsunekawa, A., Tsubo, M., & Meshesha, D. T. (2012). The dynamics of urban expansion and its impacts on land use/land cover change and small-scale farmers living near the urban fringe: A case study of Bahir Dar, Ethiopia. Landscape and Urban Planning, 106(2), 149–157.

Hashem, N., & Balakrishnan, P. (2015). Change analysis of land use/land cover and modelling urban growth in Greater Doha, Qatar. Annals of GIS, 21(3), 233–247.

Herold, M., Menz, G., & Clarke, K. C. (2001). Remote Sensing and Urban Growth Models – Demands and Perspectives. Regensburger Geographische Schriften, 35, 78–88.

Jansen, L., & Di Gregorio, A. (2000). Land Cover Classification System (LCCS): Classification Concepts and User Manual.

Jensen, J. R. (2009). Remote Sensing of the Environment: An Earth Resource Perspective 2/e. Pearson Education India.

Jiang, L., Cai, Z., & Wang, D. (2010). Improving Naive Bayes for Classification. International Journal of Computers and Applications, 32(3), 328–332.

Karimi, H. ., Jafarnezhad, J. ., Khaledi, J. ., & Ahmadi, P. (2018). Monitoring and prediction of land use/land cover changes using CA-Markov model: A case study of Ravansar County in Iran. Arab. J. Geosci., 11, 592. II.

Karul, C., Soyupak, S., Çilesiz, A. F., Akbay, N., & Germen, E. (2000). Case studies on the use of neural networks in eutrophication modeling. Ecological Modelling, 134(2), 145–152.

Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2013). Land Use/Land Cover Change Analysis Using Object-Based Classification Approach in Munessa-Shashemene Landscape of the Ethiopian Highlands. Remote Sensing, 5(5), 2411–2435.

Kotsiantis, S. B., Zaharakis, I., & Pintelas, P. (2007). Supervised machine learning: A review of classification techniques. Emerging Artificial Intelligence Applications in Computer Engineering, 160(1), 3–24.

Lambin, Geist, H., & Lepers, E. (2003). Dynamics of Land-use and land-cover change in tropical regions. Annu. Rev. Environ. Resour, 20, 49205–49241.

Lambin, Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., Folke, C., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., … Xu, J. (2001). The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change, 11(4), 261–269.

Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. Biometrics, 33(1), 159–174.

Lingereh, Z. (2017). Mapping Land Use And Land Cover Change And Their Effects On Urban _ Pre Urban Agriculture In Debre Advisor : Mapping Land Use / Land Cover Changes And Its Effects On Urban _ Peri-Urban Agriculture In Debre By Ziena

Lingereh Ayele. 2–71.

Lu, D., & Weng, Q. (2007). A Survey of Image Classification Methods and Techniques for Improving Classification Performance. Int. J. Remote Sens., 28(5), 823–870.

Maktav, D., Erbek, F. S., & Jürgens, C. (2005). Remote sensing of urban areas. International Journal of Remote Sensing, 26(4), 655–659.

Masek, J. G., Lindsay, F. E., & Goward, S. N. (2000). Dynamics of urban growth in the Washington DC metropolitan area, 1973-1996, from Landsat observations. International Journal of Remote Sensing, 21(18), 3473–3486.

McGarigal, K. (2002). FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst.

McGarigal, K., & Marks, B. J. (2002). FRAGSTATS. Spatial pattern analysis program for quantifying landscape structure. Version 2.0. Forest Science Department, Oregon State University.

Melesse, A. M., Weng, Q., Thenkabail, P. S., & Senay, G. B. (2007). Remote Sensing Sensors and Applications in Environmental Resources Mapping and Modelling. Sensors, 7(12), 3209–3241.

Meyer, W. B., & Turner, B. L. (1992). Human Population Growth and Global Land-Use/Cover Change. Annual Review of Ecology and Systematics, 23(1), 39–61.

Mishra, V. N., & Rai, P. K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. Arabian Journal of Geosciences, 9(4), 1–18.

Monica, & Moses, M. (2017). A Case Study of Nairobi Spatial Monitoring of Urban Growth Using GIS and Remote Sensing:Metropolitan Area, Kenya, pp66.

Muluneh, A., & Arnalds, O. (2010). Synthesis of Research on Land Use and Land Cover. UNU-Land Restoration Training Programme, 1–39.

Nadoushan, M. A., & Alebrahim, A. (2017). Land use dynamics and landscape pattern changes in Khomeinishahr city , Iran. Indian Journal of Geo-Marine Sciences, 46(11), 2361–2366.

Nugusa, D. G. (2020). Modeling Spatial and Temporal Urban Growth Patterns and trends by using Geospatial technologies: (The Case of Modjo Town). Unpublished, Msc Thesis Submitted to Adama Science and Technology University.

Oluwasola, O. (2007). Social Systems, Institutions And Structures: Urbanization, Poverty and Changing Quality Of Life, Paper Presented At The Training Session Of The Foundation For Environmental Development And Education In Nigeria. ILE-IFE.

Paterson, R., Handy, S., Kockelman, K., Bhat, C., Song, J., Rajamani, J., Jung, J., Banta, K., Desai, U., & Waleski, J. (2003). Techniques for Mitigating Urban Sprawl.

Pham, H. M., & Yamaguchi, Y. (2011). Urban growth and change analysis using remote sensing and spatial metrics from 1975 to 2003 for Hanoi, vietnam. International Journal of Remote Sensing, 32(7), 1901–1915.

Pontius Jr, R. G., & Chen, H. (2006). GEOMOD modeling. Clark University, 44.

Pontius, R. G. (2000). Quantification error versus location error in comparison of categorical maps. In Photogrammetric Engineering and Remote Sensing (Vol. 66, Issue 8, pp. 1011–1016).

Regassa, B. (2014). Analysis Of Urban Expansion And Modelling Of Land Use / Land Cover Changes In Adama City Using Remote Sensing And Gis. Unpublished, Msc Thesis Submitted to Adama Science and Technology University.

Reis, J. P., Silva, E. A., & Pinho, P. (2016). Spatial metrics to study urban patterns in growing and shrinking cities. Urban Geography, 37(2), 246–271.

Rimal, B. (2011). Application of remote sensing and gis, land use/land cover change in Kathmandu Metropolitan City, Nepal. Journal of Theoretical and Applied Information Technology, 23, 80–86.

Rizk, I., & Rashed, M. (2015). Monitoring Urban Growth and Land-use Change Detection with GIS and Remote Sensing Techniques in Daqahlia Governorate, Egypt, International Journal of Sustainable Built Environment 4(2015):3–8.

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy Assessment of Land Use / Land Cover Classification Using Remote Sensing and GIS. 2017, 611–622.

Sang, L., Zhang, C., Yang, J., Zhu, D., & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA–Markov model. Mathematical and Computer Modelling, 54(3), 938–943.

Sankhala, S., & Singh, B. K. (2014). Evaluation of Urban Sprawl and Land use Land cover Change using Remote Sensing and GIS Techniques : A Case Study of Jaipur City , India.

Schapire, R. E., & Singer, Y. (2000). BoosTexter: A Boosting-based System for Text Categorization. Machine Learning, 39(2), 135–168.

Shafizadeh Moghadam, H., & Helbich, M. (2013). Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model. Applied Geography, 40, 140–149.

Silva, E. A., & Clarke, K. C. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. Computers, Environment and Urban Systems, 26(6), 525–552.

Subedi, P., Subedi, K., & Thapa, B. (2013). Application of a hybrid cellular automaton–Markov (CA-Markov) model in land-use change prediction: a case study of Saddle Creek Drainage Basin, Florida. Applied Ecology and Environmental Sciences, 1(6), 126–132.

Tachizuka, S., Hung, T., Ochi, S., & Yasuoka, Y. (2007). Monitoring of Long-term Urban Expansion by the use of Remote Sensing Images from Different Sensors.

Tadese, S., Soromessa, T., & Bekele, T. (2021). Analysis of the Current and Future Prediction of Land Use/Land Cover Change Using Remote Sensing and the CA-Markov Model in Majang Forest Biosphere Reserves of Gambella, Southwestern Ethiopia. Scientific World Journal, 2021.

Tadesse, E., & Imana, G. (2017). Prospects and Challenges of Urbanization on the Livelihood of Farming Community Surrounding Finfinne.

Tegene, B. (2002). Land-Cover/Land-Use Changes in the Derekolli Catchment of the South Welo Zone of Amhara Region, Ethiopia. Eastern Africa Social Science Research Review, 18, 1–20.

Tekle, & Hedlund. (2000). Land cover changes between 1958 and 1986 in Kalu District, Southern Wello, Ethiopia. Mountain Research and Development, 20(1), 42–51.

Teshome M. (2019). The Role of Geoinformation Technology for Predicting and Mapping Urban Change Detection: Wolaita Sodo town case study. Int.J.Curr.Res.Aca.Rev, 7(10), 23–33.

Tewolde, M. G., & Cabral, P. (2011). Urban sprawl analysis and modeling in Asmara, Eritrea. Remote Sensing, 3(10), 2148–2165.

UN-HABITAT. (2016). Climate Change and Cities. Global Report on Human Settlements 2011. In Cities and Climate Change.

Veldkamp, A., & Lambin, E. F. (2001). Predicting land-use change. Agriculture, Ecosystems & Environment, 85(1), 1–6.

Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. S. A. (2002). Modeling The Spatial Dynamics Of Regional Land Use: The Clue-S Model. Environmental Management, 30(3), 391–405.

Vogelmann, J. E., Helder, D., Morfitt, R., Choate, M. J., Merchant, J. W., & Bulley, H. (2001). Effects of Landsat 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper plus radiometric and geometric calibrations and corrections on landscape characterization. Remote Sensing of Environment, 78(1–2), 55–70.

Weng, Q. (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sensing of Environment, 117, 34–49.

Wu, F., & Webster, C. J. (2000). Simulating artificial cities in a GIS environment: urban growth under alternative regulation regimes. International Journal of Geographical Information Science, 14(7), 625–648.

Xiao, J., Shen, Y., Ge, J., Tateishi, R., Tang, C., Liang, Y., & Huang, Z. (2006). Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. Landscape and urban planning, 75(1-2), 69-80.

Xu, L., Zhang, S., He, Z., & Guo, Y. (2009). The comparative study of three methods of remote sensing image change detection. 2009 17th International Conference on Geoinformatics, 1–4.

Yang, L., Xian, G. Z., Klaver, J. M., & Deal, B. (2005). Urban LandCover Change Detection through Sub-Pixel Imperviousness Mapping Using Remotely Sensed Data.

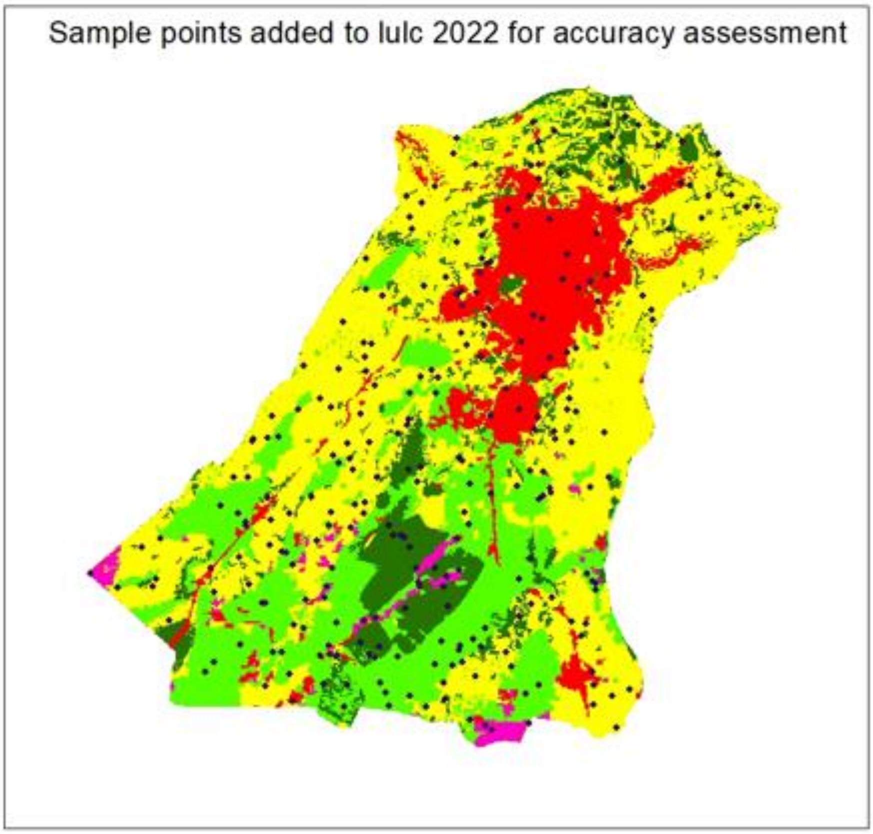
Yeshaneh, E., Wagner, W., Exner-Kittridge, M., Legesse, D., & Blöschl, G. (2013). Identifying land use/cover dynamics in the koga catchment, Ethiopia, from multi-scale data, and implications for environmental change. ISPRS International Journal of Geo-Information, 2(2), 302–323.

Yuan, F., Sawaya, K., Loeffelholz, B., & Bauer, M. (2005). Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Remote Sensing of Environment, 98, 317–328.

Zeleke, G., & Hurni, H. (2001). Implications of Land Use and Land Cover Dynamics for Mountain Resource Degradation in the Northwestern Ethiopian Highlands. Mountain Research and Development, 21(2), 184–191.

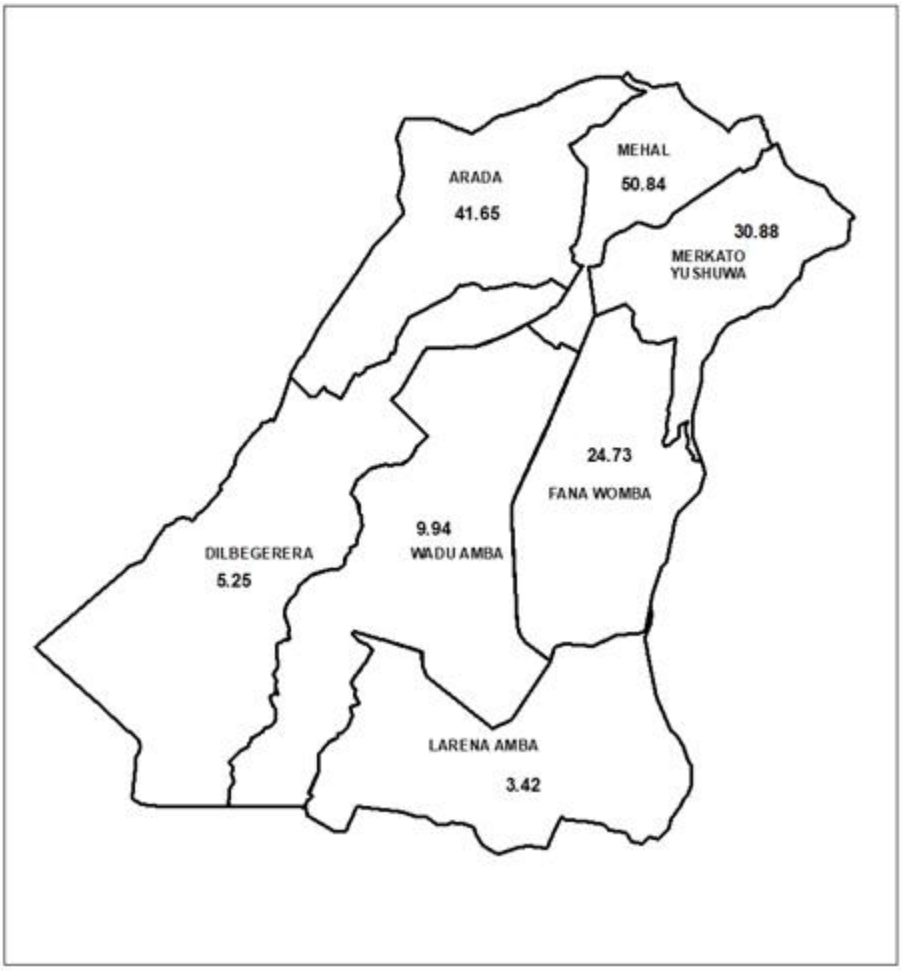
APPENDIX

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



Appendix II: Kebele name, population size, area and population density of Wolaita Sodo town.

KEBELE_NAME	Population	Area	Population Density
Arada	86155	2068.51	41.65
Mehal	52469	1032.08	50.84
Merkato Yushuwa	45798	1480.47	30.88
Fana Womba	50635	2047.30	24.73
Wadu Amba	33496	3370.96	9.94
Dilbegerera	19356	3685.78	5.25
Larena Amba	8847	2584.37	3.42



Appendix III: Comparison change amount of actual and projected LULC 2022.

LULC	2022 Actual		2022 Projected		Change	
Type	Area (ha)	%	Area (ha)	%	Area (ha)	%
Agriculture	7625.6	46.87	7596.1	46.68	-29.5	-0.19
Barren land	220.05	1.35	222.98	1.37	2.93	0.02
Build-up area	1850.31	11.37	1865.52	11.47	15.21	0.10
Forest area	2336.9	14.36	2326.71	14.30	-10.19	-0.06
Grass land	4236.61	26.04	4258.18	26.17	21.57	0.13
Total	**16269.47**	**100%**	**16269.47**	**100%**	**0.00**	**0.00**