

*Modeling Spatial and Temporal Urban Growth Patterns and trends by using
Geospatial technologies: (The Case of Modjo Town)*

By: Nugusa Duressa Geleta



*A Thesis Submitted for the Partial fulfillment of the Graduate
Geoinformatics Program in the Department of Geomatics Engineering.*

School of Civil Engineering and Architecture

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

July, 2020

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Advisor: Roba Gemechu (PHD.)



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LIST OF ACRONYMS

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

COVID_19 _Corona Virus Disease 19

DEM - Digital Elevation Model

DN - Digital Number

ERDAS - Earth Resources Data Analysis System

ETM- Enhanced Thematic Mapper

ETM+ - positive Enhanced Thematic Mapper plus

ENVI- Environment for Visualizing Images

FAO- Food and Agriculture Organization

FDI – Foreign Direct Investment

GCP- Ground Control Points

GIS - Geographical Information System

GPS- Geographic Positioning System

IGBP- International Geosphere-Biosphere Program

LCM - Land Change Modeler

LULCC- Land Use and Land Cover Change

LULC- Land Use and Land Cover

MCE_ Multi Criteria Evaluation

MAE – Mean Absolute Error

ML- Machine Learning

MLP - Multi Layer Perceptron

MOSAIC- Multimodality Operational Site Analysis and Intelligent Change-detection.

MTM - Modjo Town Municipality

NASA –National Aeronautics and Space Administration

■

OLI- Operational Land Imagery

RMSE- Root Mean Square Error

RS- Remote Sensing

SVM_ support vector machine

TM - Thematic Mapper

UN- United Nations

UA - urban agriculture

UNPD _United Nations Population Division

USGS –United State Geological Survey

UTM- Universal Trans Mercator

WGS - World Geodetic System

ABSTRACT

A rapid increase in the world's population over the last century has triggered the transformation of the earth surface, especially in urban areas, where more than half of the global populations live. Ethiopia is no exception and a high population growth rate, coupled with economic development over the last three decades, has transformed the Modjo Town into a hot spot for massive urban growth. Although urbanization presents several opportunities, the environmental and social problems cannot be underestimated. Therefore, the need to estimate the rate and extent of land use/land cover changes in the area and the main drivers of these changes is imperative. Geographic Information Systems (GIS), Remote sensing, IDRIS SELVA and ENVI techniques provide effective tools in studying and analysis land-use/land-cover change over space and time. A supervised and support vector machine algorithm (SVMs) was used for multi-temporal land satellite classification. The change detection of multiple Landsat images was conducted to map and analyzed the extent and rate of land use/land cover change in the ModjoTown between 1990 and 2019. Subsequently, the urban growth extent of the area was forecasted for the year 2030, 2040 and 2050 on the land change modeler using Multi-Layer Perceptron neural network, with combination of markov chain method, together with drivers representing proximity, biophysical, and socio-economic variables and finally the relationship between population growth and urban built-up area expansion were analyzed using regression analysis. Overall, the results show there was the extensive LULC changes in Modjo town over the study Period (29 years). Agricultural land was dominant class at the beginning of the study period and until this research conducted but declined with the continuous increase of urban land area. It can be seen that the rate of annual urban expansion greater by far, from the rest land use classes. The coverage of agricultural land was 88.25% of the total area at the beginning of the study timeframe. In the following 29 years, it dramatically dropped to about 66.34%. By contrast, the proportion of urban class was 0.93% in 1990, this figure rose to just over 15.94% in 2019, showing an increase of more than sixteen folds of its initial spatial share. It showed 55.42% of average annual expansion across the study period. Temporally, the rate of urban built-up land expansion was comparatively low in the first ten years between 1990 and 2000, which showed nearly 0.9% increase, then it peaked about 15.94% of the total area in the last year. On the other hand, vegetation class showed a remarkable increase in spatial cover between 1990–2000 has also contributed to the increase of its share of the study area from 6.67–9.01% in the first and last years of the study period, respectively. While the areal share of the barren land decreased in the first 20 years during the study timeframe however it is increased dramatically in the last 10 years. In the next coming 30 years it will be expected that urban built-up land area is increased from 15.94% to 29.46%, 32.78% and 34.84% of the total area coverage according to prediction at 2030, 2040 and 2050 respectively. As the study reveals also relationship between population growth and urban built-up area expansion were positive correlation. The success of this research is generating a future urban land-use map for 2030, 2040 and 2050, together with the other significant findings, demonstrates the usefulness of spatial models as tools for sustainable city planning and environmental management, especially for urban planners in developing countries like Ethiopia.

Keywords: land use/land cover; urban growth prediction; Markov Chain; multi-layer perceptron neural network; SVM and Land change modeler (LCM).

CHAPTER ONE: INTRODUCTION

1.1 Background of study

In today's world, more than half of the global population lives in urban areas and by 2050, this figure is projected to increase to more than 65% (United Nations 2014). Based on this projection, 2.5 billion people will add to the world's urban population, with nearly 90% of the urban growth concentrated in less developed countries. Developing countries started the process of urbanization lately, but they are the ones which are rapidly urbanizing (Montgomery 2008). As such, in the past few decades, rapid and often unplanned urban expansion has considerably accelerated more in developing countries than in developed nations (Cohen 2006; Grimm et al. 2008). Several studies (e.g. Long et al. 2007; Bhatta 2009; Thapa and Murayama 2010; Haregeweyn et al. 2012) attributed unprecedented population growth and socioeconomic development as the major drivers of such unplanned urban expansion. In most developing countries, urban expansion is recognized as an important phenomenon as it offers increased opportunities for employment, production, and goods and services (Cohen 2006). Such increased opportunities in urban areas further enhanced rural–urban migration (Chen et al. 2014). By 2050, the world population will reach 9.7 billion, with more than half of the growth occurring between now and 2050 being projected to happen in Africa. A significant percent of this growth is expected to take place in urban centers. As of (United Nations, 2014), about 40% of the African populations were living in urban centers. The percentage of urban dwellers in Africa has been forecasted to reach 56% by 2050 [United Nations, 2014]. These demographic changes, coupled with economic transformations and technological advancements, have shaped the face of the earth in both negative and positive ways.

Numerous studies support the evidence of rapid urbanization as a result of human induced land use/ land cover changes (Aljoufie, Zuidgeest, Brussel, & van Maarseveen, 2013; Briassoulis, 2000; Halder, 2013; H. Zhang, Qi, Ye, Cai, & Ma, 2013; Z. Zhang, Su, Xiao, Jiang, & Wu, 2013). It is a common observation that with growing population, urban areas are expanding. The rate of expansion, however, depends upon several other associated factors. It is understandable and several studies

also argue that human population growth and resource consumption leads to the expansion of urban land area and bring changes in its land use and land cover (Cheng & Masser, 2003; Haregeweyn, Fikadub, Tsunekawa, & Tsubo, 2012; Tian et al., 2005). Land use is the varying activities performed by human beings to divide the landscape into different patterns with concerned changes (Carole L.Jolly & Barbara Boyle Torrey, 1993) and varies with human activities and the purpose for which land is being used. It can be used for food production, provision for shelter, recreation, processing of materials, and so on (Halder, 2013). The urbanization process is mainly linked to economic growth, commercialization, and industrialization, as well as rural-urban migration and globalization (Buhaug & Urdal, 2013).

In this study we can define urbanization is the link of population growth and urban built-up area expansion, according to the study shows relationship between population growth and urban built-up area were examined using regression analysis and they have positive relationship.

Over the last three decades, advancements in remote sensing technologies have made it possible to study physical changes and patterns (Cohen, W.B, 2004). Remote sensing and Geographic Information Systems (GIS) techniques provide information and the necessary tools to study and understand land use/land cover (LULC) changes over time. GIS and remote sensing have become important tools for conducting change analysis in different parts of the world (Yaun, F.; Sawaya, K.E.; Loeffelholz, 2005). For developing countries, where geospatial technologies are not well developed, remote sensing data, especially Landsat images, provide a suitable option for monitoring urban change and expansion. Several scholars have been able to use remote sensing data to successfully quantify urban change, as well as its rate of change (Yaun, 2005; Adepoju, 2002; Kolehmainen, 2008). Prior urban studies in modjo have analyzed and exploited remotely sensed data for analyses of urban growth in the context of population growth, urban ecology, socio-economic indicators, etc. In Ghana, Møller and Yankson conducted early efforts to map urban expansion using remote sensing data (Moller_Jensen, 1994). They assessed the suitability of using Landsat Thematic Mapper images for urban change studies, as well as producing a land cover map of Accra. For a similar study area, Stow et al. (Stow, D.A, 2013) examined the relationship between urban vegetation change and the housing quality

index while using remote sensing and statistical techniques. Stow et al. (2016) also analyzed and examined the relationship between population growth and land cover change in southern Ghana using remote sensing techniques.

This is the first paper to model and predict the urban built-up area expansion in modjo town municipality and population growth and it also seeks to demonstrate how spatial models can be used in developing countries to monitor and track environmental and social changes, including forest loss, agriculture loss and urban expansion.

Different scholars have applied many land use modeling techniques with varying theoretical basis, assumptions, and inputs to model and predict land use change. Several scholars have reviewed and applied these techniques in different study areas and research fields. Musa et al. & Reba (2017) provide an overview of several urban growth models and initiatives. Pijanowski et al. (2009) used the neural network to project urban expansion in the Tehran Metropolitan area. Attua and Fisher (2011) also used the Markov chain model to predict land use change in the New Juaben municipality of Ghana. Koranteng and Niedzwiecki (2015) projected forest loss in the Ashanti region of Ghana using the Land Change Modeler tool, which was embedded in the software IDRISI. Samardžić et al. present the incorporation of Support Vector Machines (SVM) into land use modeling (Samardzi, 2016). Ahmed and Ahmed (2012) conducted a comparative study on different models for predicting land use change and concluded that a **combination of Multi-Layer Perceptron (MLP) neural network and Markov Chain** produced the most accurate land use change prediction.

1.2 Statement of the problem

Ethiopia is one of the slightest urbanized countries in the world. Even for African levels, the rank of urbanization is low. According to the Population Reference Bureau's *World Population Data Sheet* (2002), while the average standard of urbanization for Africa in general was 33% in 2002, Ethiopia had only 15% of its population reside in urban areas. Urbanization is a worldwide situation in the 21st century. The United Nations Population Division (UNPD) estimates that most population growth in the coming 30 years will happen in urban agglomerations. Already today approximately 50 % of the human population is living in urban areas. While the most rapid growth is forecasted for cities in less developed countries, it is also expected that small and middle sized urban areas will absorb most of this growth [UNPD *World Urbanization Prospects, The 2007 Revision Population Database*(August 2008)].Rapid urbanization poses considerable social and environmental challenges to city authorities and planners. Unmanaged population growth, increasing social inequality, economic disparities and poverty all increase the potential of conflict. Poor urban planning and housing development lead to construction of informal settlements that lack access to basic infrastructure and provide poor living conditions. As result, increases in unregulated traffic, noise, and underdeveloped sewage and waste management cause further environmental degradation. Close controlling of rapid urbanization is basic for the creation of sustainable urban environments (Angel, S.; Sheppard, S.C.; Civco, D. *The Dynamics of Global Urban Expansion*; the World Bank Transportation and Urban Development Department: Washington, DC, USA, 2005; p. 205.)

Historical evidences show that cities always have capacitated rapidly due to mass migration of people, high growth rate, and provision of facilities and services. They play significant role in boosting economic conditions and strengthening the countries finance. However, cities of the developing countries are facing many problems because of increasing urbanization. In cities, infrastructure and public services, overcrowded transportation systems, insufficient water supply, deteriorating sanitation, and environmental pollution are the major influence of urban growth and factors responsible for environmental degradation (Buhaug & Urdal, 2013; Herold,

Goldstein, & Clarke, 2003; López, Bocco, Mendoza, & Duhau, 2001; Nassar, Blackburn, & Whyatt, 2014). 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). Urban sprawl, another major impact of urbanization, is a low-density and dispersed spatial pattern of urban growth with both environmental and social impacts is also causing a threat for irregular urban growth (Aguilera, Valenzuela, & Botequilha-Leitão, 2011).

Another significant cause for extension of urban built-up is rapid population growth, industrial expansion and development of commercial activities that have been experienced in many developing areas like modjo. Such kind of development is occurring in an unplanned and haphazard manner mostly along new residential colonies. In view of the changes occurring in the pattern of economic activities, industrialization and urbanization, researchers argue that demographic change is the major driving factor for urban expansion as more land is demanded by increasing population (Li, Sato, & Zhu, 2003). In modjo and in many other developing countries, irregular sprawling of cities at a very high rate is creating numerous social and economic problems of complex nature. Although, urban areas comprise a very small portion of the world's land area but they contain 52% of the world's inhabitants (PRB, 2013) and their rapid expansion has caused rapid and threatening impact on natural environment (Grimm, Morgan Grove, Pickett, & Redman, 2000; Haregeweyn, et al., 2012; He, Okada, Zhang, Shi, & Li, 2008). Consequently, many problems like increase in squatter settlements, deficiency of water, lack of sewerage facilities, overburdening of municipal services, and conversion of valuable farmland into non-farm uses are rising notably on the urban scene. Urbanization in modjo is characterized by several notable factors including natural population increase, migration from rural to urban areas, changes occurring in the settlement patterns, improvements in living standards of the people, changing socio-economic conditions etc.

Modjo is first and fastest growing town that exist between Adama and Bishoftu in which the population highly increased from time to time over 30 years ((Belda, 2018). Generally ,the issues of Urban land use and land cover changes of Modjo town become the most basic problems of societies in economic, social and environmental confusion which leads health problems, cultural disturbance, uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands and protected Forest lands (Modjo Town land administration offices, 2019).

1.3 Research Questions

- I. What is the dynamics of the built-up land in Modjo Town Administration from 1990 to 2019 in spatial and temporal scales?
- II. How does the built-up land in the study area changes in 2030, 2040 and 2050 under the condition of business as usual scenario?
- III. How can the relationship between the trends of the population growth and built-up land expansion in the study area be explained?

1.4 General Objective

The general objective of the study is to analyze the spatiotemporal dynamics of built-up land in Modjo Town Administration under the influences of urbanization from 1990 to 2050.

1.5 Specific objective

The Following specific objectives were proposed in order to explore the area of study:

- I. To determine the magnitude and trend of built-up area expansion in Modjo Town Administration from 1990 to 2019
- II. To predict the extent and distribution of built-up area in the study area in 2030, 2040 and 2050 based on the past trend of urban growth
- III. To find relationship between the trends of population growth and built-up area expansion in the study timeframe

1.6 Significance of the Research

The study aims to analyses land use/land cover dynamics and predict future urban growth modeling that have gained prominence in the recent years. This is partly due to the fact that there is an increasing need for proper land use planning to control various urban problems. Some significance's of study on urban land use and land cover change and future urban growth modeling: (i) To form and implement land and policies regarding existing and future land use,(ii) Planning, management and monitoring of natural resources, and(iii) LULC is an input parameter in many fields as geology, hydrology, demography, environment etc. The study of urban land use land

cover changes is very important to have proper planning and utilization of natural resources and their management. The land use and land cover change plays an important role in global environmental change. Accurate and up-to-date land cover change information is necessary to understand both human causes and environmental consequences of such changes. Land use land cover changes also affect climate change in the long term. This study would be helpful for detecting land use/land cover change and predicting the future urban growth from LULC change analysis and determining relationship between built-up land expansion and population growth and planning the utilization of land in Modjo Town Municipality (MTM).

1.7 Scope of study

This research focus mainly on urban growth LULC change analysis from 1990_2019 and prediction of the future urban growth 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 Modjo town boundary and also the accuracy assessment was carried out for classified image , model selection , change analysis ,validation and future prediction of land use land cover change and analyzing correlation ship of population growth and built-up area expansion and finally recommendations were raised based on the findings.

1.8 Organization of research structure

The thesis was organized in to five chapters in order to successfully achieve study and the detail was explained below:

Chapter 1: This chapter deals with introduction, statement of problem, research question, objective, Significance of research, and scope.

Chapter 2: Deals about related review literature, it describes the main concept used in the study i.e. urban land use /land cover and its national and international experiences of the diverse study of land use changes and modeling techniques.

Chapter 3: Deals about Description of the study area, materials and methods of data collection, materials used, data sources, and data analysis techniques.

Chapter 4: This chapter contains results and interpretation of data analysis

Chapter five: conclusion, recommendation and limitation of research.

CHAPTER TWO: REVIEW OF RELATED LITERATURE

2.1 Theoretical Frameworks of Urban LU/LC change and future urban growth modeling

2.1.1 Introduction

Urban growth is a global phenomenon and one of the most important reforming processes affecting both natural and human environment through many ecological and socio-economic processes (Mandelas, et al, 2007). Currently, communities worldwide need spatial data to compensate for and adapt to current urban growth while planning for expected future change and its impacts on infrastructure, as well as the surrounding environment. Rapid rates of urban land use change and rate of urbanization are now at the front of local political disputes (Goetz, et al., 2003). However, these polarized debates lack adequate geospatial information for informed decision making and monitoring changes in dramatically changing environments and thereby achieving sustainable urban growth.

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

2.1.2 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 center of 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, over exploitation of natural resources and conflict.

2.1.3 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 et al., 2014). The negative effects (disorderly) urban expansion highly increase the land use and land cover changes and becomes many problems such as uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands, and loss of fish and wildlife habitat, loss of prime agricultural farmland, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, over exploitation of natural resources and conflict (Alexander, 1995; Rosenfeld, 1994).

2.1.4 Factors of LU/LC 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.

1. Demographic factors

Demographic effects include rural to urban migration and natural population growth in the city, the level of urbanization and the rank of the city/town in the country's urban hierarchy. Natural population growth is a major element in urban growth for all countries, and migration of rural to urban contributes fast growth of urban population in many developing countries (Gugler, 1996).

2. Economic factors

Economic effects include the level of economic development, 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).

3. Natural /environment factors

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

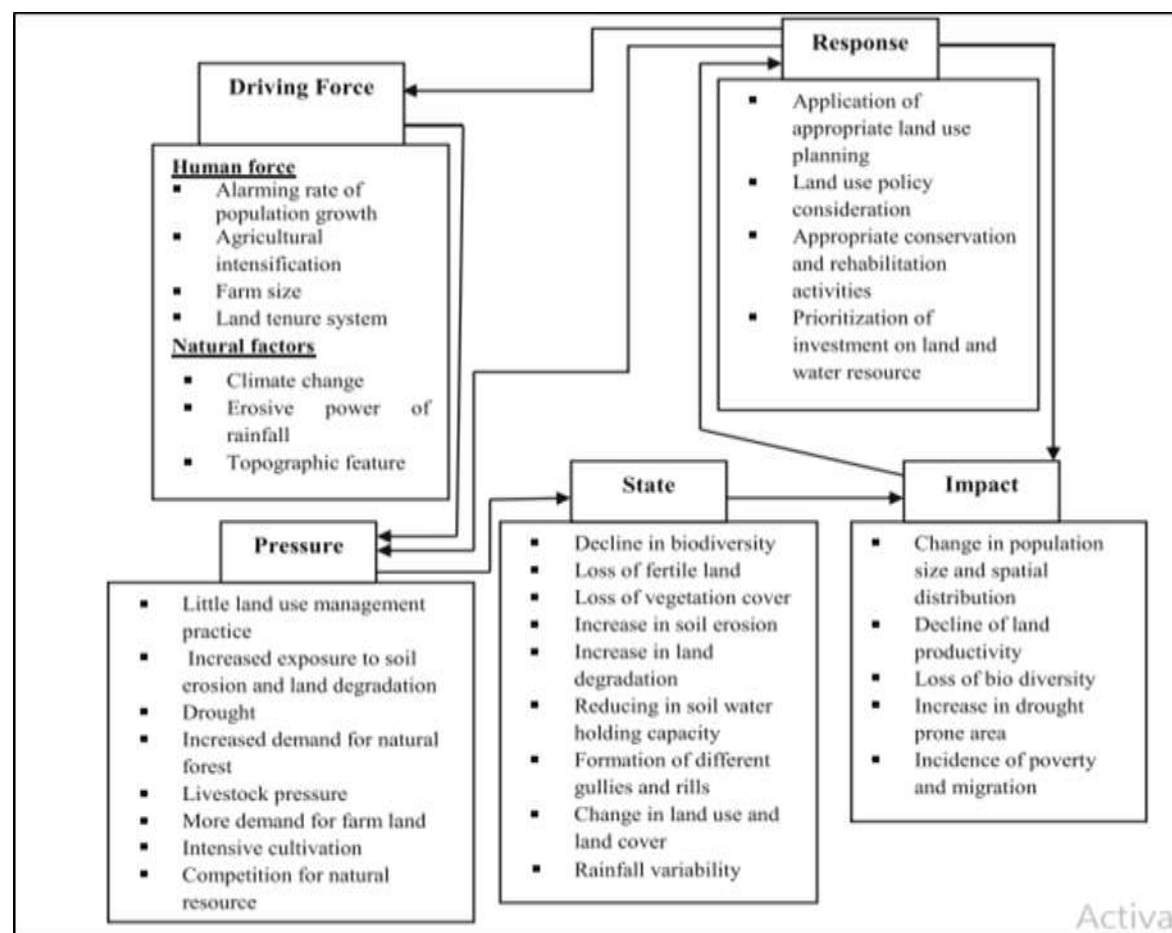


Figure 1: Conceptual framework on the driving force of land cover change and associated effect. Adopted from FAO 2004; Shiferaw 2011.

2.1.5 Land Use Land Cover (LULC)

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

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

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

2.1.6 Purpose of Land Use Land Cover

Remote sensing data can provide land cover information rather than land use information. The properties measured with remote sensing techniques related to land cover, from which land use can be inferred, particularly with ancillary data or a prior (already known) knowledge (Basudeb, 2011).

According to (Basudeb, 2011) Land use application involves both baseline mapping and subsequent monitoring, since timely information is required to have knowledge on the state of use of current quantity of land and to identify the land use changes time to time. This knowledge helps to developing strategies to balance conservation, conflicting uses, and developmental pressure. Issues driving land use studies include the removal or disturbance of productive land, urban encroachment, and depletion of forest. In addition, a reason for developing and maintaining a land cover monitoring study is to provide a consistent view of the stock and state of our natural and built resources as they change through time. Knowledge of land use and land cover is important for many planning and management activities concerning the surface of the earth. Survival of human race depends on its living in harmony.

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

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

According to (Basudeb Bhatta,2014) explanation land use applications of remote sensing include the natural resource management, wildlife habitat protection, baseline mapping for geographic information system (GIS) input, urban expansion or encroachment, routing and logistics planning for seismic/exploration/resources extraction activities, damage delineation (tornadoes, flooding, volcanic, seismic, fire, and terrorist activities),legal boundaries for tax and property evaluation and target

detection_ identification of landing strips, roads, clearings, bridges, and land or water interface.

Purpose of urban land use/land covers change study and mapping:

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

2.1.7 Urban Land Use Dynamics

Now a day, urbanization has become an environmental problem of global importance. Despite the few percentage distribution and coverage of geographic space of urbanized land, the impacts of the process of urbanization on biodiversity, ecosystem fluxes and environmental quality are profound and these days it gets much attention by scholars from diverse fields, (Breuste, et al., 1998; Pickett, et al., 2001). Urban growth affects the ecology of cities in a number of ways, such as eliminating and fragmenting native habitats, modifying local climate conditions and generating anthropogenic pollutants. It is widely recognized that the spatial pattern of a landscape affects ecological processes (Wu and Loucks, 1995). Similarly, tremendous urban expansion with high inflow of population from the local or distant places and dynamic urban changes processes in their morphology, expansion of impervious surface and conversion of productive lands in and around urbanized area, affect natural and human systems at all geographic scales. Deteriorating conditions of urban crowding, housing shortages and lack of infrastructure, as well as increasing urban expansion on fertile lands highlights much attention for sustainable and effective management and planning of urban areas. Recently, innovative approaches to urban land use planning and management such as sustainable development and smart growth has been proposed and discussed (Kaiser, et al., 1995).

2.1.8 Urban Land use land cover of Image Classification

Image classification refers to the extraction of differentiated classes or themes, usually land cover and land use categories, from raw remotely sensed digital satellite data (Weng, 2012). Image classification using remote sensing techniques has attracted the attention of research community as the results of classification are the backbone of environmental, social and economic applications (Lu and Weng, 2007). Because image classification is generated using a remotely sensed data, there are many factors that 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 constraint.

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 applied to image data. There are various image classification methods that can be applied to extract land cover information from remotely sensed images (Lu and Weng, 2007). However, their application depends on the methodology and type of data to be used. Some of these methods are: **artificial neural networks, support vector machine, 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.

2.1.9 Land use land cover Change detection

Change detection is the process of identifying differences in the state of object or phenomena by observing them at different times by using remote sensing techniques (Singh, 1989). Change detection has a wide range of applications in different disciplines such as change analysis, forest management, vegetation phenology, and seasonal changes in pasture production, risk assessment, urban expansion and other environmental changes (Singh, 1989). A change detection research to be good, it

should provide the following vital information: area change and rate of changes, spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of change detection results.

2.1.10 Supervised image classification algorithms

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

1) Linear Classifiers: Linear models for classification separate input vectors into classes using linear (hyperplane) decision boundaries (Elder, J. (n.d)). The goal of classification in linear classifiers in machine learning, is to group items that have similar feature values, into groups. Timothy Jason Shepard, P. J. (1998) stated that a linear classifier achieves this goal by making a classification decision based on the value of the linear combination of the features. A linear classifier is often used in situations where the speed of classification is an issue, since it is rated the fastest classifier (Taiwo, O. A. 2010).

2) Logistic regression: This is a classification function that uses 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 data set is larger. These statements about probabilities which make logistic regression more than just a classifier.

3) Naive Bayesian (NB) Networks: These are very simple Bayesian networks which are composed of directed acyclic graphs with only one parent (representing the unobserved node) and several children (corresponding to observed nodes) with a strong assumption of independence among child nodes in the context of their parent (Good, I.J. 1951). Thus, the independence model (Naive Bayes) is based on

estimating (Nilsson, N.J. 1965). Bayes classifiers are usually less accurate than other more sophisticated learning algorithms (such as ANNs).

4) Multi-layer Perceptron: This is a classifier in which the weights of the network are found by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard neural network training. Other well-known algorithms are based on the notion of 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 which is correct on all of the training set. This prediction rule is then used for predicting the labels on the test set (Kotsiantis, S. B, 2007).

5) Support Vector Machines (SVMs): These are the most recent supervised machine learning technique. Support Vector Machine (SVM) models are closely related to classical multilayer perceptron neural networks. SVMs revolve around the notion of a —margin—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, S. B, 2007).

6) K-means: According to (Bishop, C. M, 1995) and K means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. K-Means algorithm is employed when labeled data is not available. General method of converting rough rules of thumb into highly accurate prediction rule. Given —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 single classifier with very high accuracy, say, 99% (Rob Schapire,n.d)Machine Learning Algorithms for Classification.

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

Table 1: Comparison of various classification algorithms with large data set and more attributes (**** stars represent the best, *** medium, **, lower and * star the worst performance).

	Decision Trees	Neural networks	Naïve Bayes	KNN	SVM	Rule learners
Accuracy in general	**	***	*	**	****	**
Speed of learning with respect to number of attributes and the number of instances	***	*	****	****	*	**
Speed of classification	****	****	****	*	****	****
Tolerance to missing values	***	*	****	*	**	**
Tolerance to irrelevant attributes	***	*	**	**	****	**
Tolerance to redundant attributes	**	**	*	**	***	**
Tolerance to highly independent attributes(eg parity problems)	**	***	*	*	***	**
Dealing with discrete binary continuous attributes	***	*** (not discrete)	*** (not continuous)	*** (not discrete)	** (not discrete)	*** (not directly continuous)
Tolerance to noise	**	**	***	*	**	*
Dealing with danger of over fitting	**	*	***	****	**	**
Attempts for incremental learning	**	***	****	****	**	*
Explanation ability transparency of knowledge classifications	****	*	****	**	*	****
Model parameter handling	***	*	****	***	*	***

Table 2: Comparing learning algorithms (Machine Learning Algorithms) for Classification.

algorithm	Time(sec)	Correctly classified (%)	In Correctly classified (%)	Test mode	attributes	No of instances	Kappa statics	MAE	Precision of yes	Precision of no	Classification
Decision table	0.23	72.3958	27.6042	10-fold cross-validation	9	768	0.3752	0.341	0.619	0.771	rules
Random forest	0.55	74.7396	25.2604	10-cross-validation	9	768	0.4313	0.3105	0.653	0.791	trees
Naïve Bayes	0.03	76.3021	23.6979	10-cross-validation	9	768	0.4664	0.2841	0.678	0.802	Bayes
SVM	0.09	77.3438	22.6563	10-cross-validation	9	768	0.4682	0.2266	0.740	0.785	functions
Neural networks	0.81	75.1302	24.8698	10-cross-validation	9	768	0.4445	0.2938	0.653	0.799	functions
JRIP	0.19	74.4792	25.5208	10-cross-validation	9	768	0.4171	0.3461	0.659	0.780	rules
Decision trees	0.14	73.8281	26.1719	10-cross-validation	9	768	0.4168	0.3158	0.632	0.790	tree

MAE (Mean Absolute Error) is a measure of how close forecast or predictions are to the eventual outcome. Kappa Statistic is a metric that compares an observed accuracy with an expected accuracy (Random Chance). YES means tested positive to diabetes. NO means tested negative for diabetes Table 2 shows the results with 9 attributes of the classification and comparison of the various machine learning algorithms and parameters considered.

2.2 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 (LU/LCC 2002).

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 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 impacts of the changes that occur through time. The Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler (LCM), Earth trend, Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (Eastman, 2006). It is difficult to compare the performance of the numerous models because LU/LCC models can be fundamentally different in a variety of ways. For example, some models, such as GEOMOD, simulate change between two land categories (Silva and Clarke 2002) while others, such as CA_MARKOV, can simulate change among several categories (Pontius and Malanson 2005). However, it is difficult to compare which one gives more accurate representation (Wu and Webster 2000; Chang, 2006).

1. Land change Modeler (LCM)

Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI SELVA is used to pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation (Eastman, 2012). Land Change Models are important tools for environmental and geomatics research concerning LUCC (Pontius, 2015). Monitoring

and analysis of changes in LULC are needed in order to provide information on existing land use patterns and changes for decision makers to support sustainable development (Fan, 2007). LULCC models are used to improve and/or better understand of the alteration of land use that is induced by human activities (Brown, 2004). In LCM, tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, habitat and biodiversity impact assessment, and planning interventions (Eastman, 2012).

In IRDRISI Run Transition Sub-Model panel is where the actual modeling of transition sub-models is implemented. Three methodologies are provided for modeling: a Multi-Layer Perceptron (MLP), Similarity-Weighted Instance-based Machine Learning (SimWeight) and Logistic Regression. Multi-Layer Perceptron and SimWeight procedures perform best in modeling transitions (Eastman, 2012).

The MLP option can run multiple transitions, up to 9, per sub-model. But SimWeight and Logistic Regression can only run one transition per sub-model. Both MLP and SimWeight use half of the samples (change pixels) for training and the other half for validation. MLP generates predicted class memberships for each of the validation pixels at each iteration and reports the aggregate accuracy as well as a **skill score**. The skill score represents the difference between the calculated accuracy using the validation data and expected accuracy if one were to randomly guess at the class-memberships of the validation pixels. SimWeight calculates the mean transition potential among validation pixels that changed (i.e., went through the transition) and the mean transition potential among pixels that did not change (persisted). These express the hit rate and false alarm rate respectively. The difference between them yields the Peirce Skill Score – a value between 0 and 1. Logistic Regression. This model undertakes binomial Logistic Regression and prediction using the Maximum Likelihood method.

2. Earth Trend Modeler (ETM)

Earth observation image time series provide a critically important resource for understanding both the dynamics and evolution of environmental phenomena. As a consequence, Earth Trends Modeler (ETM) is focused on the analysis of trends and

dynamic characteristics of these phenomena as evident in time series images. Further, the system is highly interactive, with the process of exploration largely being an active process. The trends and dynamics emphasized include: Inter-annual trends, Seasonal trends, Cyclical components, Irregular but recurrent patterns in space/time (recurrent patterns in space/time including a unique form of Wavelet analysis), Teleconnections (analysis of climate patterns of variation between widely separated areas of the globe), and variability such as the coupled ocean-atmosphere (Eastman, 2012).

3. GEOMOD

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

4. Cellular Automata (CA)

Cellular Automata is, in general, a collection of cells, of an arbitrary shape, arranged in a grid like structure. These cells can "hold" different values from time to time - binary being the simplest of the forms. All the cells change their states simultaneously, i.e., at the same time according to some rule - which may be fixed at the beginning or may vary from time to time. These rules are applied on the system at a regular discrete time interval (Eastman, 2012). Cellular Automata (CA) model explain Change in urban areas over time using the variables such as Extent of urban

areas, Elevation, Slope, and Roads. Its advantage is allows each cell to act independently according to rules and its disadvantage is doesn't include human and biological factors (Agarwal et al., 2002).

5. Markov chain model

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

The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix, stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012).

Markov Model used to explain Land use change using Multi Temporal Land Use/cover Maps. Its strength is considers both spatial and temporal change and its weakness is no sense of Geography (Agarwal et al., 2002).

6. CA-Markov Model:

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

Markov model performs better in modeling land cover change in both time and spatial dimension.

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 spatial dimension to the model, and can simulate change among several categories. Its weakness is Socio economic factors are not considered and calibrating the model with MCE is too much time consuming compared to other methods (Adhikari & Southworth, 2012).

2.3 Geo-spatial technologies useful for urban LULC change analysis

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

1. Remote Sensing

According to Lambin (2004), the definition of Remote Sensing (RS) is as follows: “Remote sensing is the science and art of obtaining information about the Earth's surface through the analysis of data acquired by a device which is at a distance from the surface”. Remote sensing is an essential tool of land change science because it facilitates observations across larger extents of Earth's surface than is possible by ground-based observations by using of cameras, multispectral scanners.

2. Geographic Information System (GIS)

GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced information (Maguire (1991). GIS also allows the integration of these data sets for deriving meaningful information and outputting the information derivatives in map format or tabular format. GIS support any operation on geographic information: acquisition, editing, manipulation,

analysis, modeling, visualization, publication, and storage. GIS has four basic subsystems: input, storage, analysis and output.

3. IDRISI

IDRISI is the industry leader in raster, covering the full spectrum of GIS and remote sensing needs from 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 2002).

2.4 Conceptual Frameworks of Research and definition of basic terms

Urbanization: is the process of urban expansion but, Different researchers define urbanization in various ways, some researcher defines, urbanization process is mainly linked to economic growth, commercialization, and industrialization, as well as rural-urban migration and globalization ,while other researchers define urbanization is the link of population growth and urban built-up area expansion(Buhaug & Urdal, 2013).like that different scholars also use different models to estimate urban growth modeling in future, however these different modeling techniques have their own strength as well as weaknesses, but we select such models based on purpose of study and availability of data in the study area.

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

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

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

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

REOMTE SENSING: is an art or science of acquiring information about earth's surface at distance by recording reflectance using sensor.

Table 3: Literature review on the LULC change models.

	Model Name	Builder	Model Type	What it Explains	Variables	Strengths	Weakness
(Agarwal et al., 2002)	Markov Model	Wood et al. 1997	Spatial Markov model	Land use change	Multi Temporal Land Use/ cover maps	Considers both spatial and temporal change	No sense of Geography
(Agarwal et al., 2002)	CA	Clarke et al. 1998; Kirtland et al. 2000	Cellular Automata model	Change in urban areas over time	Extent of urban areas, Elevation, Slope, Roads	Allows each cell to act independently according to rules	Doesn't include human and biological factors
(Adhikari & Southworth, 2012)	Combination of CA and MARKOV methods	Clark Labs	Spatio-Temporal dynamic modeling	Predicts land use/cover in the future	Multi Temporal Land Use/ cover maps, Suitability maps	Creating the Data is easy, CA add spatial dimension to the model, can simulate change among several categories	Socio economic factors are not considered , Calibrating the model with MCE is too much time consuming compared to other methods
(Agarwal et al., 2002)	UrbanSim	Paul Waddell (University of California,	Cellular Automata and individual based	Spatial maps of housing units by pixel, nonresidential square footage	Parcel files, business establishment files census micro data, Environmental, political, and planning boundaries,	Structure allows multiple types of policies to be explored High degree of precision,	High data demands, designed for urban areas hard to understand the model, It has rigid

		Berkeley)	model	per cell and other economic and demographic characteristics	location grid control totals from economic regional forecasts, travel access indicators, scenario policy assumptions	Employment locations modeled, Designed to provide inputs to the transportation demand model	model structure, Output must be imported into GIS for viewing
(Li & Yeh, 2002)	Combination of ANN and CA methods	Antony Gar-On Yeh, Xia Li	ANN & Cellular Automata Model	Predicts land selected land class in the future	Multi Temporal Land Use/ cover maps	Calibrating the model with ANN	It can simulate change only in two category
(Pontius & Chen, 2008)	GEOMOD	Clark Labs	Cellular Automata	Predicts land selected land class in the future	Land use/cover map	Need only one time land use map for calibration	It can simulate change only in two category
(Torrens, 2000) (Agarwal et al., 2002)	SLEUTH	Dr. Keith C. Clarke at UCSanta Barbara	Spatially explicit Cellular Automata model	GIS maps of probability (continuous) of urbanization in a specified pixel	Multi Temporal Land Use Map, Impervious surface cover , Road networks (for each time period), Slope (%), Undevelopable land	Relatively easy to transfer among regions, incorporate many different land use classifications systems ,it generates continuous measure of density of development , take into consideration the future developments (such	Designed for urban settings, Data demands are high, Un-calibrated model would produce more error ,Difficult to use

						as road)	
	Land Change Modeler	Clark Labs	Markov Chain , MLP, Logistic Regression , SimWeight	Change Analysis , Predicts land use/cover in the future	Land Use Land Cover data, Road ,DEM, Other Infrastructure	Environmental modeling platform, taking into consideration the future projects, Using the ANN for development of transition potentials, calculating the changes in two time periods	Land Change Modeler
(Agarwal et al., 2002)	CLUE (Conversion of Land Use and Its Effects)	(Veldkamp and Fresco 1996a)	Discrete, finite state model	Predicts land use/cover in the future	Land suitability for crops, Temperature/Precipitation, Effects of past land use, Impact of pests, weeds, diseases, Human Drivers, Population size and density, Technology level, Level of affluence, Political Structures, Economic conditions, Attitudes and values	Covers a wide range of biophysical and human drivers at differing temporal and spatial scales	Limited consideration of institutional and economic variables

CHAPTER THREE: STUDY AREA, MATERIALS AND METHODS

3.1 The study area

Modjo town is found in Lume woreda , East Showa Zone of Oromia Regional State of Ethiopia. It is located 73 km in the Eastern side of Addis Ababa and 25 km in the West side of Adama City. The town shares boundaries by Kurma Fatole kebele in the south, Ejersa town kebele in the north, Tade kebele in the east and Shera-Debandiba kebele from the west. The town is divided in to two kebele (Modjo town administration annual report, 2016/2017). The town was established in 1925 E.C based on the construction of Ethio-Djibuti railways and the name of the town is derived from the River nearby the town which is called "Modjo". The town has got recognition from Oromia regional state as administration town in July 1998 E.C And previously it is the administrative center of Lume woreda, But now the **town** is separated from Lume woreda and is served as zonal administrations (Modjo town administration annual report, 2016/2017).

The study area, Modjo town has various advantages that make it an appropriate selection for this study. Town is experiencing rapid urbanization that can contribute to expansion from center to outwards this leads to change in urban growth. Moreover, the study area is located in a place where it is easy to find data to map, verify, and interpretation of the findings. Geographically it is stretched between 8 degrees 32' North – 8 degrees 38' North latitude and 39 degrees 06' East – 39degrees 10' East longitude with an elevation between 1788 and 1825 meters above sea level. Mojo is not only accessible by road (a road connecting the town to Adama was built before the Italian conquest) but has been the location of a train station of the Addis Ababa - Djibouti Railway since the line was extended from Dire Dawa to Akaki in 1915. With the railroad, Modjo also gained telegraph (later telephone) service and a restaurant to serve travelers (Hollywood: Tsehai, 2003, p. 60). Based on figures from the Central Statistical Agency in 2005, Modjo has an estimated total population of 39,316. The 1994 national census reported this town had a total population of 21,997. According to land use land cover analysis in this study, the town currently covers the total area of about 5,282.1 hectares. The temperature of the area ranges from 16°C to 24°C and its

topography is characterized by flat land. Due to its proximity to the national capital, Modjo is very important for the attraction of both domestic and foreign direct investment (FDI). The town is center of investment sector includes mega projects such as Mojo Dry port, Leather industries , high way which runs from Qality to Adama cross around it and the like provide job opportunities for town's dwellers. Besides, the micro and small enterprise (MSE) also create employment opportunities for a significant number of women's and youths organized in a different sector. It shares part of the Great East African Rift .This has contributed to the rapid expansion of the town.

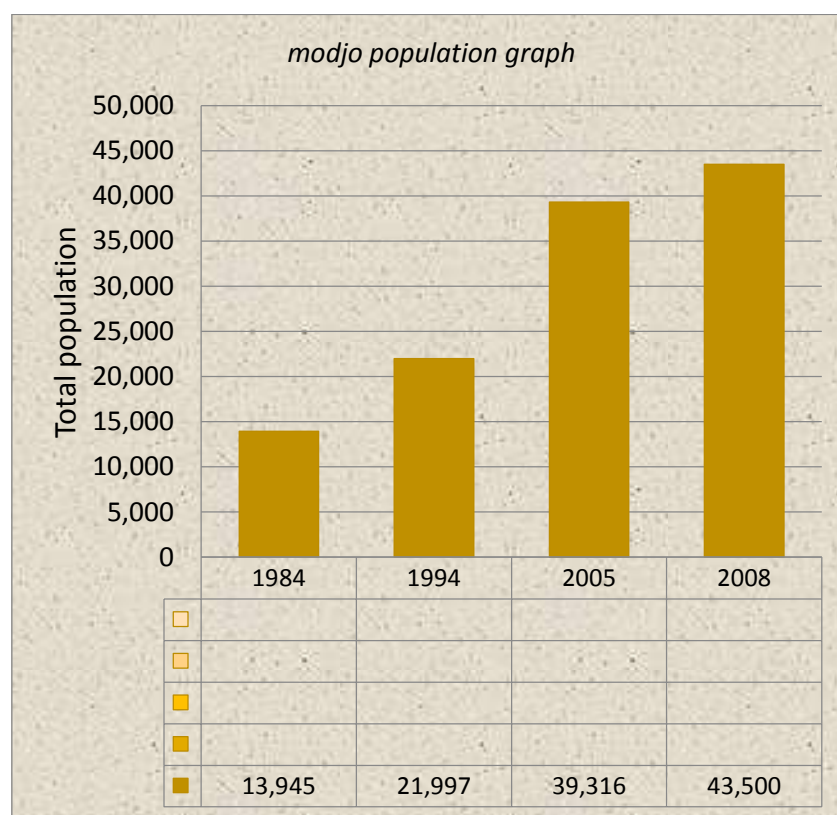


Figure 2: population growth of Modjo Town in the past 30 year (source Modjo administration office, (2012).

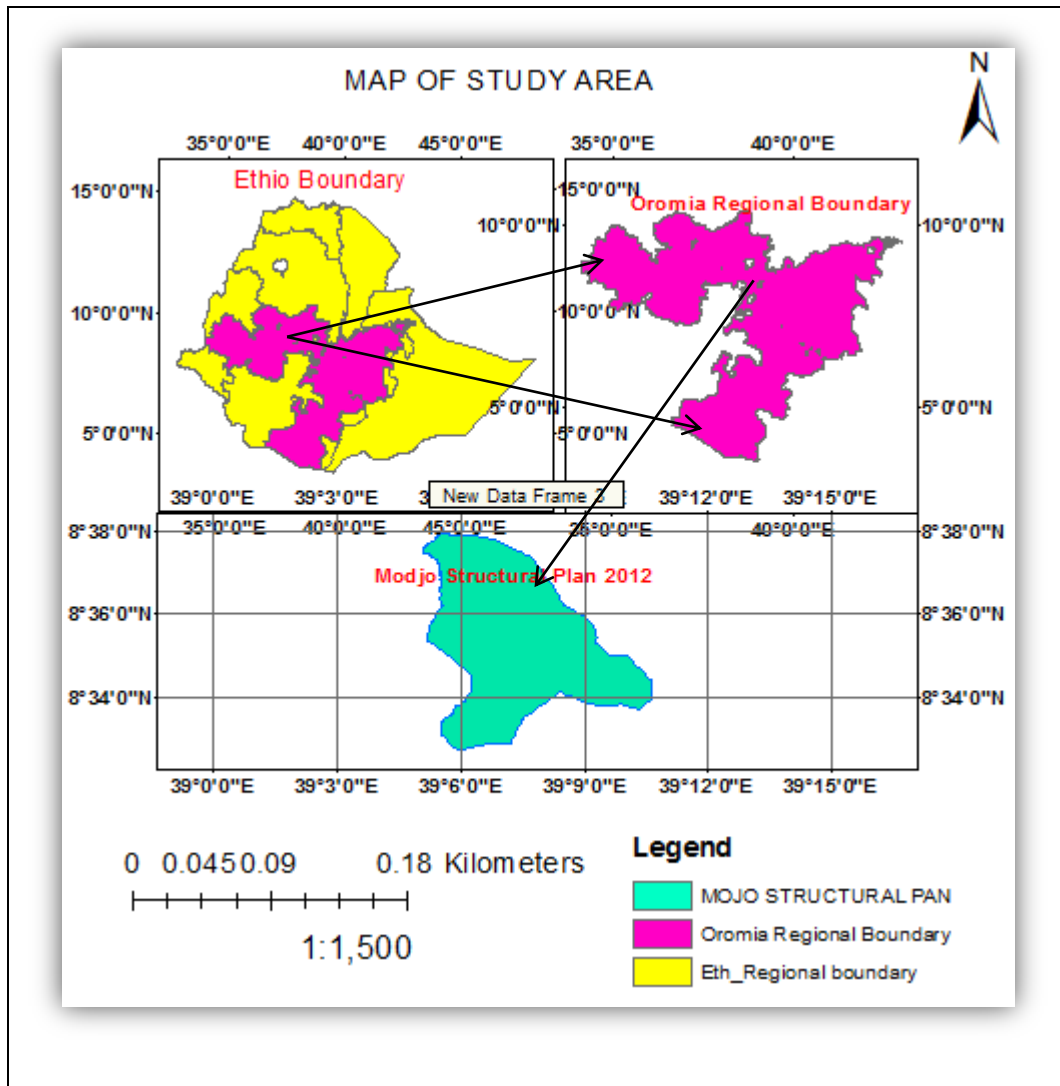


Figure 3: Location Map of study area

3.2 Material and Software

In this research different soft wares used for different purposes in order to achieve the proposed objective .There are a number of different kinds of methods, strategies and techniques to process input data to generate the required output with desired quality. The methodology integrate remote sensing and GIS tools as well as urban growth modeling using LCM imbedded in IDRISI software.

Table 4: materials and software used

<u>NO</u>	<u>Software used</u>	<u>Its functions</u>
1	ArcGIS (10.5)	visualization, map layout and accuracy assessment for classification
2	ERDAS (2014)	Digital image preprocessing, layer stacking, radiometric correction, and delineation of area of interest (AOI) or subset
3	ENVI(5.2)	For scan line removal and Image classification
4	IDRISI (17)	For change analysis, multi criteria and multi-objective decision support, simulation modeling and predict for the future LULC map.
5	Google Earth	Visualization and verification of classification and point data collection for accuracy assessment of 1990,2000 and 2010 map
6	Microsoft office (2016)	Writing, chart preparing, graphs and statistical analysis
7	Handle GPS	Collect Ground Controls Points (GCPs)

3.3 Data used on this research

The research was conducted using Landsat 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. Four satellite images, specifically Landsat 5TM, Landsat 7TM, Landsat 7ETM+, and Landsat 7ETM+, for the years 1990, 2000, 2010, and 2019, respectively, were obtained from the United States Geological Survey (USGS) online data portal (Table 5). In order to obtain images with less clouds and avoid extreme difference in land cover reflectance, the images were acquired between January and early February, which corresponds to the dry season area. The unavailability of images for some years and the presence of clouds and scan lines on some of the images made it impossible to maintain a constant year difference between the four satellite images that were used in the study. All of the images were radiometrically calibrated using ERDAS software. The images were also projected into the WGS 1984_UTM zone 37 North projections.

Table 5: Characteristics and properties of the Landsat images used

Acquisition Date	Path/Row	Landsat	Sensor	Spatial Resolution	Number Bands
10/01/1990	168/54	Landsat 5	TM	30 m	7
25/02/2000	168/54	Landsat 7	TM	30 m	11
15/01/2010	168/54	Landsat 7	ETM+	30 m	11
27/01/2019	168/54	Landsat 7	ETM+	30 m	11

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 roads, administrative boundaries and population data were also obtained from modjo land administration office. All of the datasets used in the study were geometrically calibrated using WGS 1984_UTM zone 37 North projections.

3.4. Image pre-processing

Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. (*Kragujevac J. Math*, 2009). In this research, some pre-processing techniques of image transformation includes geometric correction or image registration, atmospheric correction and radiometric calibration was used essentially. In addition, image analysis was carryout by using image analysis window such as adjusts the displayed contrast characteristics of image, adjusts the displayed brightness characteristics of image, adjusts the transparency of image, adjusts the gamma transformation applied to all four year Landsat image.

In addition to these processes, image filtering small neighboring pixels corresponding to one real object have the same or similar brightness value and to produce a new brightness value in the output image was used.

3.4.1 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 extent (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. It depends on the purpose/objectives of your study. In this research only band 1, 2, 3 were selected for layer stacking in order to decrease processing time and image size.

3.4.2 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 (Basudeb B., 2011). 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 present 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 (Lillesand and Keifer, 1979). It is 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 enhanced using ERDAS software and by IDRISI SELVA image analysis window.

3.4.3 Sub-setting of Study area Images

The first step in image pre-processing is image extraction. Some irrelevant parts of the image can be removed and the image region of interest is focused. Taking out the project area from the whole part of the image is important to reduce the size of the image file to include only the area of interest (AOI). This not only eliminates the extraneous data in the image. But it speeds up processing due to a 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 Arc GIS Software was important. In this process each Landsat scene was clipped through by the project area (Modjo shape file). It has to be done after layer stacking or composite image.

3.5 Data analysis techniques

The analysis was conducted in two steps, as depicted in Figure 5 and 6. Step one (Figure 5) produced 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 trend were analyzed and predicted urban growth at 2030, 2040 and 2050. The second step (Figure 6) derived the population figures for Modjo town for the period under investigation and investigated the relationship between built-up areas and population change for the period under investigation. The methodologies are described in detail in figure 6 and 7 last of this section.

3.5.1 Major Land use land cover classes exist in study area

In study area there are four major land use land cover classes based on Modjo municipality LULC category April, 2007; those are Built-up area, Agricultural land, Vegetation and barren lands. Definition of each land use land cover classes were

explained in table 6, Sources: Laotian Ministry of Agriculture and Forestry guideline (Thongphanh et al. 2006).

Table 6: Land use/land cover classification scheme used in the study.

<i>LULC types</i>	Definition
<i>Built-up area</i>	Comprises areas with all types of artificial surfaces, including buildings and transportation infrastructure (asphalt, gravel, Railway). Areas under construction are also included
<i>Barren land</i>	Includes a surface with no or little vegetation, open land, exposed soil, rocks and sand(eroded gullies)
<i>Agricultural</i>	Includes areas used for cultivation (both annuals and perennials) and grazing
<i>vegetation</i>	Comprises areas with vegetation cover, such as areas Covered with both indigenous and exotic tree and shrub land. It also includes green spaces in built-up areas: an area of grass, trees, or other vegetation set apart for recreational or aesthetic purposes inside urban built environment

3.5.2 Training sample selection

Training samples for each class were collected from each image. 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 (2000). 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.

3.5.3 Image Classification

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 (Basudeb Bhatta, 2011). Classification is the most popularly used information extraction technique in digital remote sensing.

3.5.3.1 Classification algorithm

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 (Phiri D, Morgenroth J, 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 D, Weng Q, 2007). In this respect, non-parametric classifiers provide better results as compared to parametric classifiers in complex landscapes.

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

Reference sample data depends upon two types of sampling units, i.e., pixels (points) and polygons (patches) but this research used point sample data for accuracy assessment. Various mathematical theories develop to determine adequate sample sizes for Classification of Accuracy Assessment but no standardized consent reach yet regarding the adequate sample size determination. Gao (2009) proposed that the minimum sample size for each LULC class, necessary for 85% and 90% accuracy interpretation is to be set to 20 and 30, respectively. On the other hand, Jensen (2005), Lillesand et al. (2008) and Congal-ton and Green (2009) argue that any sample size of less *than 50* will be unsatisfactory for error estimations and in most cases a minimum

of 50 samples for each map class should be collected for maps of *<4,000 km² in size and fewer than 12 classes*. Thus, by considering the size of Modjo town area, and LULC types classified into four, namely: urban (Built up area), Agricultural land, vegetation and barren land classes with sample size a minimum of *50 point* per LULC category was used.

3.5.5 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 (**Cagalon and 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 (**Cagalon 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 (Congalton, R., 1991)

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. Various mathematical theories develop to determine adequate sample sizes for Classification of Accuracy Assessment but no standardized consent reach yet regarding the adequate sample size determination. For this research Congal-ton and Green (2009) was used. For the accuracy assessment overall kappa which is a statistical measure of overall agreement between two categorical items (Cohen's kappa,) and conditional kappa which includes, user's accuracy, producer's accuracy and overall accuracy were calculated. An error matrix

is a square assortment of numbers defined in rows and columns that represent the number of sample units assigned to a particular category relative to the actual category as confirmed on the ground. The rows in the matrix represent the remote sensing derived land use map, while the columns represent the reference data that will be 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 and Green, 1999).

3.5.5.1 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 were classified correctly. Overall accuracy is the easiest to calculate and understand but ultimately only provides the map user and producer with basic accuracy information. The diagonal elements represent the areas that were correctly classified. To calculate the overall accuracy you add the number of correctly classified sites and divide it by the total number of reference site.

3.5.5.2 Omission Error

Errors of omission refer to reference sites that were left out (or omitted) from the correct class in the classified map. The real land cover type was left out or omitted from the classified map. 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.

3.5.5.3 Commission Error

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

3.5.5.4 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, $\text{Producer's Accuracy} = 100\% - \text{Omission Error}$.

3.5.5.5 User Accuracy

The User's Accuracy is the accuracy from the point of view of a map user, not the map maker. The User's accuracy essentially tells us how often the class on the map will actually be present on the ground. This is referred to as reliability. The User's Accuracy is complement of the Commission Error, $\text{User's Accuracy} = 100\% - \text{Commission Error}$. 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.

3.5.5.6 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.

$$K = \frac{[N\sum X_{ii} - \sum(X_i * X_j)]}{[N * N - \sum(X_i * X_j)]}$$

Where k=kappa coefficients, N=Total number of pixel points, X_{ii} = correctly classified points (observation) in row i and column i, X_i =sum of Row points, X_j =sum of Column points.

3.5.6 Model of Land use land cover (Land Change Modeler)

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

Land change prediction in Land Change Modeler is an empirically driven process that moves in a stepwise fashion from Change Analysis to Transition Potential Modeling from Transition potential to Change Prediction.

3.5.6.1 Change Analysis

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

The change analysis panel provides a rapid quantitative assessment of changes, allowing the researcher to generate evaluations of gains and losses, net change, persistence and specific transitions graphical form. It also provides a means of generalizing the pattern of trend between two land cover map transitions (Eastman, 2006). Using change analysis of LCM of the Modjo Town 1990, 2000, 2010 and 2019 of LULCC in graphs of gains and losses, contributions to net change, transitions of land cover classes between different categories and spatial trend were analyzed.

3.5.6.2 Markov Chain Model Analysis

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

$$L(t+1) = P_{ij} \times L(t)$$

$$P_{ij} = \begin{bmatrix} P_{11} & p_{12} & \dots & \dots & \dots & p_{1n} \\ p_{21} & p_{22} & \dots & \dots & \dots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \dots & \dots & \dots & p_{nn} \end{bmatrix}$$

Where $L(t)$ and $L(t+1)$ represents land use status at time t and $t + 1$ respectively. Including

$\sum_{j=1}^n P_{ij} = 1$ and $(i, j = 1, 2, m)$ is the transition probability matrices that state i changes to state j and p = transition probability. The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix (Mousivand et al., 2007), stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012).

3.5.6.3 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.

3.5.6.4 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 (Artificial Neural Networks, n.d.). There are many types of ANN like Single Layer Perceptron, Multi-Layer Perceptron, Recurrent Network, Hopfield Network, Spiking Neural Network and many more (Neural Network, 2010).

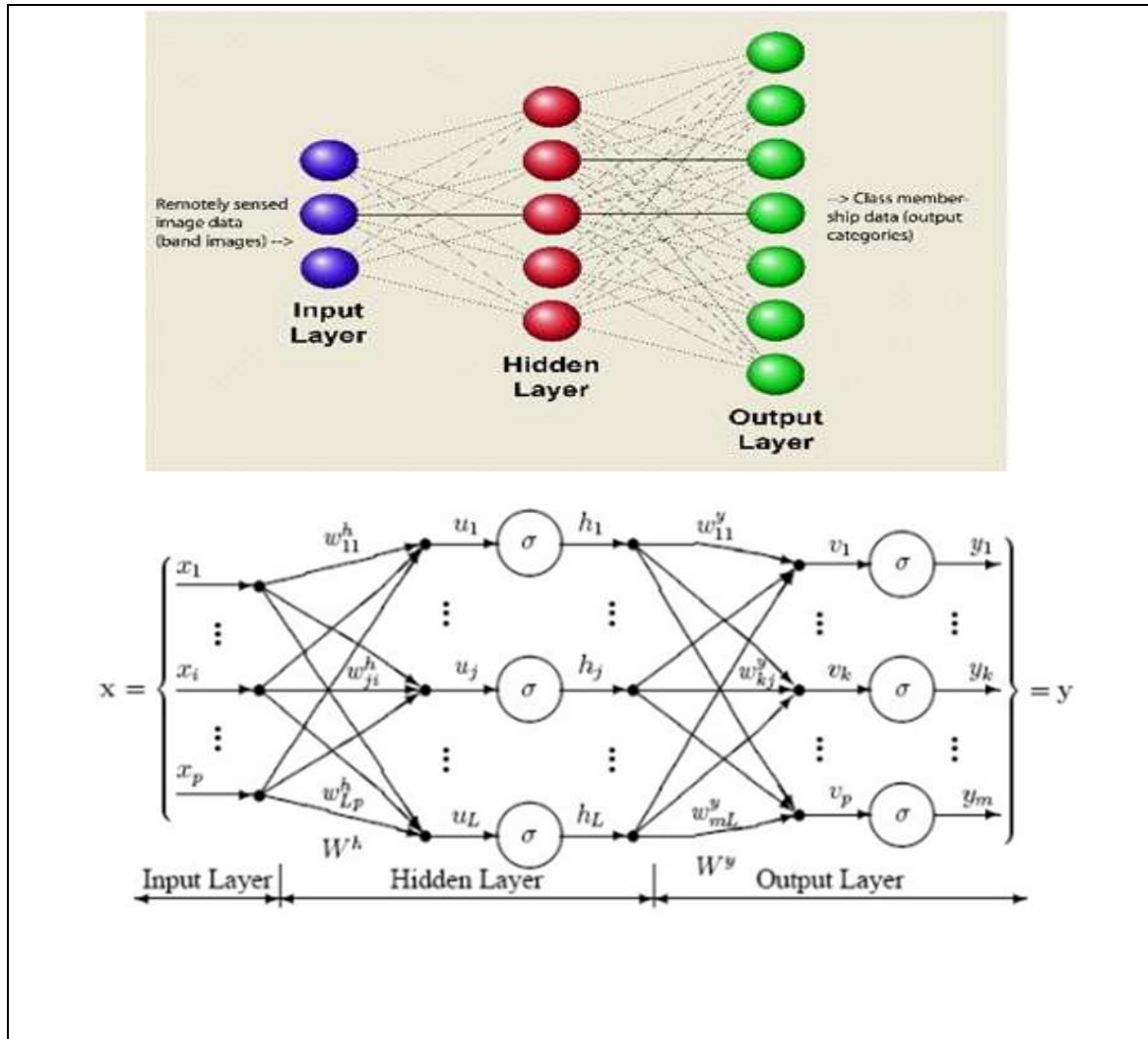


Figure 4: Multilayer Perceptron feed forward ANN.

Multilayer Perceptron feed forward ANN is a network of simple neurons called the perceptron (Multilayer Perceptron, n.d.). It is composed of an input layer, output layer and hidden layers between input and output layer. It is a feed forward method which means data flows in one direction from input to output. The main algorithm of this model is computing the linear output from nonlinear inputs according to the weights by using a nonlinear activation function (Multilayer Perceptron, n.d.). Feed-forward means that data flows in one direction from 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 (Atkinson, P. M. et al, 1997). This can also be ancillary data like slope, elevation, soil type, zoning etc (Civco, D. L, 1993).

For this Research five inputs variable values for prediction in the network were used (distance from Road, LULC2010, distance from Built up area 2010, 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 (Atkinson, P. M. et al, 1997). The activity of each hidden unit is determined by the activities of the input units and the weights of the connections between the input and the hidden units. After arriving to the hidden layer, the value from each input neuron is multiplied by a weight (W_{ji}). The resulting weighted values are added together producing a combined value u_j . The weighted sum (u_j) is then modified with a transfer function (σ) that outputs a value h_j . The outputs from the hidden layer are distributed to the output layer (Karul, C, 2006).

In general, the larger the number of nodes in the hidden layer, the better the neural network represents the training data (Atkinson, P. M. et al, 1997). The number of hidden layer nodes is estimated by the following equation (IDRISI Taiga Help System, 2009). $N_h = INT\sqrt{(N_i * N_o)}$

Where, N_h = the number of hidden nodes, N_i = the number of input nodes

N_o = the number of output nodes and INT is integer

3. Output Layer

The output layer presents the output data. For image classification, the number of nodes in the output layer equals to the classes in the classification. After arriving to the output layer, the value from each hidden layer neuron is again multiplied by a weight (W_{kj}). The resulting weighted values are added together producing a combined value v_j . The weighted sum (v_j) is then modified with a transfer function

(σ) that outputs a value y_k . The y values are the outputs of the network (Atkinson, P. M. et al, 1997). For this research output layer are transition potential and training files in map and MLP Model Results that contains General Model Information (input files, Parameters and Performance and Model Skill Breakdown by Transition & Persistence), Weights Information of Neurons across Layers (Weights between Input Layer Neurons and Hidden Layer Neurons and Weights between Hidden Layer Neurons and Output Layer Neurons) ,and Sensitivity of Model to Forcing Independent Variables to be Constant.

3.5.6.5 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, C, 2006).The acceptable error rate is evaluated based on the Root Mean Square (RMS) Error (Karul, C, 2006).

$$RMS = \frac{\sum(e_i)^2}{N} = \frac{\sum(t_i - t_{ai})^2}{N}$$

Where, N = the number of elements, i = the index for elements

e_i = the error of the i th element, t_i = the target value (measured) for i th element

t_{ai} = the calculated value for the i th 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.

3.5.6.6 Change Prediction

Change Prediction provides the controls for a dynamic land cover change prediction process. After specifying the end date, the quantity of change in each transition can

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

3.5.6.7 Model Validation

After prediction the Model validation which refers to comparing the simulated and reference maps was conducted. Sometimes the simulated maps can give misleading results. In that case, it is necessary to validate the projected/simulated map with the base/reference map. Therefore, model validation is an important step in 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. It produces numerical expressions to compare two maps (Vliet, J. V., 2009). The best way to validate a model is to compare the predicted map of time t_2 with the reference map of time t_2 (Pontius, G. R., e Chen, H., 2006).

In this case for validating the output of the simulated LULC map in 2019, two maps were compared, the reference LULC map of 2019 and the simulated LULC map of 2019. 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 K_{no}) and Kappa for grid-cell level location (denoted as $K_{Location}$) (Pontius, R. G., 2000).

1. Kappa: Kappa is a statistical measure of overall agreement between two maps (e.g. output of classified/simulated map and ground truth/reference map) or a matrix (Canada Centre for Remote Sensing, 2010).

Table 7: Kappa statistic of Map comparison.

Predicted 2019 map		Reference (Classified) 2019 Map					Total
		1	2	3		N	
	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, A., 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, A., 2002).

$$P(A) = \sum_{n=1}^m P_{nn}$$

$$P(E)_{RL} = \sum_{n=1}^m P_n * P_m$$

Where, **P_{nn}** = the proportion of cells that is of category ‘n’ in map A and ‘m’ in map B.
P_{mn} = the proportion of cells that is of category n in map A and category m in map B.
 Strength of Agreement for Kappa Statistic (Landis, J., 1977) shown below.

Table 8: Strength of Agreement for Kappa Statistic.

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

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, A., 2002). Kappa can be negative. This is a sign that there is no effective agreement between the two rates (Simon, S., 2008).

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

3. klocation: Klocation indicates the success due to the simulation’s ability to specify location divided by the maximum possible success due to a simulation’s ability to specify location perfectly” (Pontius, R. G., 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, R. G., 2000).

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

$$K_{location} = \frac{P(A) - P(E)}{P(\max) - P(E)} = \frac{\sum_{n=1}^m (P_{nn} - P_m)}{\sum_{n=1}^m (\min(P_n * P_m) - (P_n * P_m))}$$

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.

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

$$K_{histo} = \frac{P(\max) - P(E)}{1 - P(E)} = \frac{\sum_{n=1}^m (\min(P_n * P_m) - (P_n * P_m))}{1 - \sum_{n=1}^m \min(P_n * P_m)}$$

In order to ensure that the model is reliable in predicting an 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 2019, and the second map is a predicted (simulated) 2019 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 2000 and 2010 maps were used for simulating 2019 maps. The validate module in IDRISI Taiga was used for validating the model by producing several parameters: Kno, Klocation, and Kstandard that are used to identify the accuracy of the model.

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

First phase: The general data analysis results methodology to achieve the proposed specific objective number 1 and 2 is shown below.

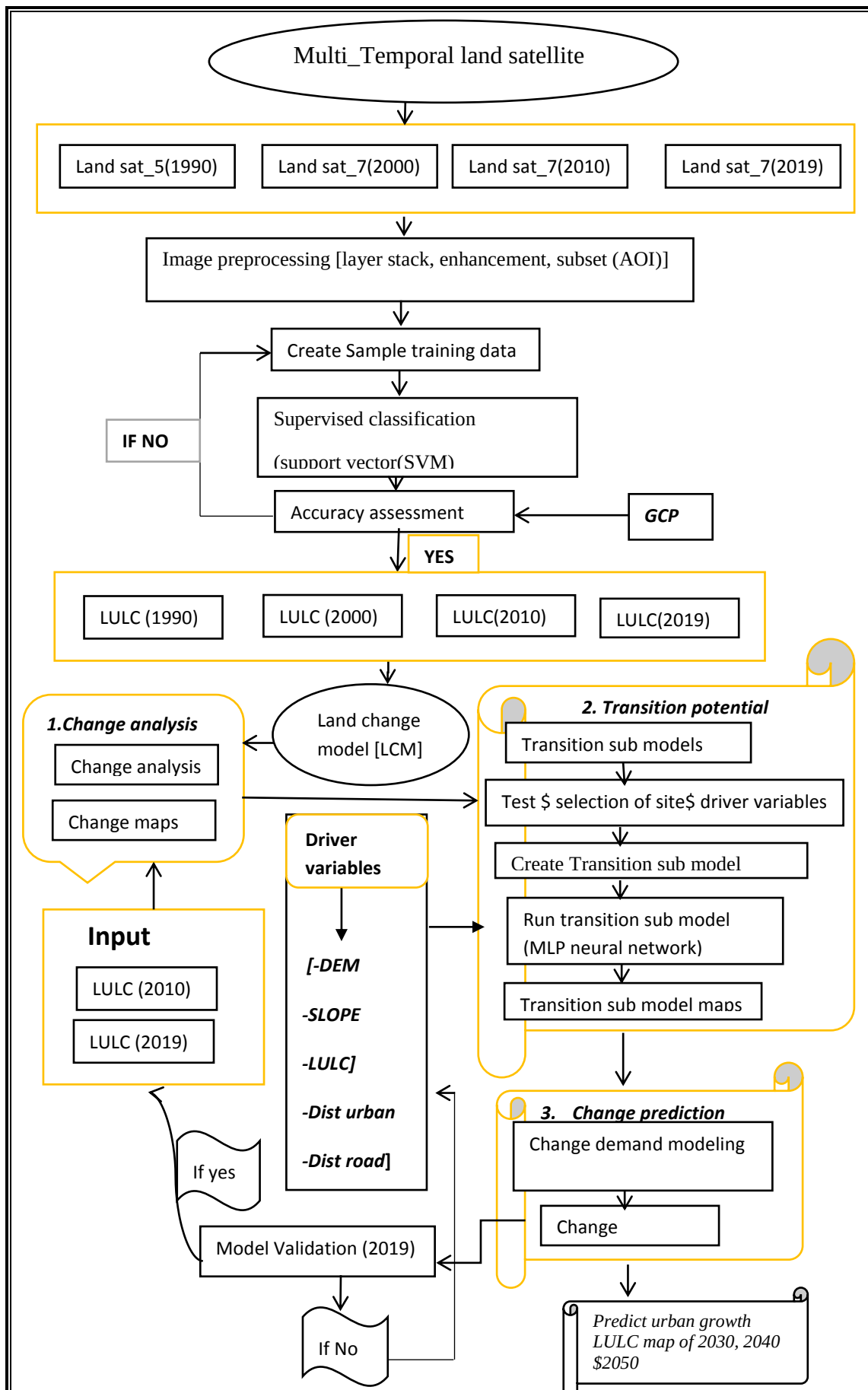


Figure 6: Flow chart describes urban built-up area change analysis and prediction.

Second phase: methodology analyzes correlation ship between built-up area expansion and population growth.

3.6 Relationship between population growth and built-up area expansion

In order to relate population growth with urban expansion of the town, it is necessary to project (interpolate) population growth as usual scenario like LULC prediction (T. W. Anderson; Wiley; New York, 1971). The projection of population growth was required in research in order to get specific data to fulfill the purpose of the study in study time frame (1990_2050).so it is possible to project population growth based on existing census data 1984,1994,2005 and 2008 to determine correlation between built-up land area expansion and population growth in modjo town. This can be done using regression analysis.

3.6.1 Regression analysis

In statistical modeling, **regression analysis** is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome variable') and one or more independent variables (often called 'predictors', 'covariates', or 'features'). The most common form of regression analysis is linear regression. A researcher finds the line (or a more complex linear combination) that most closely fits the data according to a specific mathematical criterion (M. S. Bartlett; *Biometrics*, 1949). The method of ordinary least squares computes the unique line (or hyper plane) that minimizes the sum of squared distances between the true data and that line (or hyper plane). This allows the researcher to estimate the conditional expectation (or population average value) of the dependent variable when the independent variables take on a given set of values (K. N. Berk, 1977). Regression analysis is primarily used for two conceptually distinct purposes. First, regression analysis is widely used for prediction, where its use has substantial overlap with the field of machine learning. Second, in some situations regression analysis can be used to infer causal relationships between the independent and dependent variables. Importantly, regressions by themselves only reveal relationships between dependent variable and a collection of independent variables in a fixed dataset (*David A. Freedman, 2009*).

Correlation: is statistical measure which determines co_relationship or association of two variables. Correlation can be positive, negative or no correlation. Positive correlation: when the value of one variable increases with respect to another. Negative correlation: when the value of one variable decreases with respect to another. No correlation: when there is no linear dependence or no relation between two variables.

Correlation is utilized to assess the strength of the relationship between variables and for modeling the future relationship between them.

3.6.1.1 Simple linear regression

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 estimate the values of the variables using least square method.

$$Y = AX + B + e$$

Where: **Y** = Dependent variable, **X** = **Independent** (explanatory) variable

B = Intercept and A = Slope and e = Residual (error).

Degree of correlation is **perfect** if the value is near ± 1 , then it is said to be a perfect correlation, as one variable increases, other variable tends to also increases (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. This can be done using the following method see fig 7.

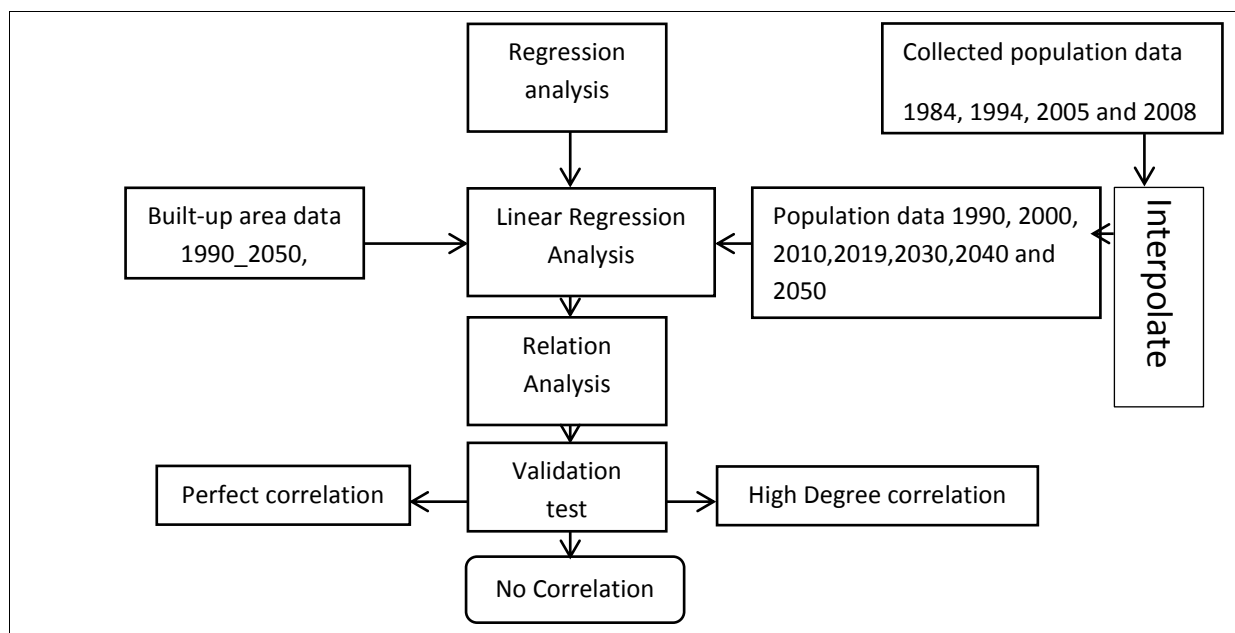


Figure 7: flow chart showing correlation analysis between Population growth and built-up area expansion.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.0 classified LULC map of land satellite image

Training samples for each class were collected from each image. 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 (2000). 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. (Bulti,D.T, 2019). 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.D.T, 2019). 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 prevent their description based on data distribution (Lu & Weng 2007). In this respect, non-parametric classifiers provide better results as compared to parametric classifiers in complex landscapes. The following is landsatimage1990 enhanced and layer stacked which was ready for classification and the rest of Landsat were prepared as such.

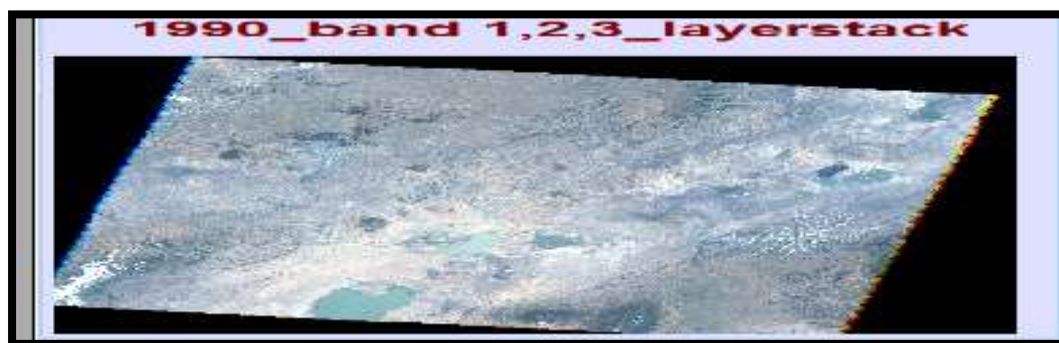


Figure 8: Enhanced and layer stacked land sat 1990 prepared for classification.

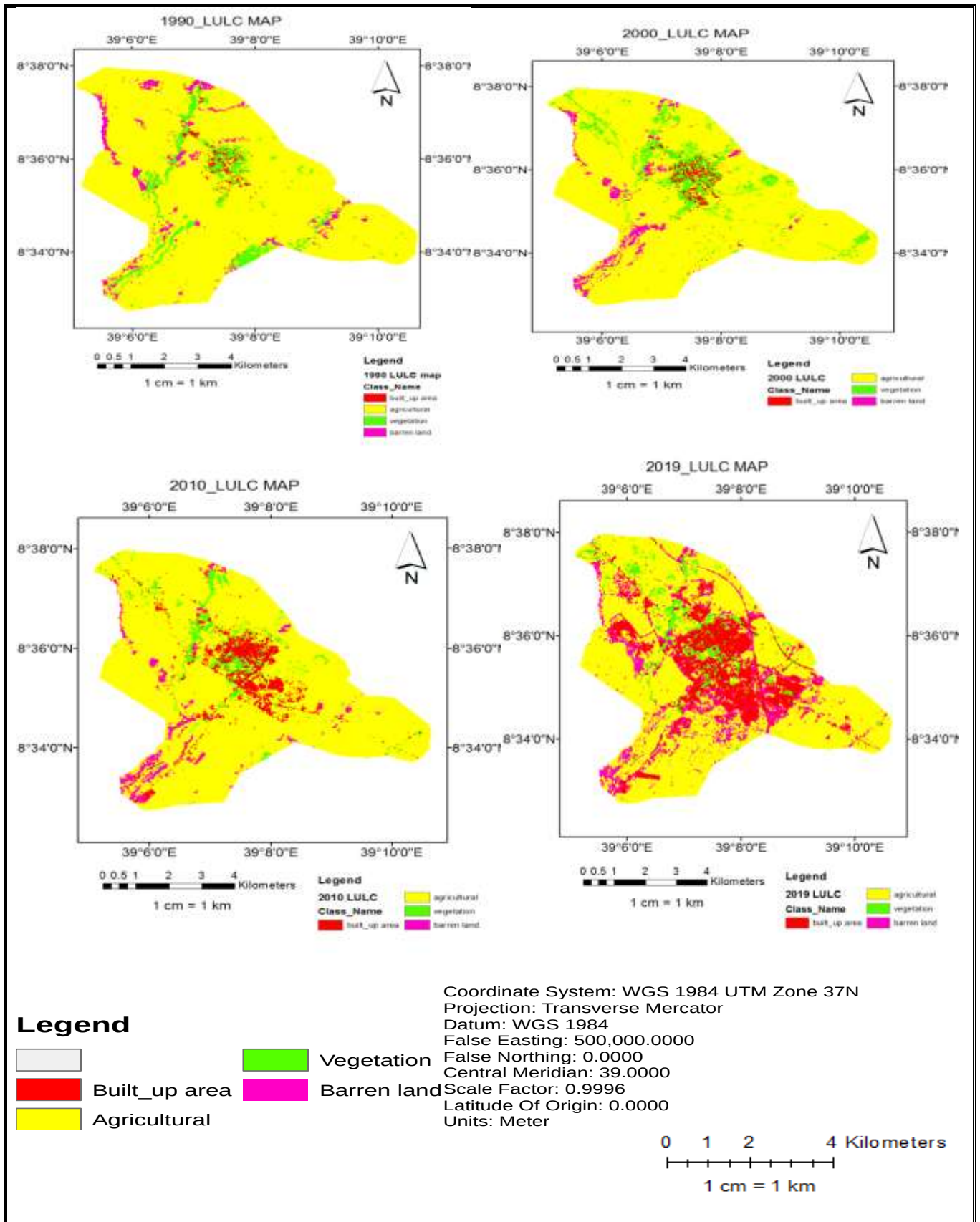


Figure 9: classified land use land cover map 1990, 2000, 2010 and 2019.

4.1 Accuracy Assessment for classified Land use land cover image

LULC classification accuracy was assessed quantitatively using error matrix which is the commonly used method in LULC classification accuracy assessment (Built,D.T, 2019). In this regard, sample pixels were selected from each of classified images through a stratified random sampling scheme in ARCGIS software. The samples were overlaid with google earth (for 1990, 2000, 2010 and 2019) and existing map (for 2007) and digital orthophoto (for 2018) to visually interpret and determine their respective classes. Based on the error matrix generated for each classified map, overall accuracy, user's accuracy and producer's accuracy were calculated, in addition to kappa variance. The accuracy requirements for change detection analysis were determined based on the suggestion of Congalton and Green (2009). The details of Error matrix tables' results were shown in Table 9, Table 10, Table 11 and Table 12.

Table 9: Landsat _5TM classification accuracy for 1990.

	<u>Reference map</u>							
<u>Classified map 1990 LULC</u>		Built-up area	agricultural	vegetation	Barren land	Row total	Com error	User accuracy in %
	Built-up area	45	5	0	0	50	0.1	90
	agricultural	0	49	2	0	51	0.039	96.1
	vegetation	3	4	49	2	58	0.155	84.5
	Barren land	3	0	0	48	51	0.058	94.2
	column total	51	58	51	50	210		
	Omission error	0.118	0.155	0.039	0.04			
	Producer acc in %	88.2	84.5	96.1	96			
	Over all accuracy in% = 90.95				Kappa coefficient(K) = 0.88			

$$\text{Over all accuracy} = \frac{\sum X_{ii}}{N} = \frac{45+49+49+48}{210} = \underline{90.95\%}$$

$$K = \frac{[N\sum X_{ii} - \sum (X_i * X_j)]}{[N * N - \sum (X_i * X_j)]} = \frac{[210\sum (45 + 49 + 49 + 48) - \sum (50 * 51 + 51 * 58 + 51 * 58 + 51 * 50)]}{[210 * 210 - \sum (50 * 51 + 51 * 58 + 51 * 58 + 51 * 50)]}$$

= 0.88 , others can be calculated like this.

Landsat _5TM image (1990) was classified for four land cover classes successfully. However, agricultural lands and built-up areas were classified with a lower producer's accuracy (84.5% and 88.2) respectively than other classes. This is due to the combination of omission and commission errors particularly mixing with built-up areas and vegetation classes. Therefore for evidence for both Systematic commission and omission errors, watching the higher overall classification accuracy of (90.95%), it was acceptable as good classification.

Likewise, Landsat TM image (2000) was classified into four classes. It indicated better overall classification accuracy (91.9%). In classifying the third Landsat ETM image (2010), less overall and kappa coefficient (85.76% and 0.8) was achieved. But in classifying fourth land sat ETM image (2019) the overall accuracy and kappa coefficient (97.62% and 0.97) was achieved this was higher accuracy due to the utilization of more ancillary data in collecting training samples for classification and the season of the image during the process of classification. In general, there was some evidence for both systematic commission and omission errors resulting from the classifier side as incorrectly commits pixel of the class being sought to other classes as well when some class on the ground were misidentified as another class by the classifier.

Table 10: Landsat TM classification accuracy for 2000.

	<u>Reference map</u>							
		Built-up area	agricultural	vegetation	Barren land	Row total	Com error	User accuracy in %
Classified 2000 LULC	Built-up area	48	2	0	3	53	0.094	90.6
	agricultural	1	46	3	0	50	0.08	92
	vegetation	2	3	47	0	52	0.096	90.4
	Barren land	0	2	1	52	55	0.055	94.5
	column total	51	53	51	55	210		
	Omission error	0.059	0.132	0.078	0.055			
	Producer acc in %	94.1	86.8	92.2	94.5			
	Over all accuracy in% = 91.9				Kappa coefficient(K) = 0.89			

Table 11: Landsat ETM classification accuracy for 2010.

<u>Reference map</u>								
<u>Classified 2010 LULC</u>		Built-up area	agricultural	vegetation	Barren land	Row total	Com error	User accuracy in %
	Built-up area	50	3	0	3	56	0.107	89.3
	agricultural	4	43	0	5	52	0.173	82.7
	vegetation	0	5	41	4	50	0.18	82
	Barren land	4	0	4	44	52	0.154	84.6
	column total	58	51	45	56	210		
	Omi error	0.138	0.157	0.089	0.214			
	Producer acc in %	86.2	84.3	91.1	78.6			
	Over all accuracy in % = 85.76			Kappa coefficient(K) = 0.8				

Table 12: Landsat ETM classification accuracy for 2019.

<u>Reference map</u>								
<u>Classified 2019 LULC</u>		Built-up area	agricultural	vegetation	Barren land	Row total	Com error	User accuracy in %
	Built-up area	48	0	1	1	50	0.04	96
	agricultural	1	53	0	0	54	0.019	98.1
	vegetation	0	1	50	0	51	0.019	98.1
	Barren land	0	0	1	54	55	0.018	98.2
	column total	49	54	52	55	210		
	Omi error	0.02	0.019	0.038	0.018			
	Producer acc in %	98	98.1	96.2	98.2			
	Over all accuracy in % = 97.62			Kappa coefficient(K) = 0.97				

This level of accuracy found almost perfect agreement because of the heterogeneity of the study area and also kappa agreement accuracy was almost perfect agreement level which means it can be used (Pontius, 2000).

- < 0: Less than chance agreement
- 0.01–0.20: Slight agreement
- 0.21– 0.40: Fair agreement
- 0.41–0.60: Moderate agreement
- 0.61–0.80: Substantial agreement
- 0.81–0.99: Almost perfect agreement (Pontius, 2000)

4.2 CHANGE ANALYSIS

Using the approaches adopted in the methodology, land use land cover maps were generated for all the four years see (Fig: 9) area estimates and change statistics are computed. Individual class area and change statistics for the four years were summarized in Table 13 and 14. In the study periods the major land cover classes identified includes built-up area, agriculture, vegetation and barren land. Among all the land cover types identified in the last periods (2019,) agriculture and built-up area constituted the predominant type of land cover with an approximate area of 82.28% in their spatial extent in the town. Vegetation and barren land accounted for 17.72 % of the total area of the town representing the small proportion of the land cover classification (Table 13).

Table 13: Area statistics and Percentage of the land use/cover units from 1990-2019.

LULC types	1990		2000		2010		2019	
	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%
Built-up	0.49	0.93	0.96	1.82	3.53	6.68	8.42	15.94
Agricultural	46.62	88.26	45.02	85.22	44.96	85.12	35.04	66.34
Vegetation	3.52	6.66	4.76	9.01	2.42	4.58	2.72	5.15
Bare land	2.19	4.15	2.09	3.95	1.91	3.62	6.64	12.57
Total	52.82	100	52.82	100	52.82	100	52.82	100

There are several ways to quantify the land cover change results. Among others, one basic method is to tabulate the total land cover changes for each land use/land cover type and examine the trends of change between the years. During the investigation Periods, distinct changes have occurred on the major land use/land cover types. From 1990 to 2000, the built up environment increased approximately 0.47km² (95.92%) while agricultural land decreased 1.6km² (3.43%), vegetation areas increased 1.24km²(35.23%), and barren land decreased 0.1km² (4.57%). During the second period between 2000 to 2010, the built up environment increased drastically by 2.57km²(267.7%) while agricultural land decreased 0.06km²(0.13%), vegetation continuously converted and decreased by 2.34km² (49.16%), barren land decreased 0.18km² (8.61%). Urban areas in general increased from 1990 to 2010, by 620.4%

with the greatest increase occurring from 1990 to 2010, 620.4% within 20 years period as compared with 138.5% within 9 years between 2010-2019. The relative trends of these changes are further depicted in Table 14. In order to determine the extent and rate of change in the land cover dynamics in the town, the following variables are developed and computed.

- Total area (Ta)
- Changed area (Ca)
- Change extent (Ce)
- Annual rate of change (Cr)

These variables can be described by the following formula:

$$Ca = Ta(t_2) - Ta(t_1);$$

$$Ce = Ca / Ta(t_1);$$

$$Cr = Ce / (t_2 - t_1);$$

Where t_1 and t_2 are the beginning and ending time of the land cover Studies conducted.

Table 14; overall amount, extent and rate of land cover change (1990-2019).

LULC types	1990_2000			2000_2010			2010_2019		
	change (Δ /km ²)	Extent (%)	rate of Δ (%/yr)	change (Δ /km ²)	Extent (%)	rate of Δ (%/yr)	change (Δ /km ²)	Extent (%)	rate of Δ (%/yr)
Built-up	0.47	95.92	9.6	2.57	267.70	26.8	4.89	138.5	15.4
Agricultural	-1.6	-3.43	-0.34	-0.06	-0.13	-0.01	-9.92	-22.1	-2.45
Vegetation	1.24	35.23	3.52	-2.34	-49.16	-4.9	0.3	12.4	1.4
Bare land	-0.1	-4.57	-0.46	-0.18	-8.61	-0.9	4.73	247.6	27.5

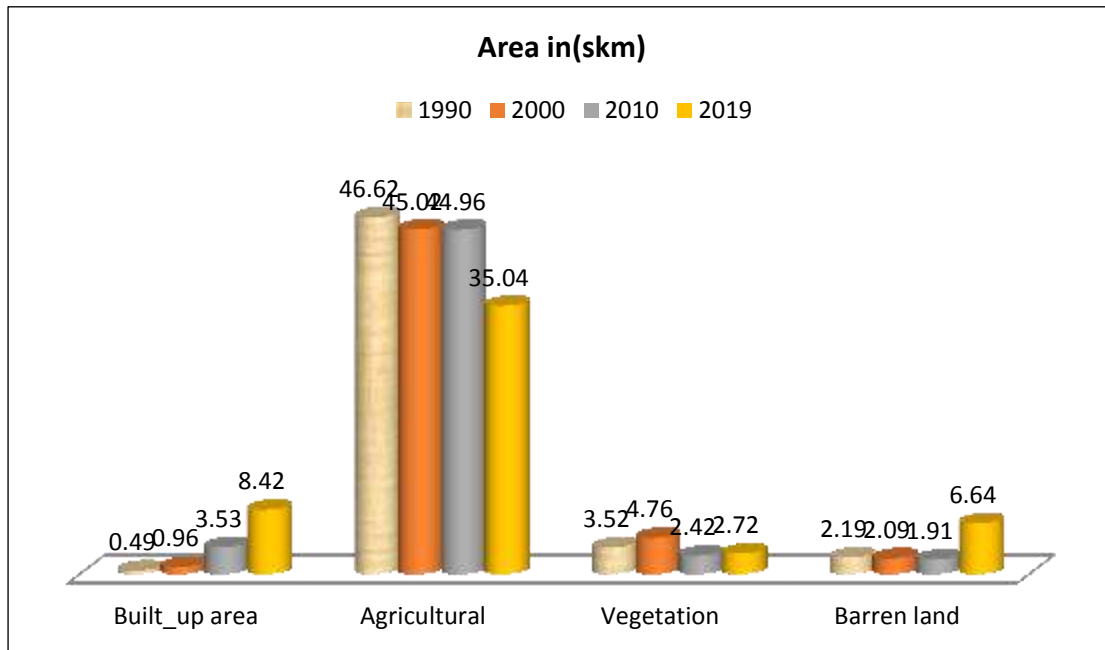


Figure 10: Nature of relative land cover changes 1990 to 2019.

Figure 10 depicted the relative land cover change trends from 1990-2019 in the modjo town Municipality. The built up area had an increasing positive trend of change in its areal extent while agricultural lands decreased continuously in the four periods. There has been also an observable increasing and decreasing trend of change in the other land cover classes of vegetation and barren land. The average annual rate of change in built-up area as determined from the Landsat change statistics was **9.6%** from 1990 to 2000, **26.8%** from 2000 to 2010 and 55.8 % for the entire period of 1990 to 2019. On the other hand, agriculture and vegetation and barren land areas showed an average reduction of change approximately 1% annually. In general, the change values in the Table 14 and figure 10 indicated that increase in built up /urban areas mainly emanated from conversion of other land covers in particular agriculture to urban land uses during the past 29 years (1990-2019) following increasing development pressure within the municipality. Besides the summary statistics, graphical representations of the classification and visual comparison offer a general insight into the relative amounts of the defined classes across the landscape and the changes observed in (Figure 11).

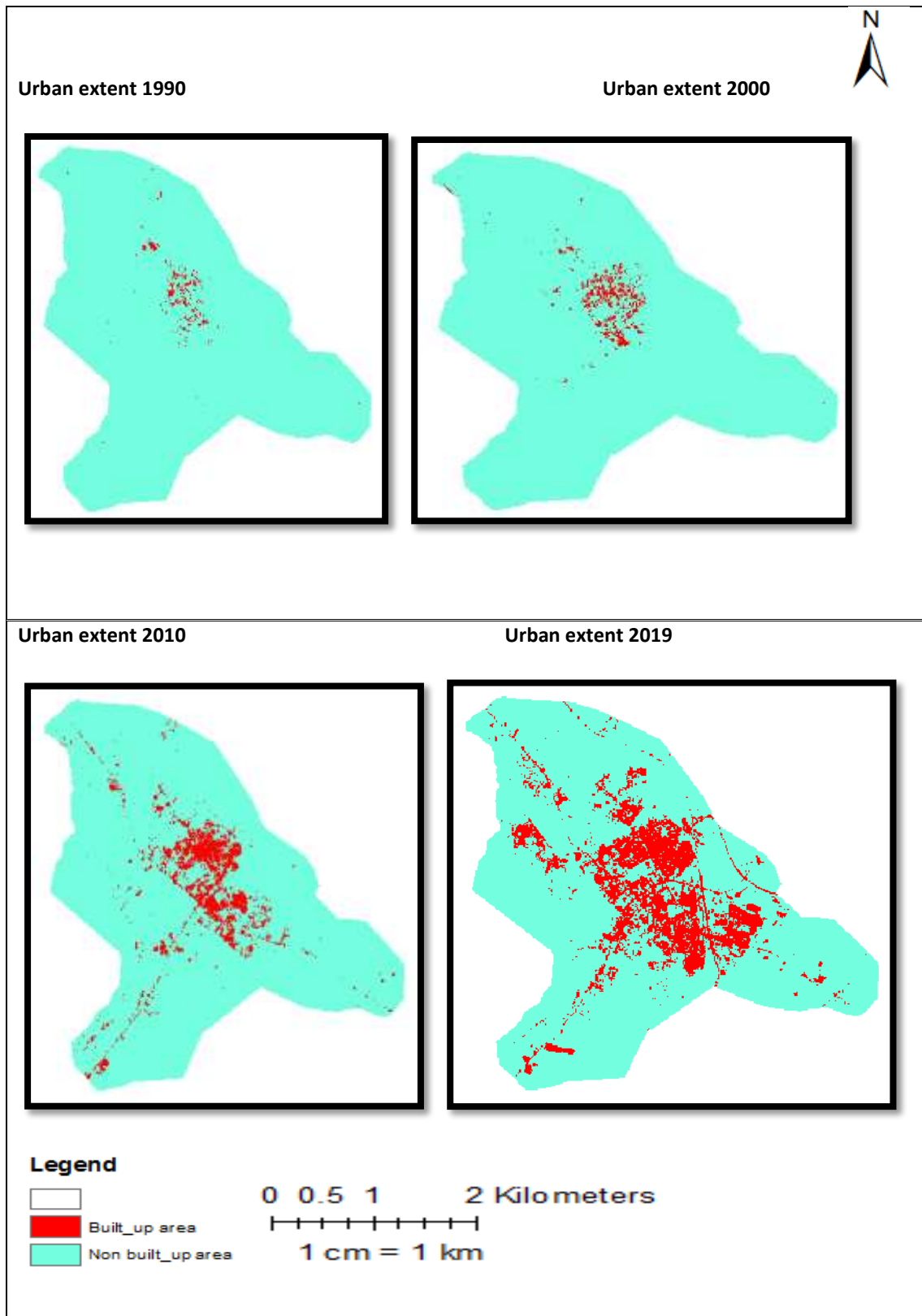


Figure 11: when land sat of study area classified in to two classes built-up and non-built-up area.

The change in urban built-up area in study time frame can be seen from figure12.

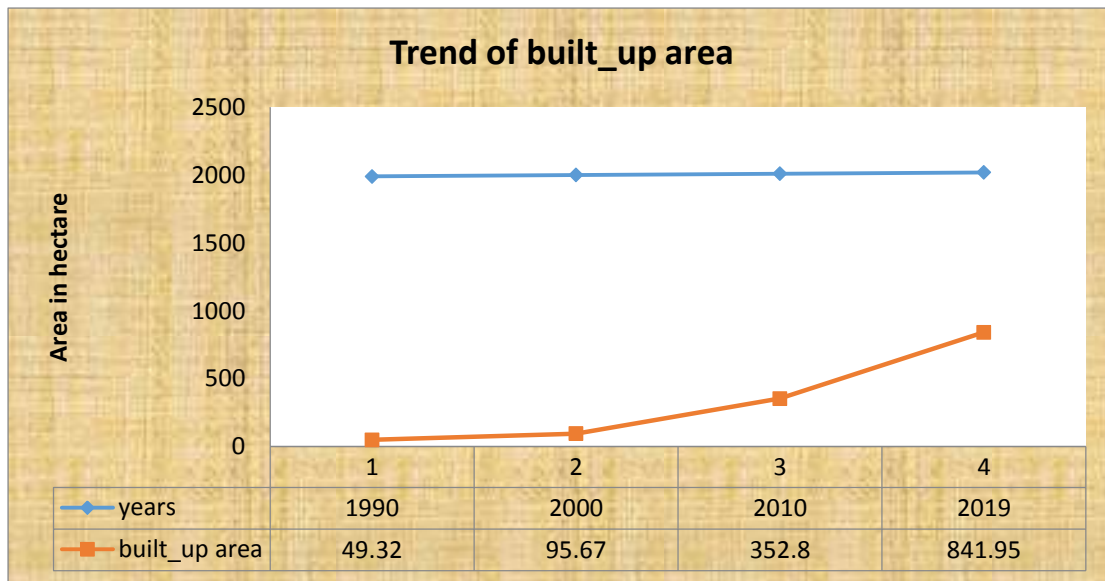


Figure 12: Change Trend of built-up area expansion from 1990 to 2019.

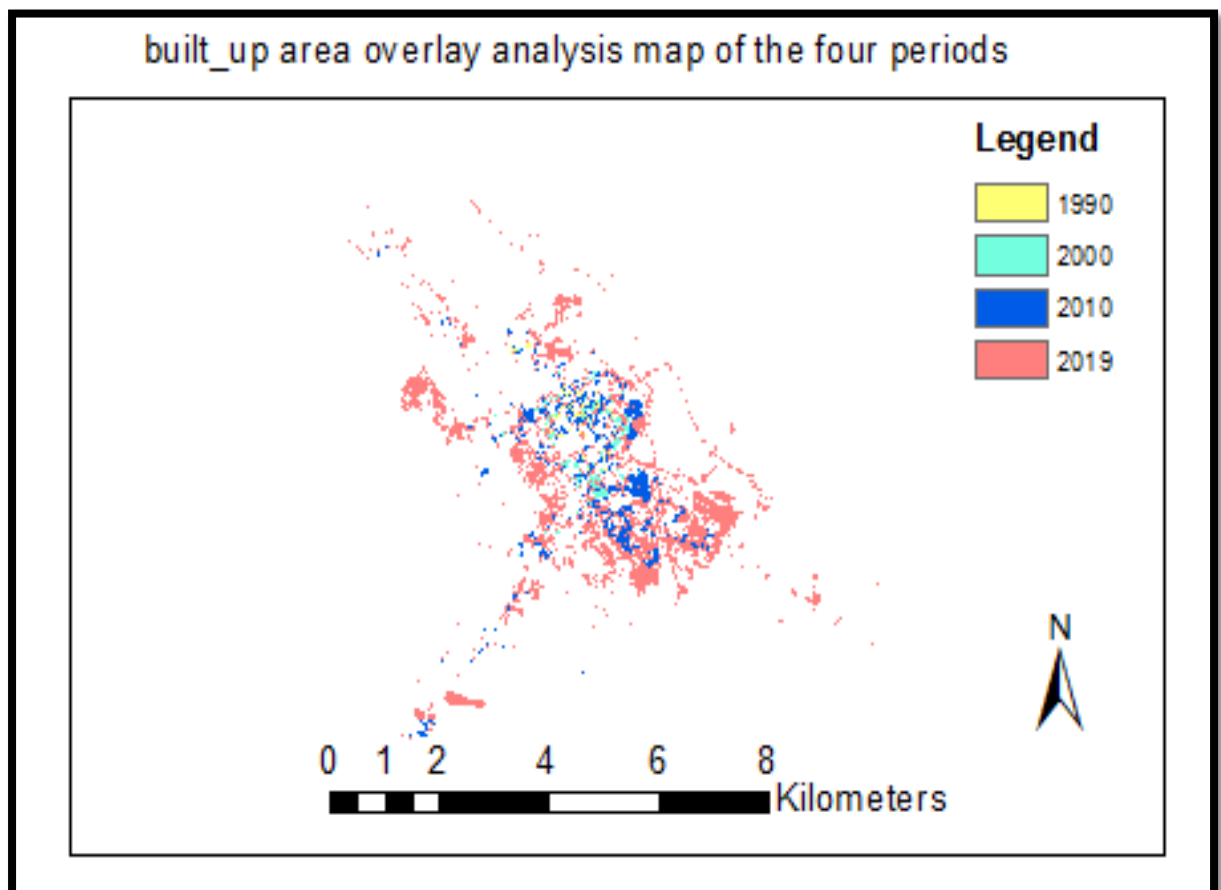


Figure 13: An increasing built-up area expansion from (1990_2019).

4.2.1 Temporal Patterns of Land Use/Land Cover Changes

Land use/land cover classifications and relative changes from 1990 to 2019 in the Modjo town municipality were depicted in Fig. 9. Furthermore, in a close look at (Figure 10 and figure 11) spatial patterns of land cover revealed that built up areas expansion/growth followed certain developing highways and relative population growth .Built-up areas showed dramatic increase while other non-built-up surfaces substantially decreased from 1990 to 2019. Expansion of built up surfaces has exhibited a consistent response since 1990 to 2019 in its areal extent (Fig. 12). There had been a continuous conversion of non-built up surface to built-up environments especially in areas adjacent to the existing urban boundaries in temporal dynamics. Figure 14 below shows trends of LULC change from 1990_2019.

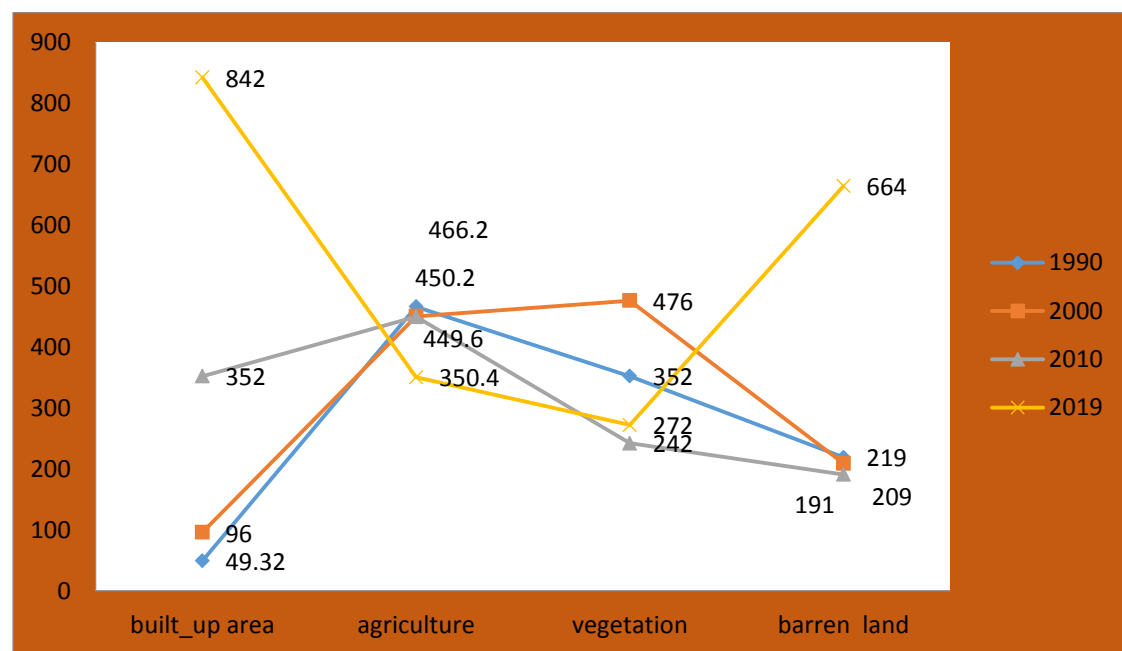


Figure 14: Patterns of land use/land cover changes (1990_2019).

4.2.2 Changes between 1990_2019

Table 15: gains/losses and net change of LULCC in (Ha and %) Modjo Town during (1990_2019).

LULC Types	1990_2000			2000_2010			2010_2019		
	Gains	Losses	Net change	gains	losses	net change	gains	losses	net change
	Ha ,%	Ha,%	Ha,%	Ha,%	Ha,%	Ha,%	Ha,%	Ha,%	Ha,%
built-up area	75 ,0.77	-29 , -0.29	46, 48.45	280, 2.86	-23, -0.23	257, 72.88	574 , 5.86	-85, -0.87	489, 58.10
agricultural	297, 3.03	-457 , -4.67	-160, -3.55	323, 3.29	-328, -3.35	-5, -0.12	166, 1.69	-1158,-11.83	-992, -28.32
Vegetation	338 ,3.45	-214 , -2.18	124, 26	86, 0.88	-320, -3.27	-234, -96.58	150, 1.53	-120, -1.23	30, 10.87
Barren land	115 , 1.17	-125, -1.27	-10, -4.83	83, 0.85	-101, -1.04	-18, -9.43	565, 5.77	-92, -0.94	474, 71.27
	1990_2010			2000_2019			1990_2019		
	Gains	Losses	Net change	gains	losses	net change	gains	losses	net change
	Ha ,%	Ha ,%	Ha ,%	Ha ,%	Ha ,%	Ha ,%	Ha ,%	Ha ,%	Ha ,%
built-up area	325, 3. 32	-21, -0.22	303, 86.02	765, 7.81	-19, -019	746, 88.64	811, 8.28	-18, -0.18	793, 94.14
agricultural	320, 3.27	-485, -4.96	-165, -3.68	254, 2.59	-125, -12.78	-998, -28.47	263, 2.69	-1421,-14.51	-1158,-33.04
Vegetation	154, 1.57	-264, -2.70	-110, -45.46	145, 1.48	-349, -3.56	-204, -75.22	193, 1.97	-274, -2.80	-81, -29.66
Barren land	106, 1.08	-134, -1.37	-28 , -14.71	559, 5.71	-103, -1.05	456, 68.56	566, 5.78	-120, -1.23	446, 67.05

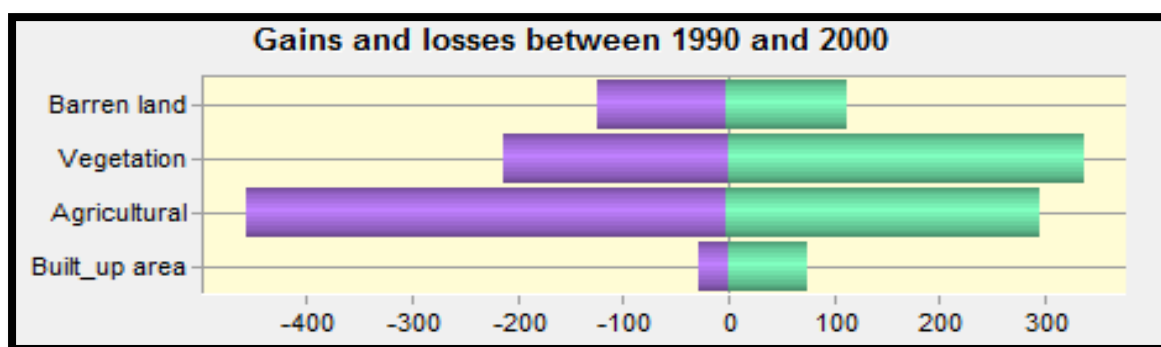


Figure 15: Gain and losses between 1990 and 2000 in hectare.

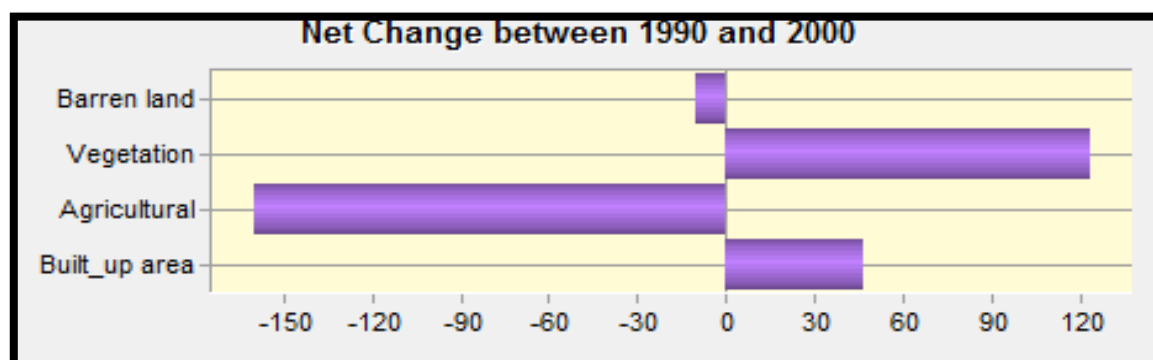


Figure 16: Net change between 1990 and 2000 in hectare.



Figure 17: Gain and losses between 2000 and 2010 in hectare.

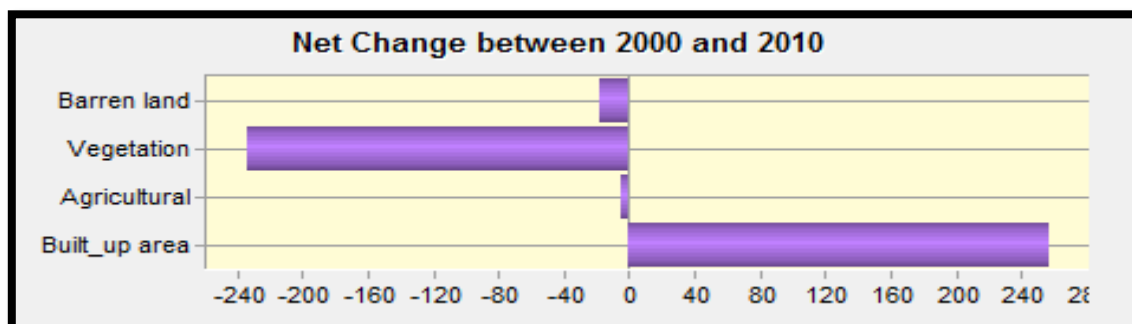


Figure 18: Net change between 2000 and 2010 in hectare.

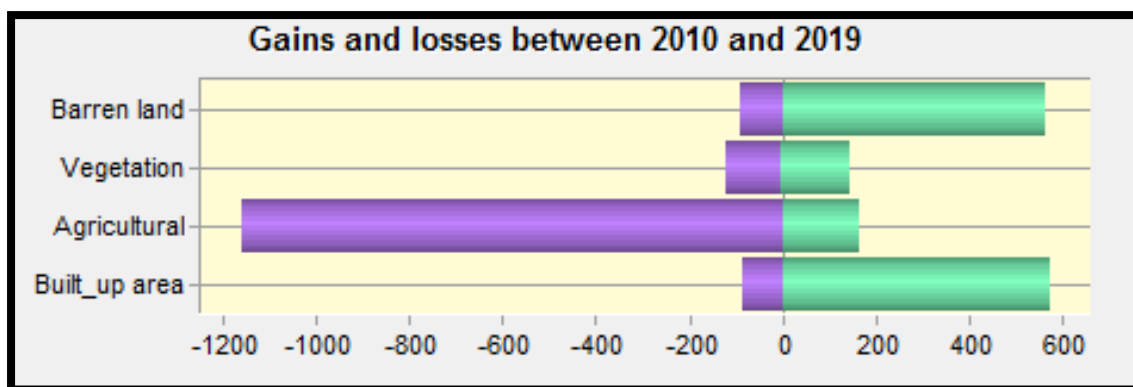


Figure 19: Gain and losses between 2010 and 2019 in hectare.

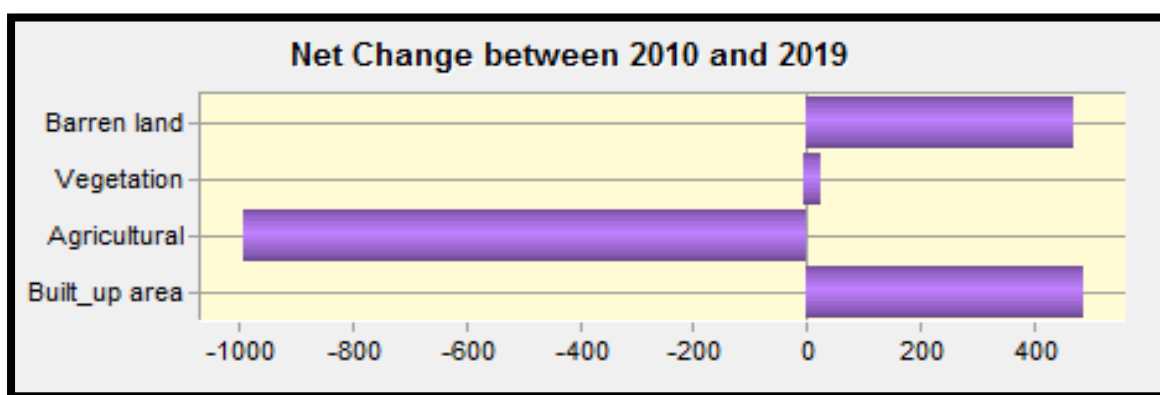


Figure 20: Net change between 2010 and 2019 in hectare.

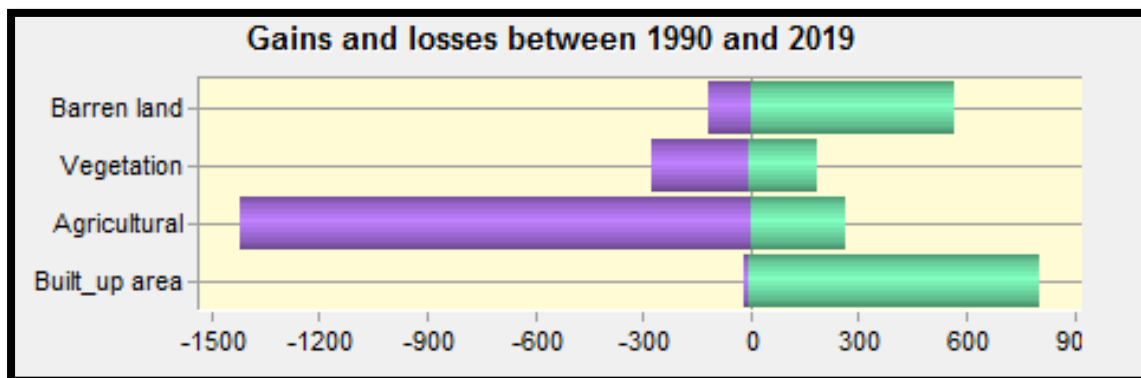


Figure 21: Gain and losses between 1990 and 2019 in hectare.

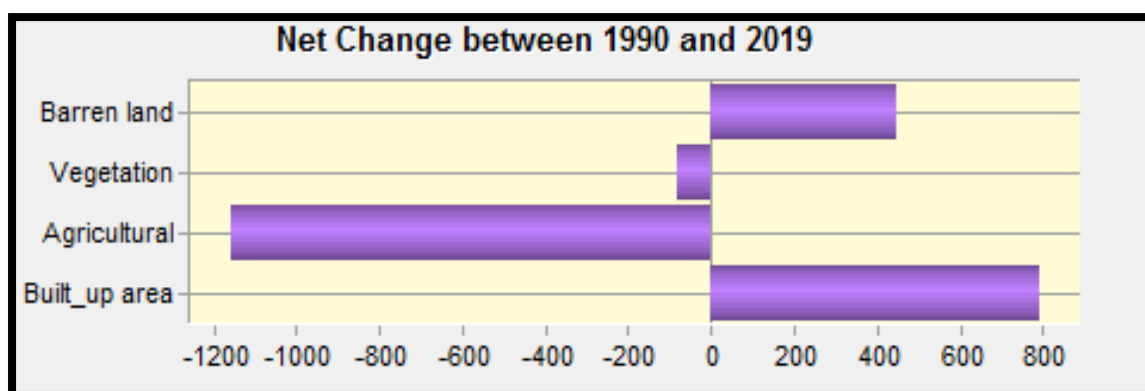


Figure 22: Net change between 1990 and 2019 in hectare.

In ModjoTown for the last three decades or 29 years, from (1990_2019) Built up area is increased by 793Ha(94.14%) and the agricultural 1158Ha(33.04%), vegetation 81Ha(29.66%) are decreased and barren land are increased by 446ha(67.05%).

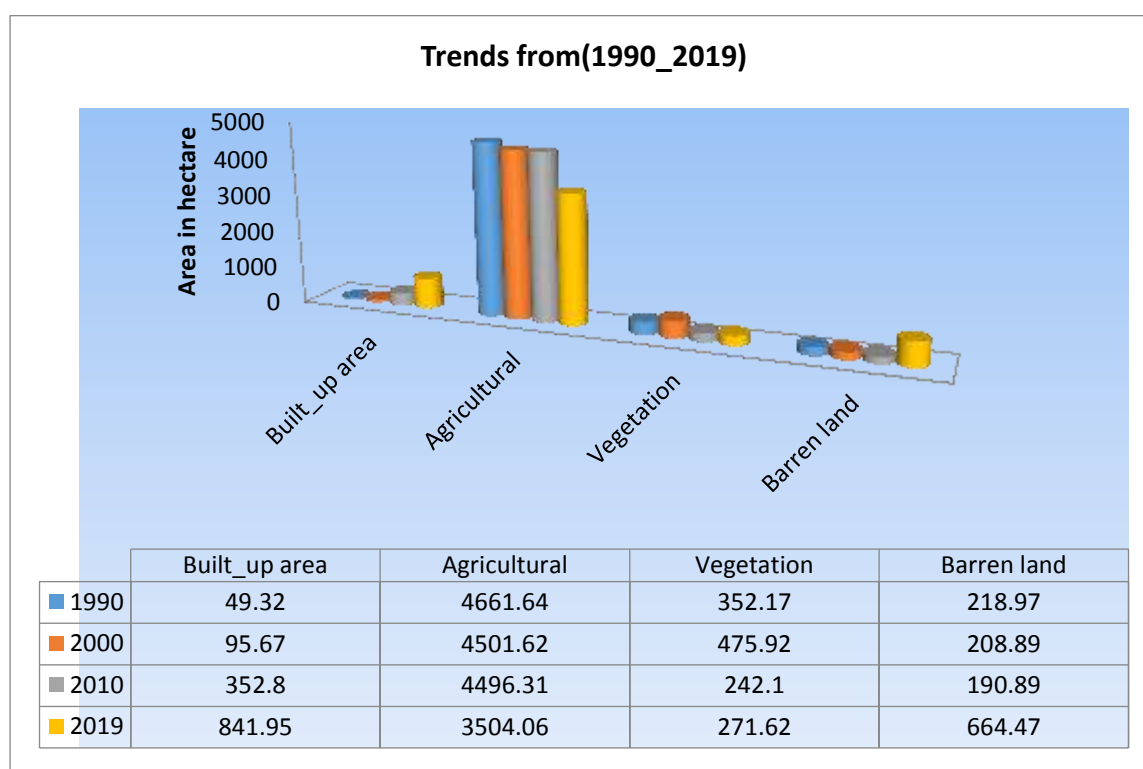


Figure 23: Historical Change trends of LULC from 1990_2019 for all classes.

In the study area built-up LULC was highly changed in the last 29 years relative to the others.

4.3 Transition potential modeling

Transition Potential modeling, is probability that determine the potential of land to transition from one state to other state see table below.

Table 16: Transition of LULC Classes from all to all between 1990_2019.

Categories	LULC transitions		1990_2000	2000_2010	2010_2019	1990_2019
	From	To				
1	Built-up area	Built-up area	20.43	73.17	267.84	31.23
2	Agricultural	Built-up area	48.78	171.27	514.62	715.95
3	Vegetation	Built-up area	24.39	91.89	45.27	80.82
4	Barren land	Built-up area	2.07	16.47	14.22	13.95
5	Built-up area	Agricultural	5.76	11.34	24.93	5.13
6	Agricultural	Agricultural	4204.71	4173.66	3338.19	3240.99
7	Vegetation	Agricultural	174.96	227.88	64.53	158.94
8	Barren land	Agricultural	116.19	83.43	76.41	99.00
9	Built-up area	Vegetation	21.96	10.17	24.21	10.98
10	Agricultural	Vegetation	309.24	74.34	124.65	78.30
11	Vegetation	Vegetation	138.33	156.06	121.77	7.38
12	Barren land	Vegetation	6.39	1.53	0.99	1.98
13	Built-up area	Barren land	1.17	0.99	35.82	529.74
14	Agricultural	Barren land	98.91	82.35	518.85	34.11
15	Vegetation	Barren land	14.49	0.09	10.53	98.64
16	Barren land	Barren land	94.32	107.46	99.27	174.96

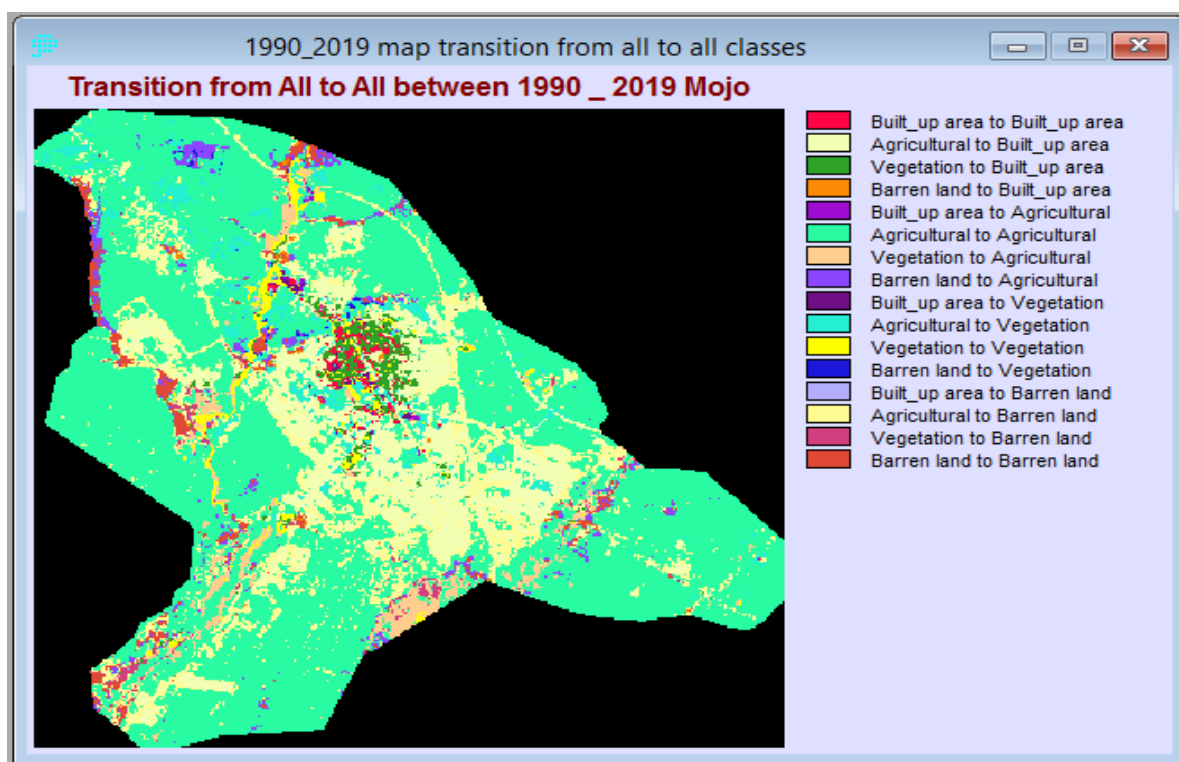


Figure 24: transition map from all to all classes between 1990_2019.

LULC classes contribution to net change in Built up area for three decades shown in table below.

Table 17: Modjo LULC classes' contribution to net change in Built up area from (1990_2019).

LULC classes	Changed to Build up area (ha)			
	1990_2000	2000_2010	2010_2019	1990_2019
Agricultural	43	160	490	711
Vegetation	2	82	21	70
Barren land	1	15	-22	12

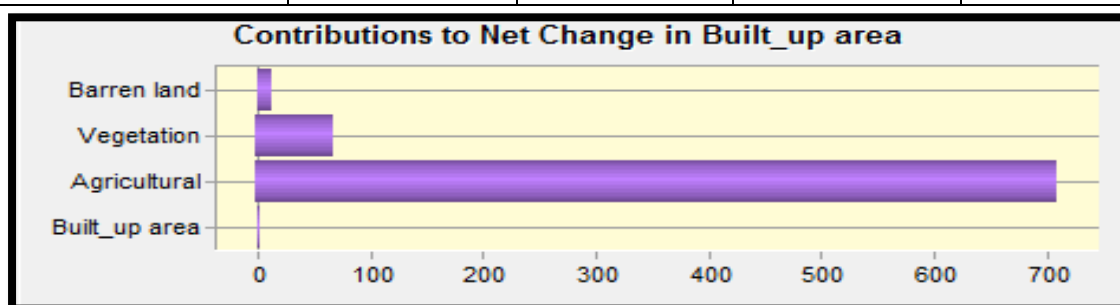


Figure 25:(1990_2019) contribution to net change in built-up area.

Generally Modjo Town LULC Classes that contribute more Net change in Built up area for three decades (1990-2019) is agricultural land that contribute (711Ha),vegetation (70 Ha) and barren land is least contribute (12Ha).

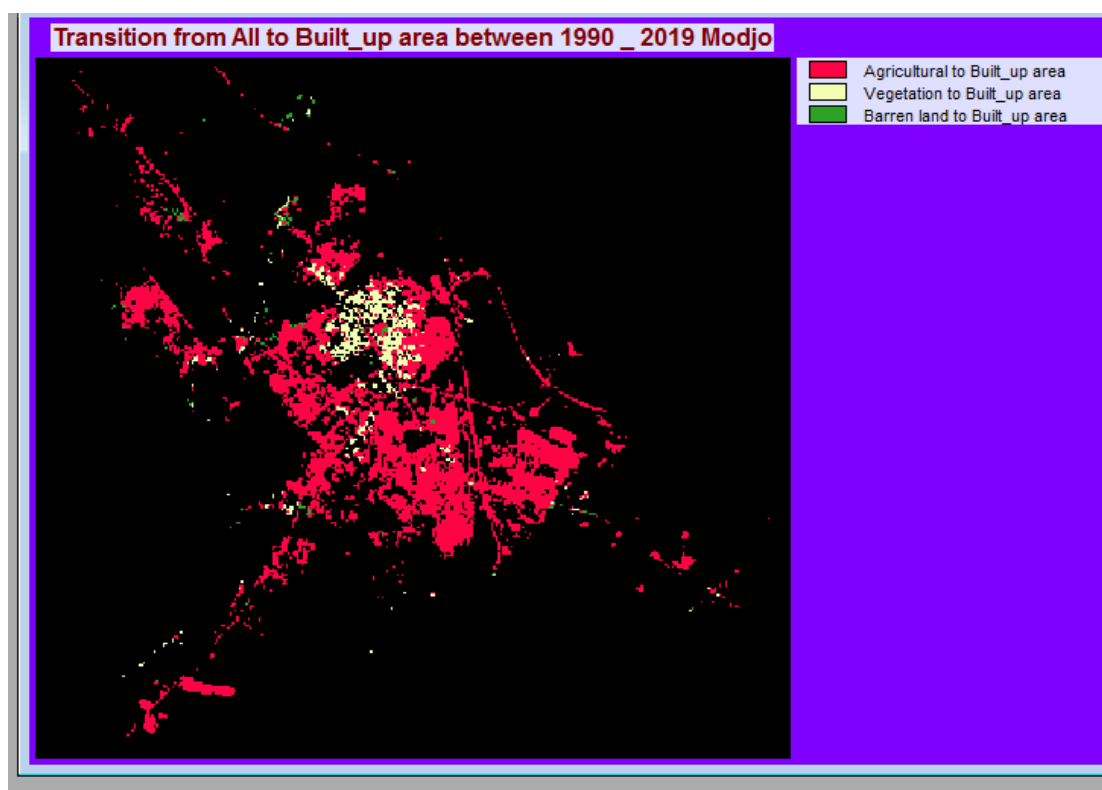


Figure 26: LULC Transition from all to built-up area map from (1990_2019).

Table 18: Markov chain Transition potential modeling matrix of LULC from 2000-2010 to project 2019 LULC.

Probability of changing to project 2019 LULC				
LULC classes	built-up area	agricultural	vegetation	barren land
built-up area	0.7912	0.0948	0.1042	0.0098
Agricultural	0.0288	0.9335	0.0142	0.0234
Vegetation	0.1797	0.4562	0.3641	0
barren land	0.0716	0.2997	0.0046	0.6242

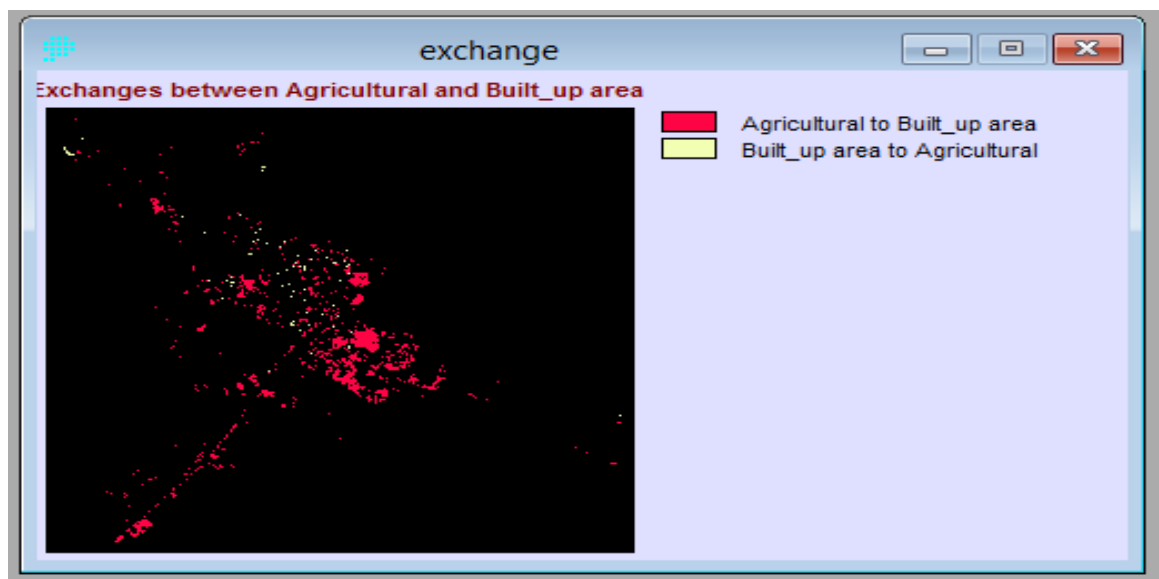


Figure 27: Exchange between agriculture and built-up area.



Figure 28: Gain and losses in agriculture from 2000 to 2010.

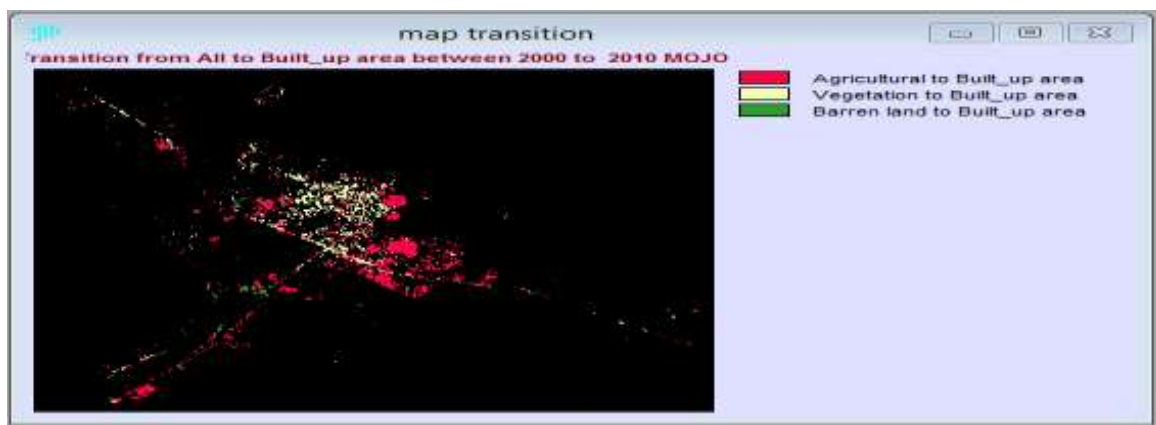


Figure 29: Transition from all to built-up area between 2000 to 2010 modjo town.

4.4 Future Prediction and Modeling land use/land cover

The LU/LC modeling is incomplete without validating the model with actual data. So, the results of LU/LC simulated areas need to be compared with actual area. Therefore, the simulated LU/LC areas of 2019 was compared with the actual areas interpreted from 2019 land satellite image and the result tested with kappa, location and histogram in order to ensure relevancy of the selected variable with LULC change in the model.

4.4.1 Markov Chain

The Markov Chain mathematical model invented by Andrei Andreyevich Markov in 1906, it is a Markov process where space is discrete and it is a stochastic process which means it is mainly based on probabilities not 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.).

The basic assumption in the model is that; the state at some point in the future ($t+1$) can be determined as a function of the current state (t), in other words the future change will be only depend on the existing change, so the transition between two times can be modeled mathematically (Iacono & Levinson, 2012). Mathematically it can be formulated as; $X_{t+1} = f(X_t)$

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

4.4.1.1 Implementation of Markov Chain to Study Area

The variables used for the model summarized in table 25. In the study area the t is LULC map of 2000 and $t+1$ are LULC map of 2010 to predict the 2019.

Variables	value
<i>t</i>	2000
<i>t+1</i>	2010
Time periods for simulation	9 years

According to MARKOV model the relation between 2000 and 2010 has been modeled to be used in the 2019 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 19.

Table 19: Markov conditional probability of changing among LULC type.

Class	built-up area	agricultural	vegetation	barren land
built-up area	0.7826	0.1037	0.1039	0.0098
Agricultural	0.0346	0.9327	0.0155	0.0172
Vegetation	0.1870	0.4584	0.3546	0.0000
barren land	0.0740	0.3750	0.0057	0.5453

A transition areas matrix: This contains the number of pixels which are expected to change from each land use/cover type to other land use/cover type over the specified time period (Eastman, 2012).The number of cells expected to be transformed to other classes can be observed in table 20.

Table 20: Cells expected to be transformed to other classes.

Class	built-up area	agricultural	vegetation	barren land
built-up area	813	126	113	11
Agricultural	1903	46374	826	915
Vegetation	1021	2532	1734	1
barren land	183	927	17	1194

4.4.1.2 Multilayer Perceptron and Markov Chain

The model which was used for modeling the future LULC of the study area was the combination of Markov Chain and Artificial Neural Network based methods. In this model ANN used for defining the spatial allocation of simulated LULC categories, in other works for transition potential development and Markov Chain used for prediction based on transition potentials.

In this case the first stage of the method is detecting the changes; this has been explained in detail in methodology section of change detection. The second step of the method is transition modeling which helps to create the transition maps from each LULC category to urban areas, which can be done by using the MLP method. The third step was the change modeling and the validation of the model with the accuracy assessment. Before the implementation of the model the theory of the ANN and MLP need to be understood so, it was described in methodology part.

4.4.1.3 Combination of Multilayer Perceptron and Markov Chain Methods

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

4.4.1.4 Transition Sub Model Development

For this research the effect of the urban area was the main indicator, for this reason the changes from other categories to urban used as a transition sub model. In order to model the changes, the main variables which have the effect on the changes need to be detected. These variables are distance to urban centers, distance from road, digital elevation model (DEM), slope and LULC map of 2010 see (figure30).

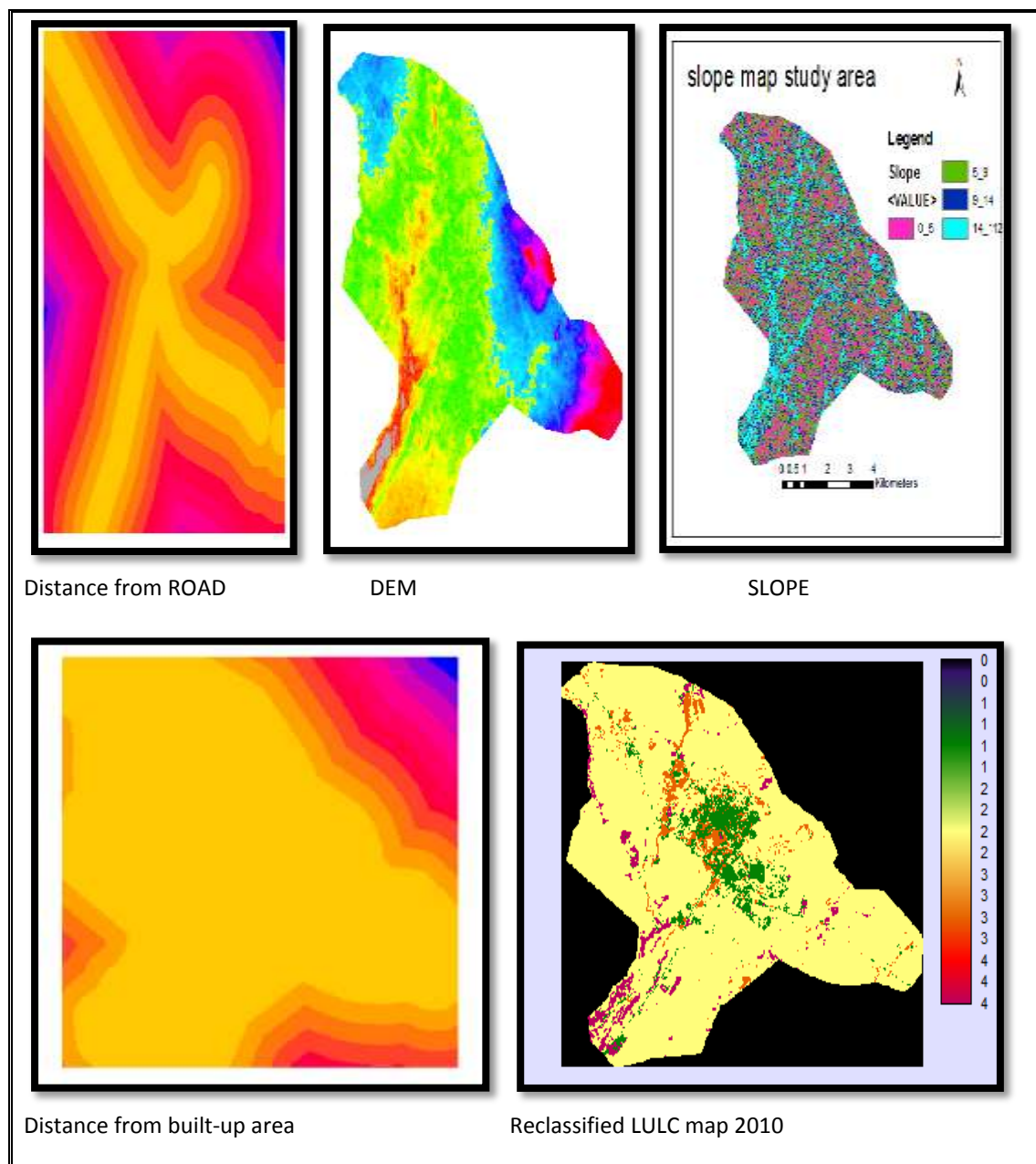


Figure 30: driver variables used for simulation.

4.4.1.5 Transition Potential Development

In order to calculate and map these potentials MLP, which is a successful method in solving complex systems, has been used. As it has been explained in MLP definition the one of the basic component of the method is input layer, in this study the input layers are described in above figure.30. As it has been illustrated in the figures below the result of the simulation is

more or less similar to the existing situation but this need to be tested by accuracy assessment.

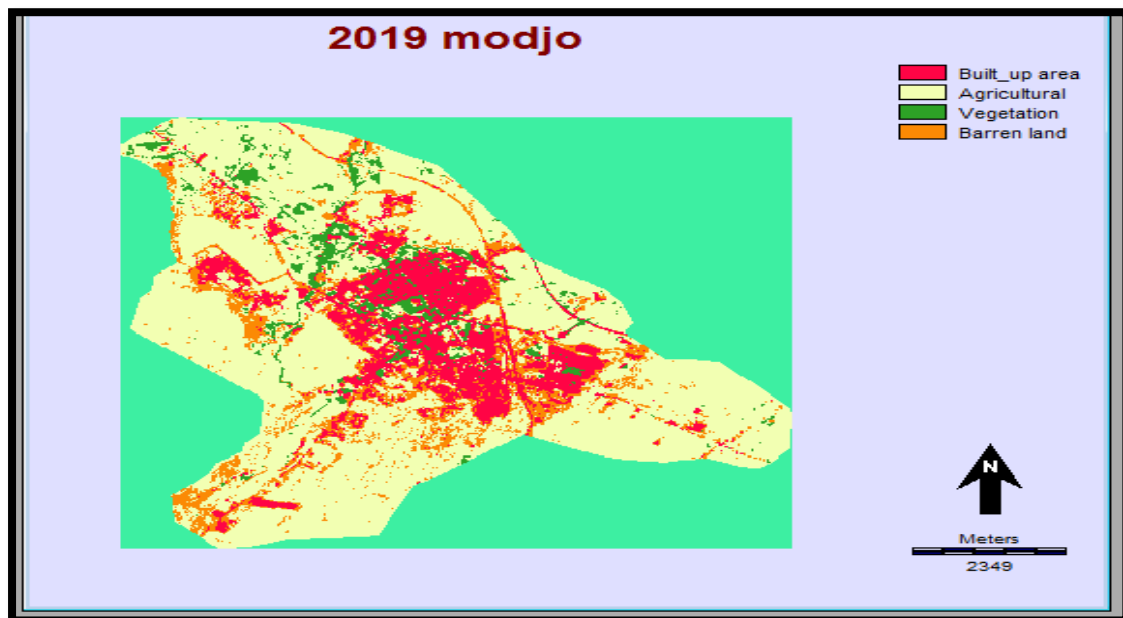


Figure 31: Image classification result of 2019 LULC map

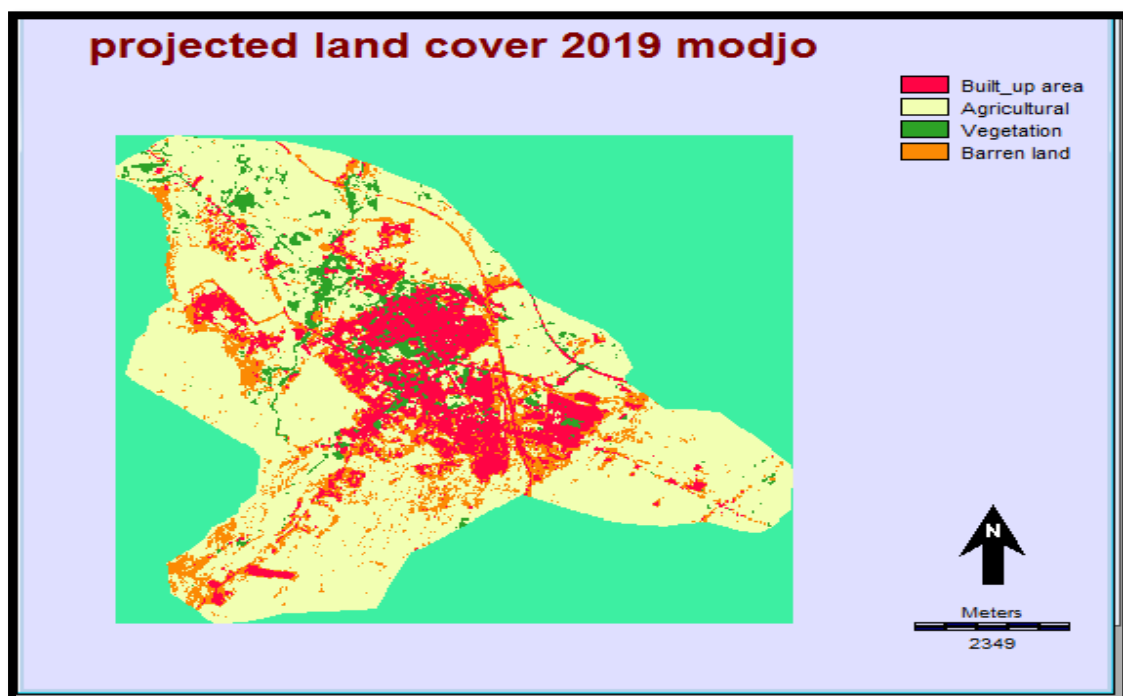


Figure 32: Projected LULC for 2019 (MLP and MARKOV).

4.5 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 has been used for the accuracy assessment Pontius & Millones (2011). The aim was to observe the main changes between 2019 classified and then comparing the results with the predicted map, in order to understand if the overall changes have been predicted correctly or not.

4.5.1 Kappa

The method used for the accuracy assessment, calculating kappa values related to the location and the quantity in order 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 spatial distribution of classes but does not differentiate between classes that are close or distant and it is independent from the total number of cells per class (Serna, 2011); (Pontius, 2000). Khisto measures quantitative similarity between two maps, in other words it checks the similarity in the amount of the cells in testing map and reference map (Serna, 2011).

The accuracy assessment result for the model can be observed in table 21 from this table it can be observed that the overall kappa is 0.95.

Table 21: Accuracy assessment (MLP and MARKOV)

Per Category Values	Accuracy for individual
Kappa	0.97
Klocation	0.95
Kno	0.92
khisto	0.96
Overall accuracy	0.95

As result of accuracy assessment, since the overall kappa is 95%, Strength of Agreement for Kappa Statistic is almost perfect (**Landis, J., 1977**), and the crammers value was tested for each drivers 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 22: 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

4.6 Influence of Driver Variable on Urban Growth

The sensitivity analysis revealed that, “Distance to urban” areas was the most influential driver variable (Table 23).The second most influential driver variable was “Distance to road”. According to the analysis, slope was the driver variable with the least influence on the model. The elimination of the slope variable from the model increases the accuracy of the model from 90.14% to 90.18%. Consequently, the inclusion of this variable in the model marginally reduces the accuracy of the model by 0.04%.See table 23 as below:

Table 23: Relative significance of driver variables generated by forcing independent variables to be constant.

Model (Constant variable)	Accuracy (%)	skill measure	influence order
With all variables	91.23	0.88	N/A
Slope	39.92	0.87	5(least influential)
Elevation (DEM)	47.65	0..85	4
LULC_2010	79.52	0.75	3
Distance to road	89.36	0.35	2
Distance to urban	90.14	0.25	1(most influential)

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 1556.1ha, 1731.6ha and 1840.5 of land in the Town will be covered by built-up area respectively, which covers roughly 29.46%, 32.78% and 34.84% of the Town. This means that, between 2019 _2030, 2030_2040 and 2040_ 2050, the total areas that are covered by built-up area will increase by 13.52% (714.15 ha), 3.32 %(175.5ha) and 2.06 %(108.9ha) respectively.

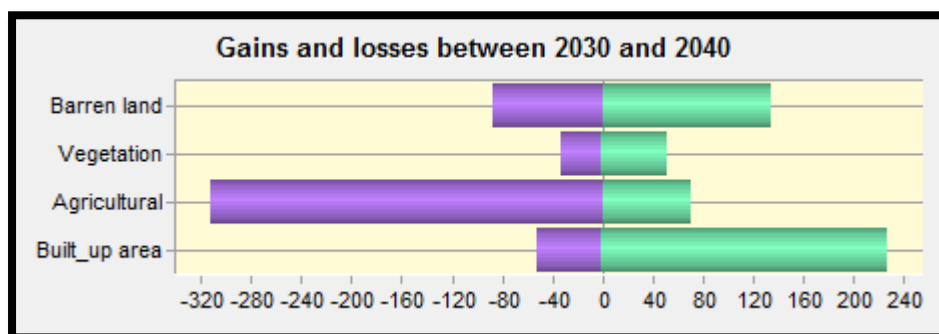


Figure 33: Gain and losses between 2030 and 2040 LULC.

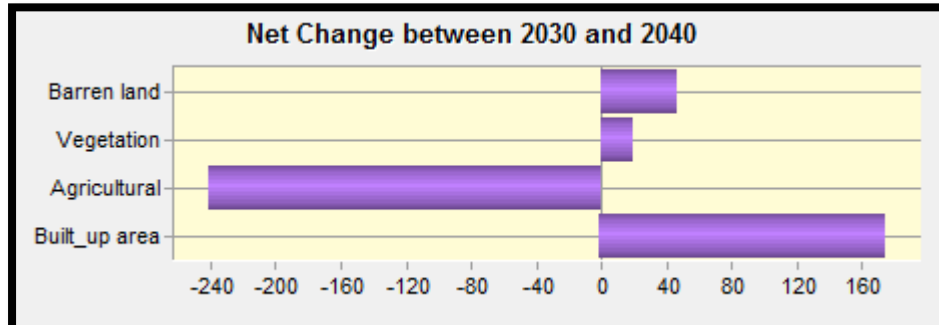


Figure 34: Net change in LULC between 2030 and 2040.

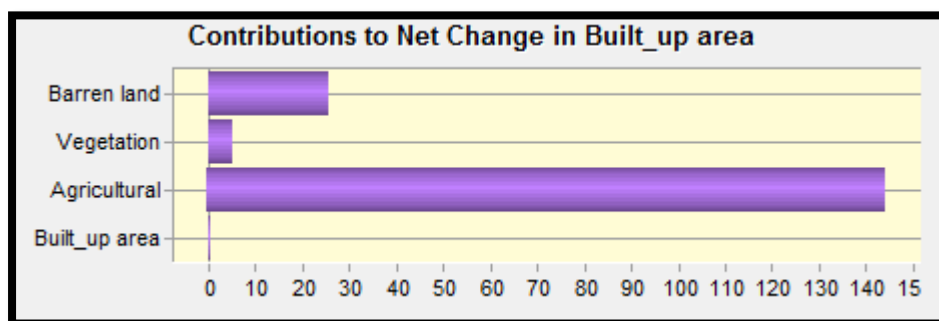


Figure 35: contribution to net change in built-up area.

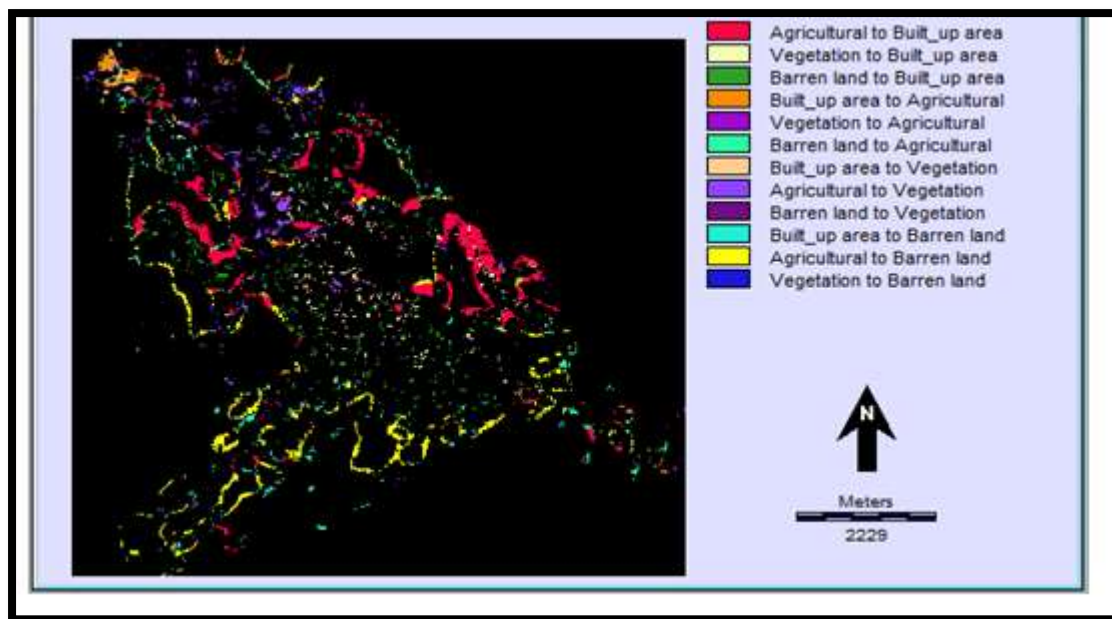


Figure 36: change map from 2030 to 2040 modjo town.

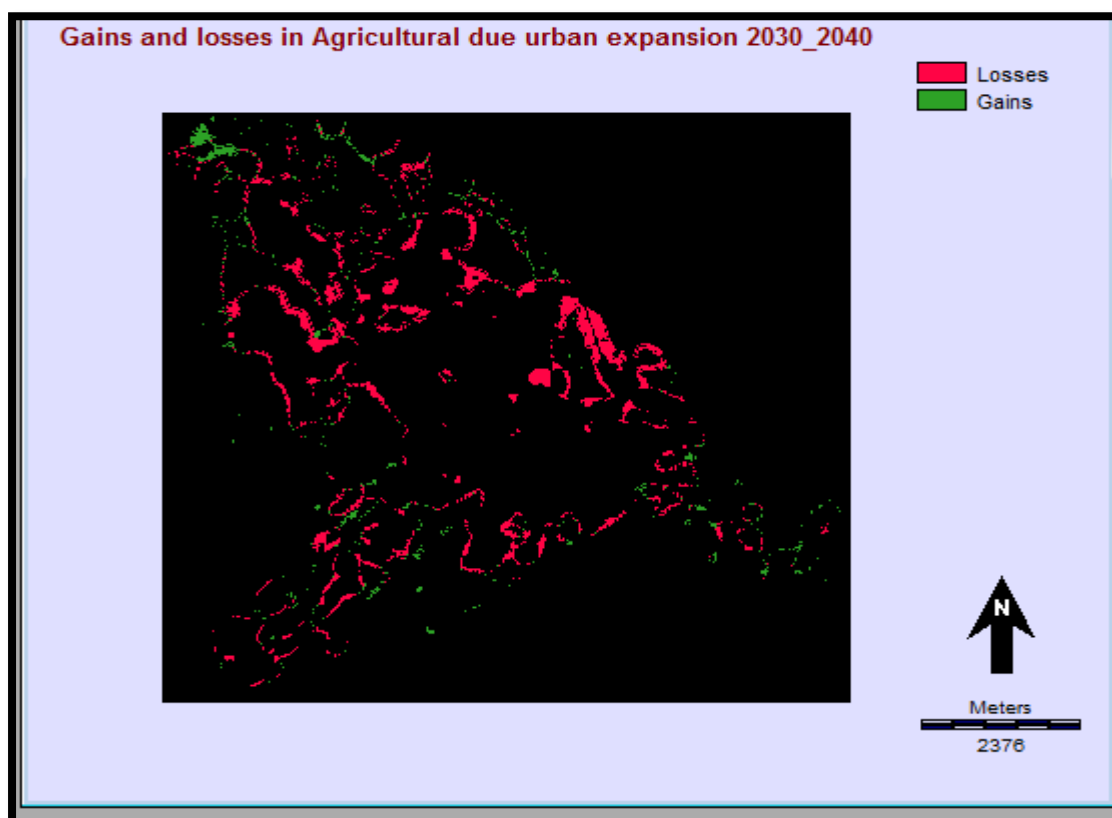


Figure 37: Gaain and losses in agriculture due to urban expansion 2030_2040.

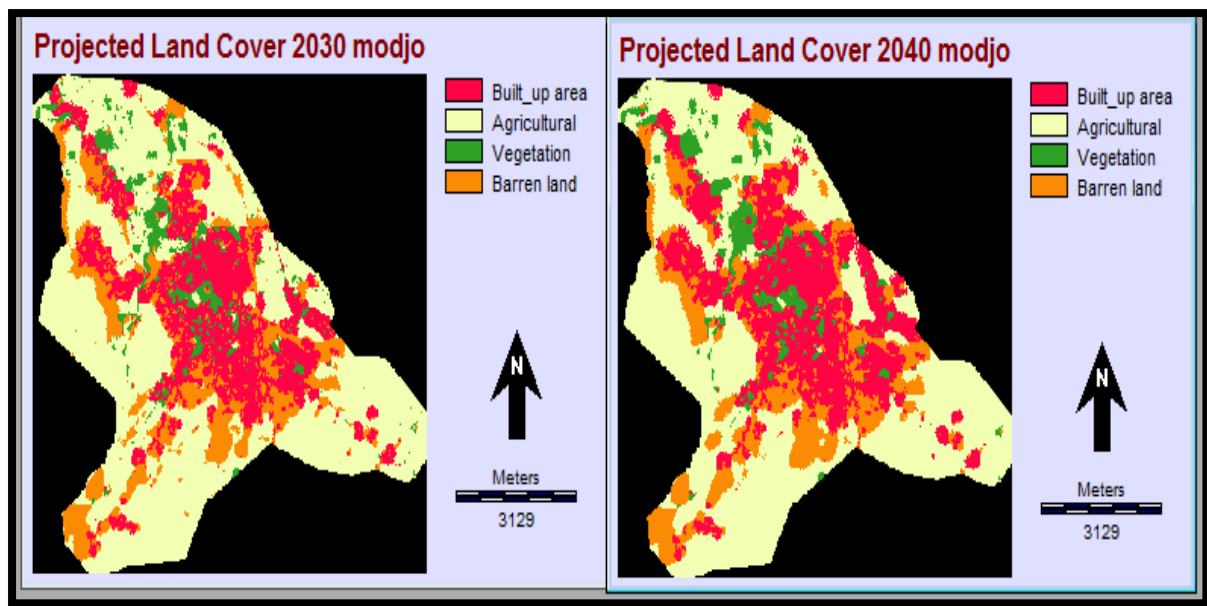


Figure 38: The projected urban extent for the year 2030 and 2040.

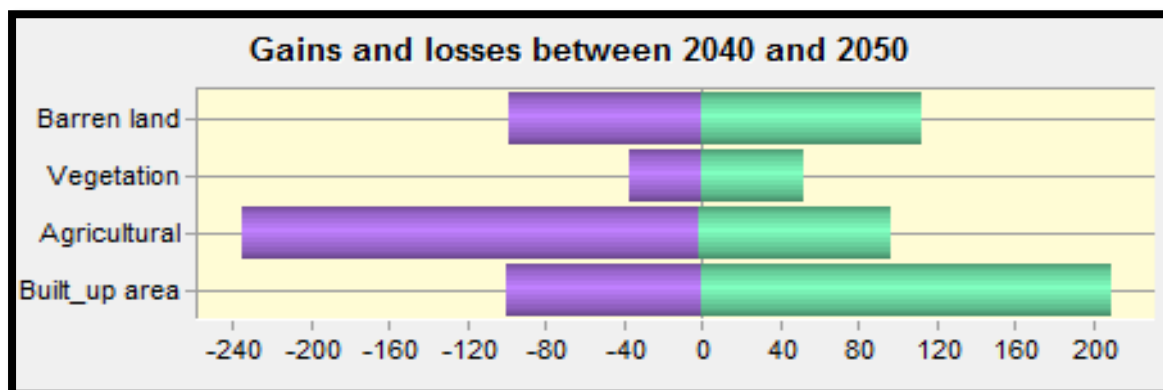


Figure 39: Gain and losses in LULC between 2040 and 2050.

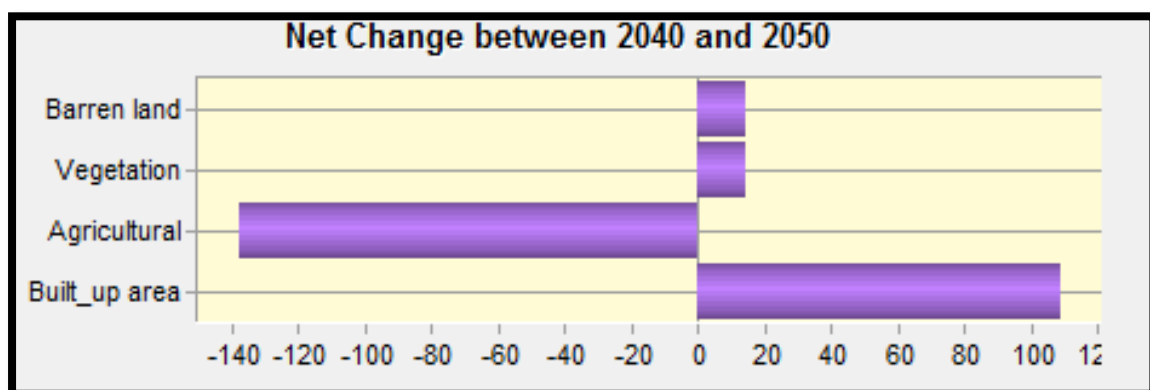


Figure 40: Net change in LULC between 2040 and 2050.

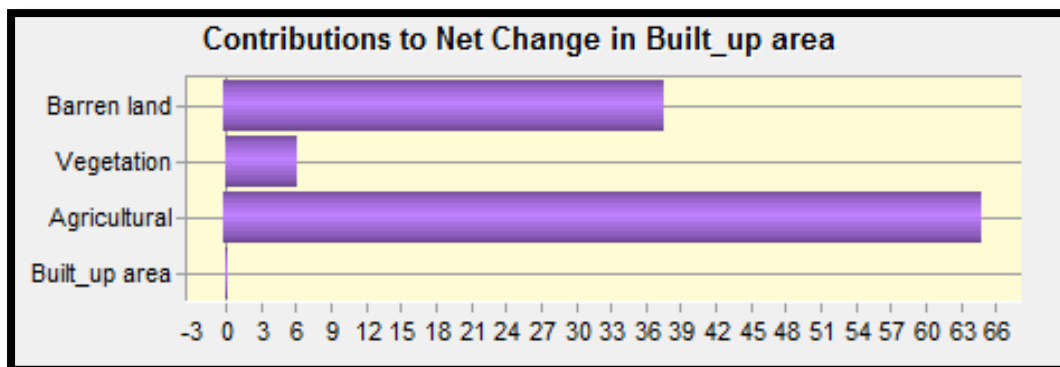


Figure 41: contribution to net change in built-up area.

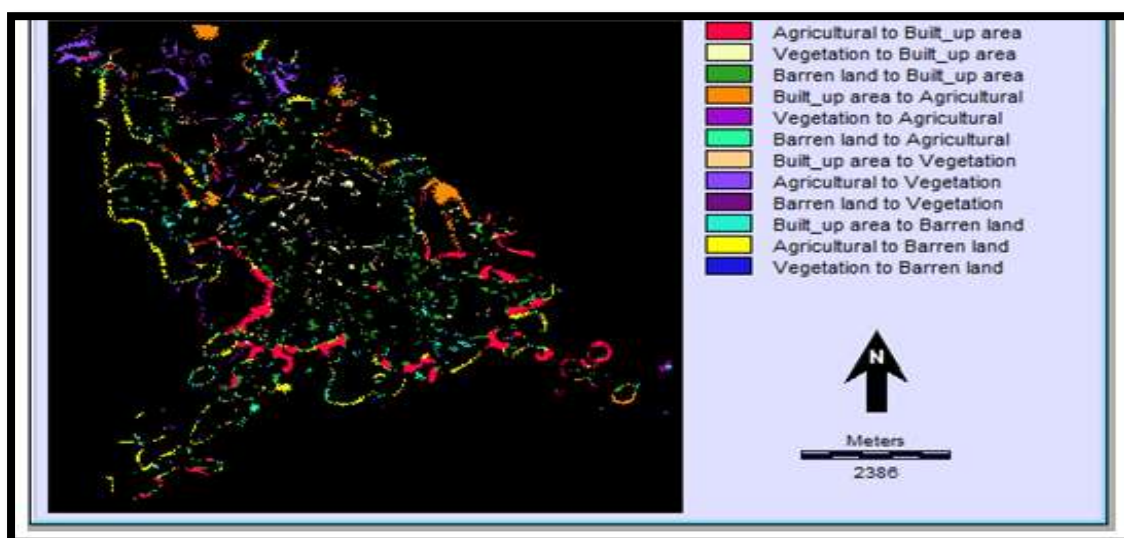


Figure 42: change map from 2040 to 2050 modjo tow



Figure 43: Gain and losses in agriculture due to built-up area 2040_2050.

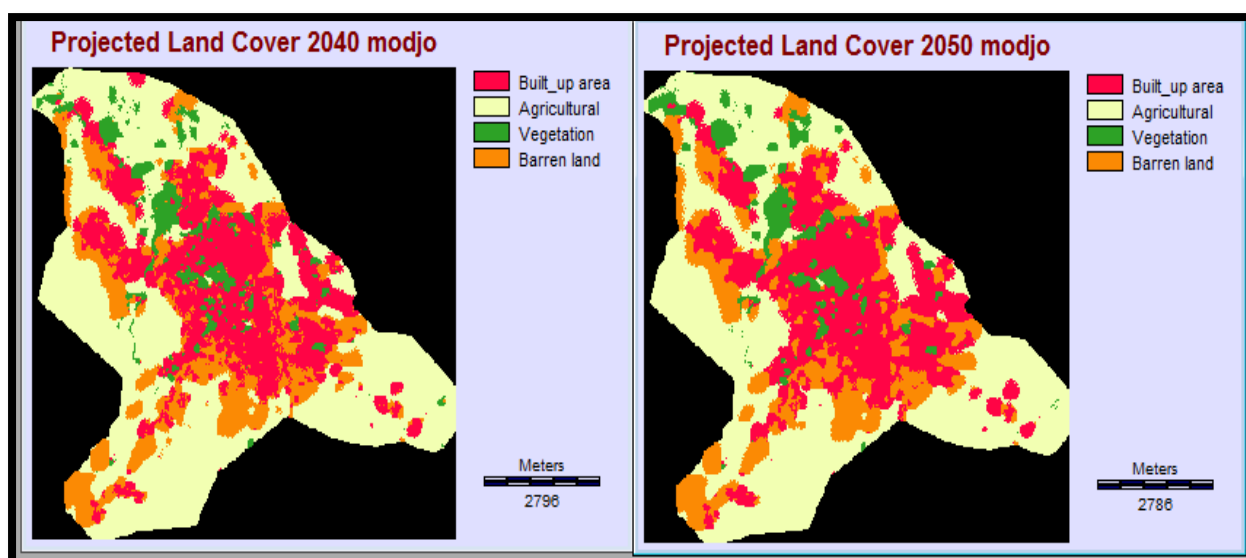


Figure 44: The projected urban extent for the year 2040 and 2050.

Table 24: Areal extents and percentage change over time of land use/land cover classes in Modjo town.

Class	Area in (ha)			Percentage change (%)		Annual average change (%)
	2030	2040	2050	2030_2040	2040_2050	2030_2050
Built-up area	1556.1	1731.6	1840.5	11.28	6.29	0.91

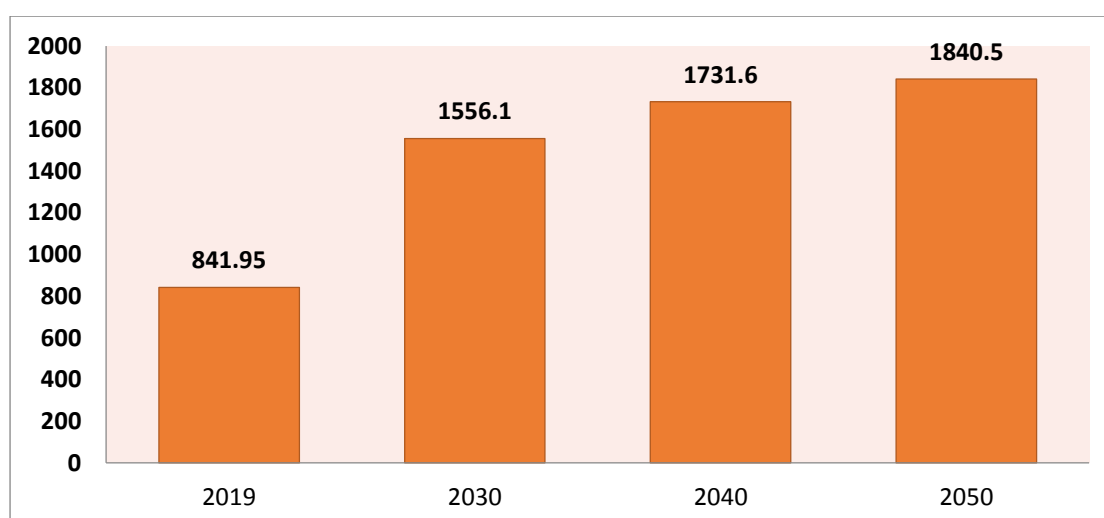


Figure 45: future expected trend of built-up area expansion from 2019_2050.

4.7 Relationship between population growth and built-up area expansion in the study area

The population growth in 1990, 2000 2010 and 2019 was projected from existing census population data 1984, 1994, 2005 and 2008. 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.

$$\text{Land consumption rate} = \frac{\text{Total built_up area}}{\text{Total population}}$$

Table 25: projected and observed population data and analyzed and projected built-up area expansion from (1990_2050).

year	population growth	Built-up area expansion	consumption rate
1990	18777	49.32	380
2000	31444	95.67	328
2010	54336	352.8	154
2019	70412	841.95	83
2030	88191	1556.1	56
2040	105971	1731.6	61
2050	123749	1840.5	67

Graphs that fit collected data points drawn by scatter plot on excel.

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

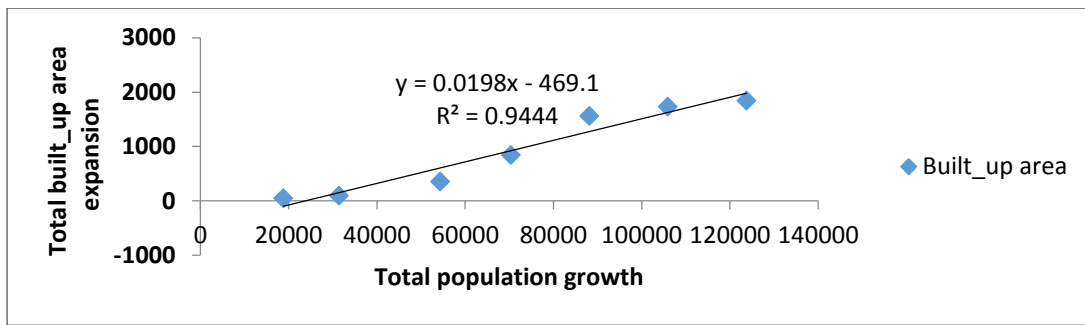


Figure 46: regression line that indicates Correlation between Built-up area expansions and population growth.

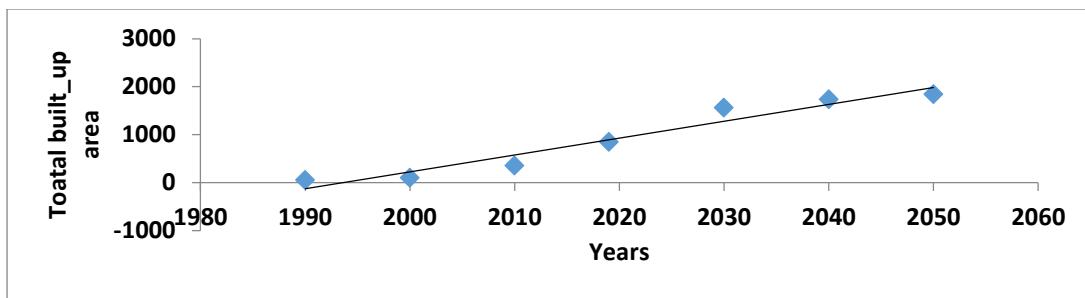


Figure 47: Tend of built-up area expansion in study period from (1990_2050).

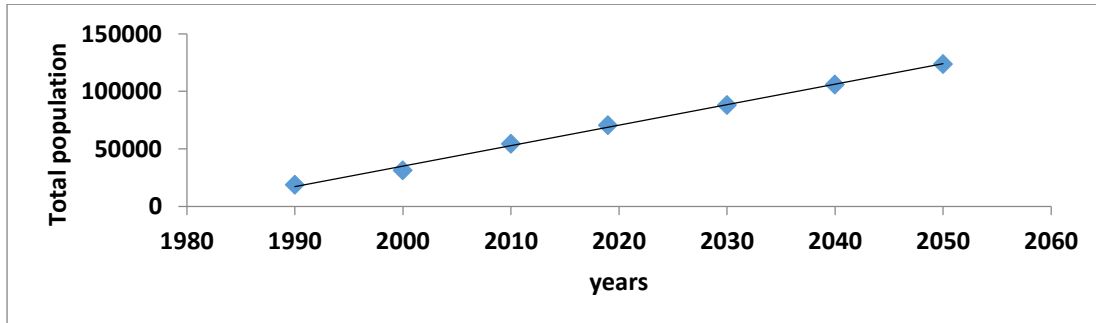


Figure 48: Trend of population growth in study period from (1990_2050)

$$B = 0.0198P - 469.1$$

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. So they have positive correlation due to the slope positive and one variable increases with respect to another variable and the two variables have linear relationship. Built-up area increases by 1.98% for each 1 increment in population growth and the other parameters obtained was, $R^2 = 0.9444$, this indicates accuracy of regression model.

4.8 DISCUSSION

Figure 9 demonstrates the LULC maps of Modjo town for 1990, 2000, 2010, and 2019. Overall classification accuracies are 90.95%, 91.9%, 85.76%, and 97.62%, for the year 1990, 2000, 2010 and 2019, respectively. The values of Kappa statistics for classified images are greater than 0.8, indicating strong agreement between the classified LULC classes and ground truth, hence the maps satisfied accuracy criteria for LULC change detection analysis. The information summarized in Table 14 shows the spatial extents; percentage changes over time as well as the annual average growth of the four LULC classes (agriculture, barren land, urban and vegetation) in Modjo town between 1990 and 2019. Besides Fig. 9 demonstrates the spatiotemporal variations of the proportions of each class occurred over the span of 29 years. Overall, the results show the extensive LULC changes in Modjo town over the study period. Agricultural land was dominant class at the beginning of the study period, but declined with the continuous increase of urban land area. It can be seen that the rate of annual urban expansion greater by far, from the rest land use classes. The coverage of agricultural land was 88% of the total area at the beginning of the study timeframe. In the following 10 years, it moderately decreased to about 85.22% before it dramatically dropped to nearly 66.34% in the final year. By contrast, the proportion of urban class was 0.93% in 1990, this figure rose to just over 15.94% in 2019, showing an increase of more than approximately sixteen folds of its initial spatial share. It showed nearly 55.8% of average annual expansion across the study period. The average annual rate of change in Built-up area as determined from the Landsat change statistics was **9.6%** from 1990 to 2000, **26.8%** from 2000 to 2010 and 55.8 % for the entire period of 1990 to 2019. On the other hand, agriculture and vegetation and barren land areas showed an average reduction of change approximately 1% annually. Minimum net change was observed in built-up area between 1990_2000 which was 75 ha and this just rose to 489 ha between 2010_2019. In ModjoTown for the last three decades or 29 years, from (1990_2019) Built up area is increased by 793Ha (94.14%) and the agricultural 1158Ha (33.04%), vegetation 81Ha (29.66%) were decreased and barren land was increased by 446ha (67.05%). During transition potential modeling the greatest transition was observed when agriculture was converted to Built-up land which was 715.95 ha in the entire period from 1990_2019. lastly based on LCM model urban growth was projected based on the past trends for 2030 ,2040 and 2050 ,it reveals that built up area will be 1556.1 ha, 1731.6 ha and 1840.5 ha respectively. The regression analysis was also performed for built-up area expansion and population growth in order to determine strength of relationship between them and to define what urbanization is in study area, so linear regression was selected to analyze relationship between the two variables, since we have one dependent and one independent variable and so, analyze reveals that they have positive linear relationship and degree of correlation was high degree.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study conducted to analyze impacts of urbanization on LULC change, the existing patterns and to predict the future LULC maps in order to lead the planning authorities for a sustainable development using land change modeler (LCM). While making this research some research questions prepared to define the scope of work. After finishing the study the answers of those questions were summarized in this section in order to understand the success of the study both in methods and the result of the study were achieved as it was proposed in the specific objectives and results also answers prepared the research questionnaire's':

The built up area had an increasing positive trend of change in its areal extent while agricultural lands decreased continuously in the four periods. There has been also an observable increasing and decreasing trend of change in the other land cover classes of vegetation and barren land. The average annual rate of change in built-up area as determined from the Landsat change statistics was 9.6 % (47ha) from 1990 to 2000, 26.8 % (257ha) from 2000 to 2010 and 13.8 % (489 ha) from 2010 to 2019, 55.8 % (793ha) for the entire period of 1990 to 2019. On the other hand, agriculture, vegetation and barren land areas showed an average reduction of change approximately 1% (15 ha) annually.

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 1556.1ha, 1731.6ha and 1840.5 of land in the Town will be covered by built-up area respectively, which covers roughly 29.46%, 32.78% and 34.84% of the Town. This means that, between 2019 _2030, 2030_2040 and 2040_ 2050, the total areas that are covered by built-up area will increase by 13.52% (714.15 ha), 3.32 % (175.5ha) and 2.06 % (108.9ha) respectively.

The study concludes that there is a significant increase in urban area that has reached from 49.32 hectare in 1990 to 841.95 hectare in 2019. This happened due to rapid increase in population which reached from 18,777 in 1990 to 57,511 in 2019. 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 29 years that have consumed several hundred hectare of farmland. 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 city systems is essential need of the time otherwise urban problems may aggravate further in near future.

5.2 Limitation of the Research

The main limitation of the research was finding the high resolution multi temporal images which could help to increase the accuracy of the classification later on the accuracy of the model and simulation. Unfortunately this data couldn't be found and low resolution Landsat images used for the research. The second limitation of the research was finding the multi temporal ground truth data in order to perform the supervised classification of the images. Without ground truth, the classification accuracy always is lower than expected. Third limitation was limitation of model LCM itself not possible to use socioeconomic and climate change data that increase the accuracy of the model .the fourth limitation was the coming Covid 19 diseases spread throughout the world and researcher was not stay at university and get enough internet access and not communicate with advisors face to face for advice.

5.3 Recommendations

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

- The use of high resolution imageries such as IKONOS and Quick Bird are important in generating good quality of land cover maps. Because urban areas have complex and heterogonous features, high resolution imagery provides better information by mapping these areas. Moreover, the use of ancillary data as ground truth helps for better accuracy of an image classification.
- Consistent multi-temporal Landsat satellite data for each year provides detail comparison of images, change analysis and modeling. Especially for Markov chain method, it is a requirement of equal interval of images acquisition although there have been uneven temporal availability of data.
- Socio-economic data, land policy, biophysical and human factors (population density, technology, political) could improve the performance of land use models for future predictions. Hence, it is important to the planners, decision makers and stakeholders for efficient utilization of land.
- Urban areas like Modjo, small and middle sized and recently developing town will use and adopt this research approach and methodology designed, in order to really accomplish their study anywhere else.
- Any researcher with related and in this field of study can be use this research as related material and developed source, with their weaknesses it has.
- Any city planners and responsible persons who want to manage their urban expansion and forecast trends of urban expansion in the future scenarios will be able to share this material.

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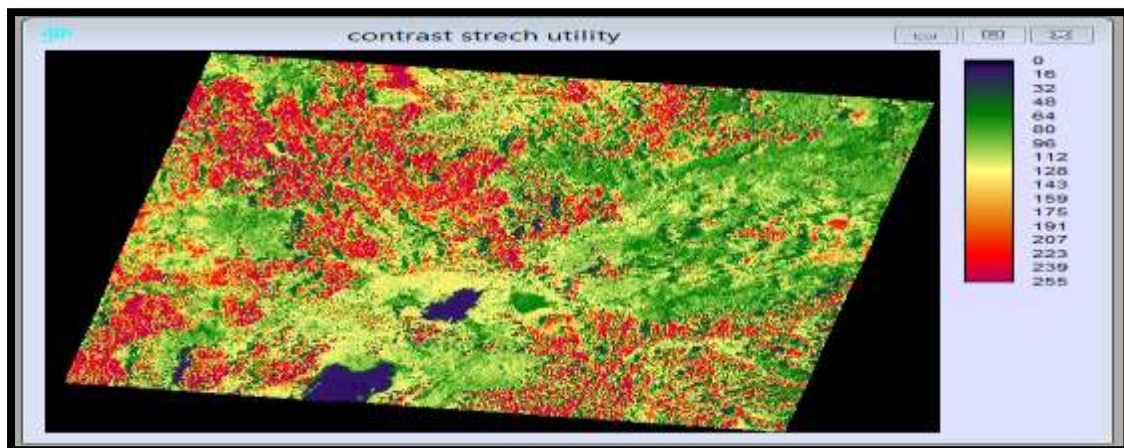
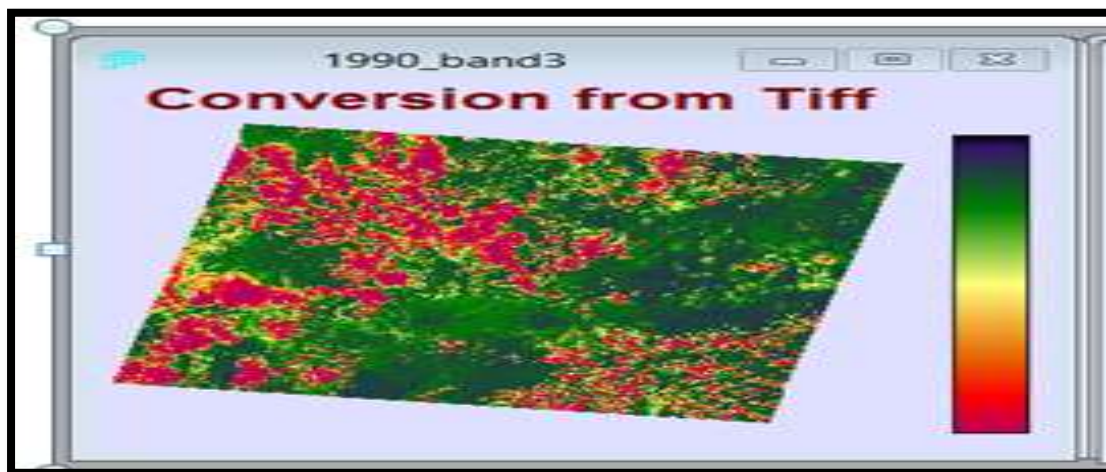
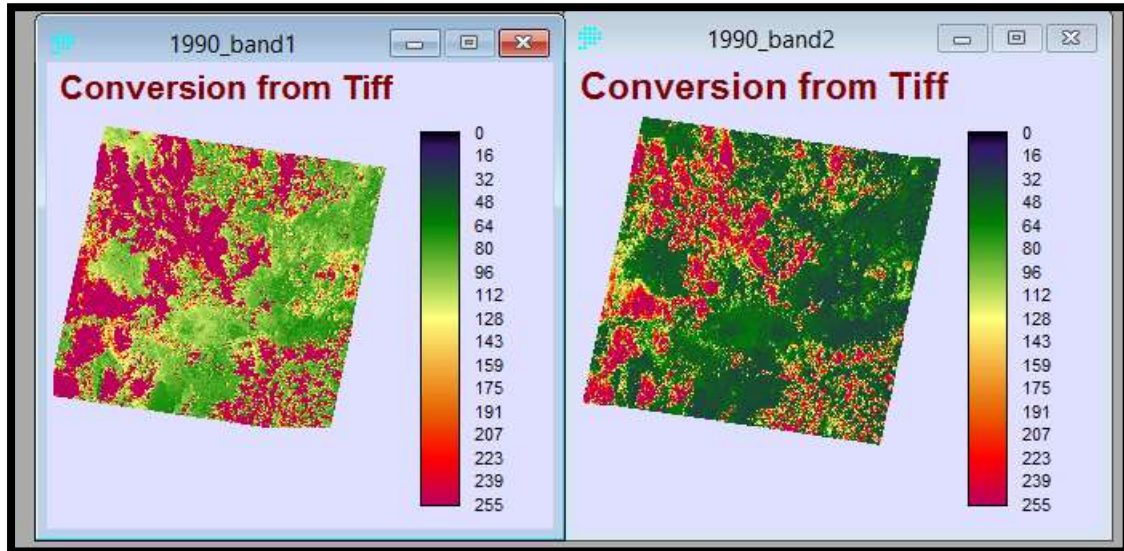
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Appendices

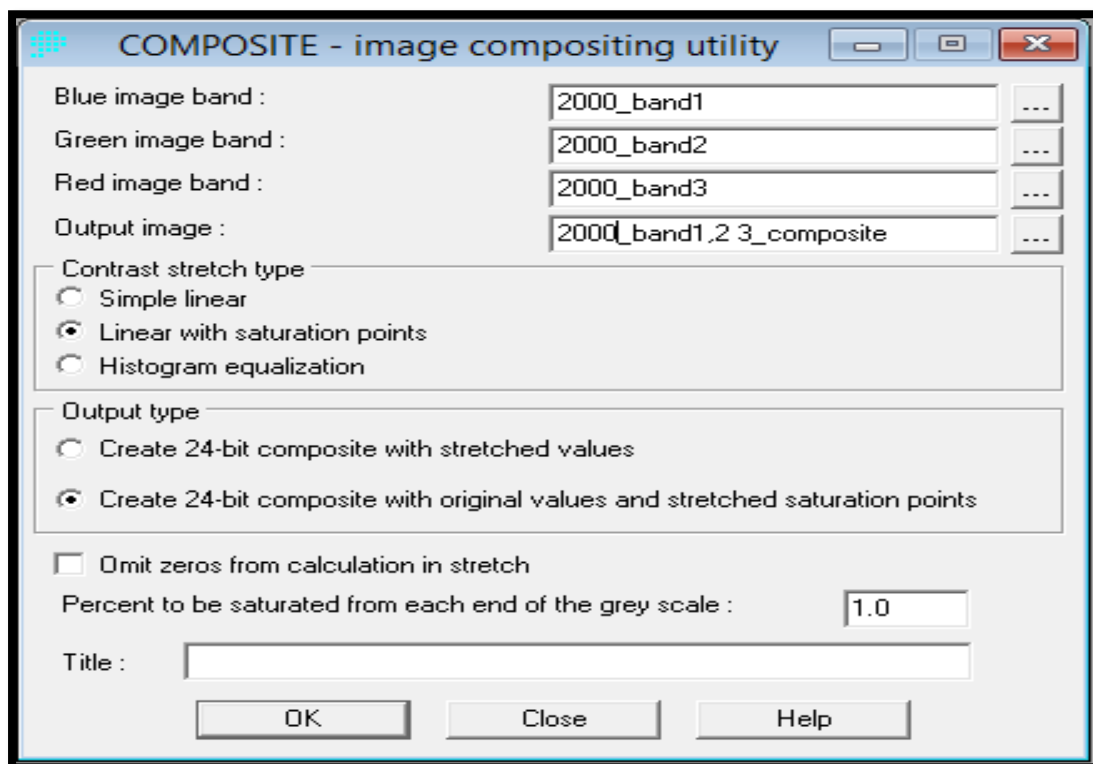
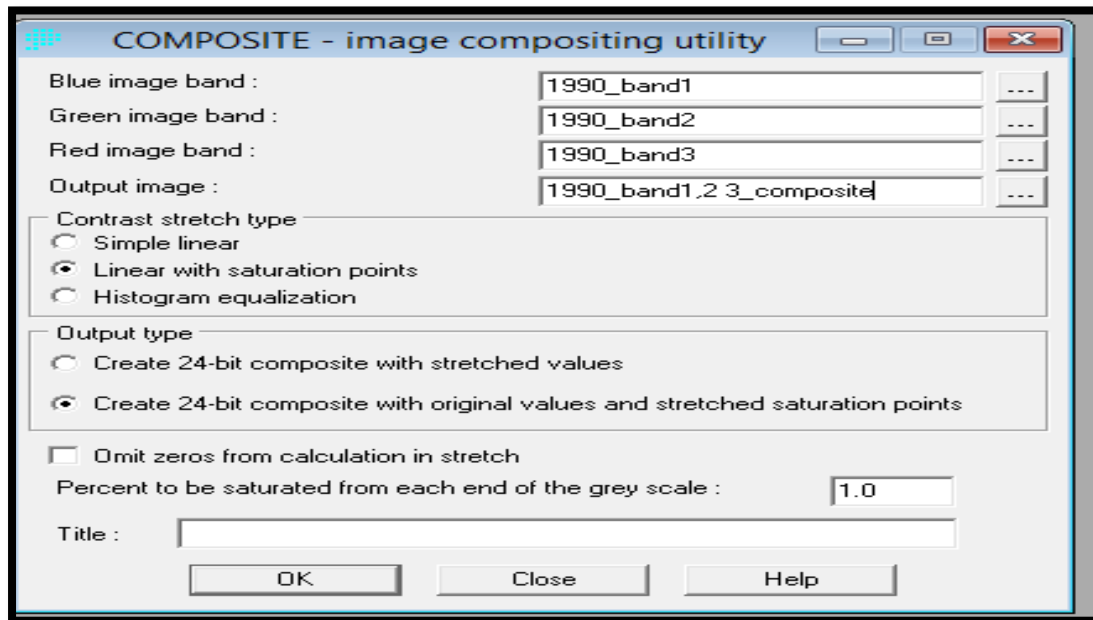
APENDIX I: IMAGE CONVERSION FROM GEOTIFF/TIFF_TO_IDRISI FORMAT.

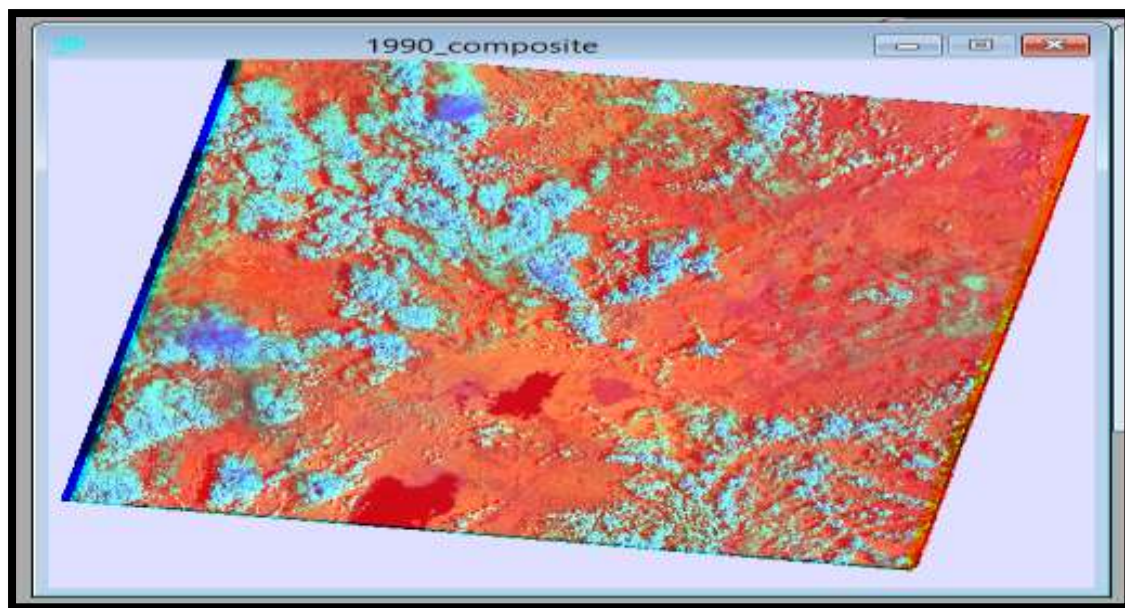


APENDIX II: IMAGE ENHANCEMENT BEFORE USED FOR ANALYSIS

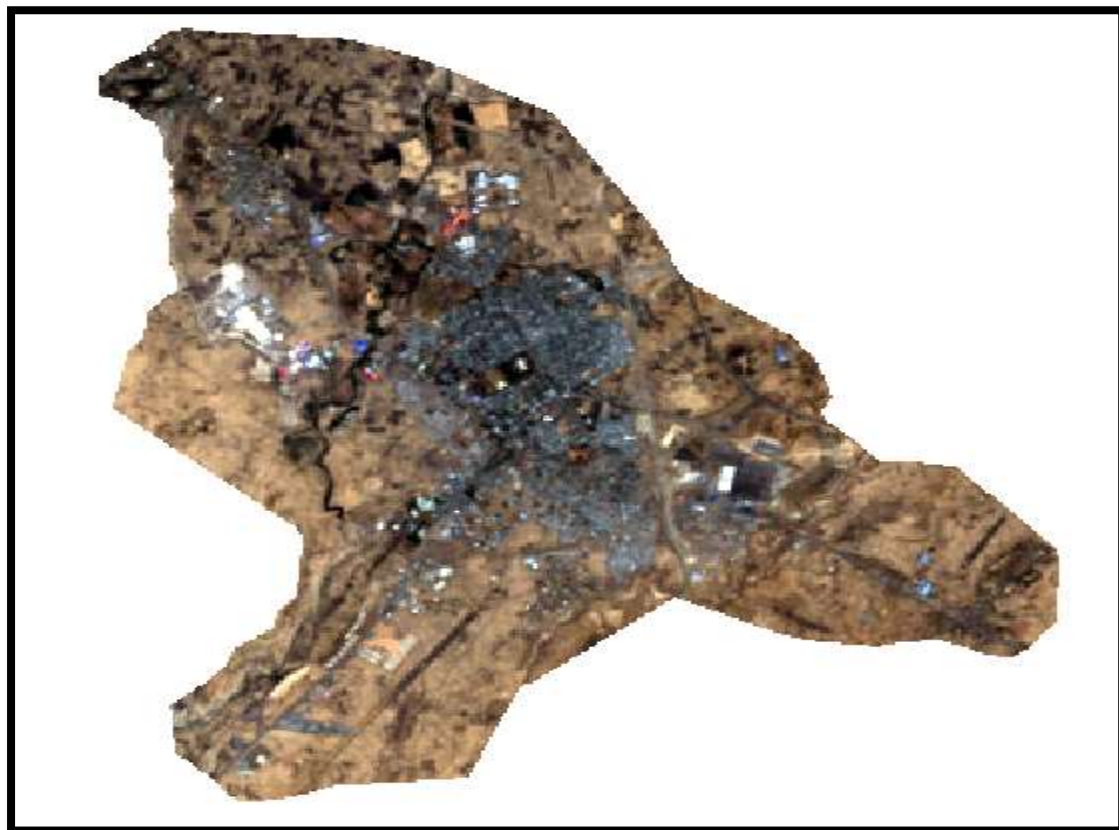
1.BAND COMPOSITION USING DIFFERENT BAND ORDER

OPTION OF COMPOSING IMAGE





False composite of the whole image of 1990 land sat.

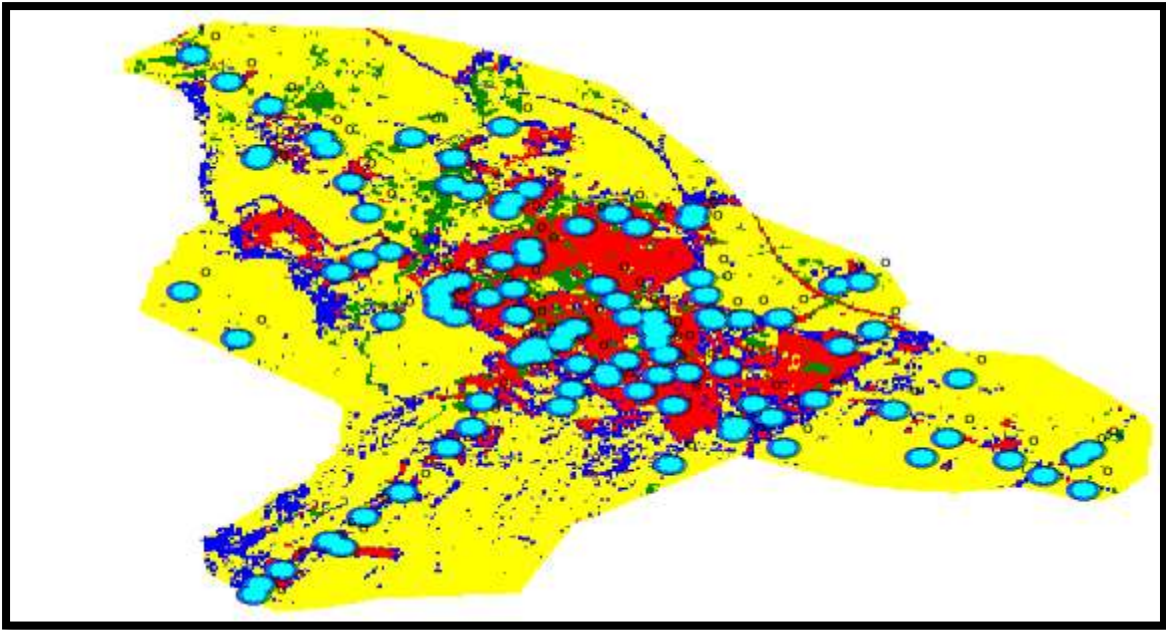


True composite of study area prepared for classification land sat of 2010.

Appendix III: Sample Ground control point collected for accuracy assessment and classification from field and Google earth.

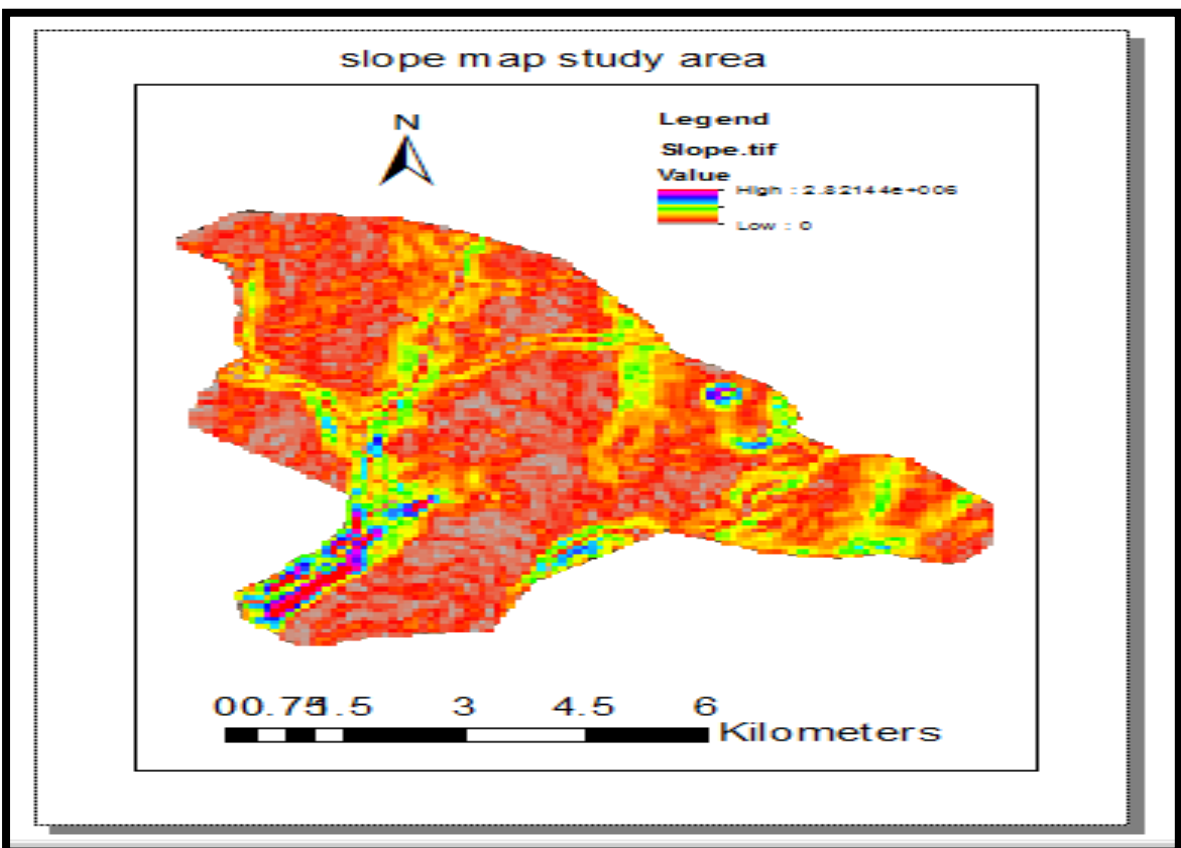
ID	POINT_X	POINT_Y	Description	ID	POINT_X	POINT_Y	DESCRIPTION
1	510015.4496	953719.0926	Agriculture	21	513324.8	950587.4	Built_up area
2	510364.5369	953289.7469	Agriculture	22	513075.7	950358.1	Agriculture
3	510768.5634	952887.6871	Agriculture	23	513352.5	950430.3	Built_up area
4	511273.8932	952347.2046	Built-up area	24	511751	951145.6	Barren land
5	511346.8745	952198.3499	Built-up area	25	511967.5	950518.9	Agriculture
6	510687.4917	952099.8674	Barren land	26	511707.8	950378.2	Agriculture
7	510652.0802	952018.8456	Agriculture	27	511451.7	950179.1	Built_up area
8	511567.7545	951639.7892	Built-up area	28	512631.9	950033	Built_up area
9	512187.4749	952366.5259	Agriculture	29	512509.6	949965	Barren land
10	512602.0357	952039.7531	Barren land	30	512438.2	949857.4	Agriculture
11	512784.5558	951501.0141	Agriculture	31	512469.6	949708.8	Agriculture
12	512569.8513	951599.3297	Built-up area	32	512457.6	949568.4	Agriculture
13	513350.5613	951517.3069	Built-up area	33	512609.2	949439.1	Agriculture
14	513180.0792	951341.3741	Built-up area	34	512933.2	949764.3	Built_up area
15	513120.0787	951189.1145	Agriculture	35	513189.8	949899.5	Barren land
16	514205.7063	951120.8657	Built-up area	36	513236.1	949476	Built_up area
17	513842.7091	950930.857	Built-up area	37	513238.7	949463.8	Barren land
18	514423.7846	950905.4215	Built_up area	38	511938.3	949376.7	Barren land
19	514981.4264	951146.1577	Barren land	39	513266.6	948792.6	Built_up area
20	514950.5993	951024.6494	Built_up area	40	513308.5	948840.5	Built_up area
21	513324.8199	950587.3987	Built_up area	41	513329.4	948872.4	Vegetation
22	513075.6973	950358.0777	Agriculture	42	513374.9	948917.8	Vegetation
23	513352.4514	950430.3388	Built_up area	43	513413.7	948969.7	Agriculture
24	511750.9755	951145.5809	Barren land	44	513452.5	948823.2	Vegetation
25	511967.4954	950518.9416	Agriculture	45	513642.6	949021	Built_up area
26	511707.7721	950378.2426	Agriculture	46	513704.6	949183.2	Built_up area
27	511451.6942	950179.0801	Built_up area	47	513808.9	949273.8	Vegetation

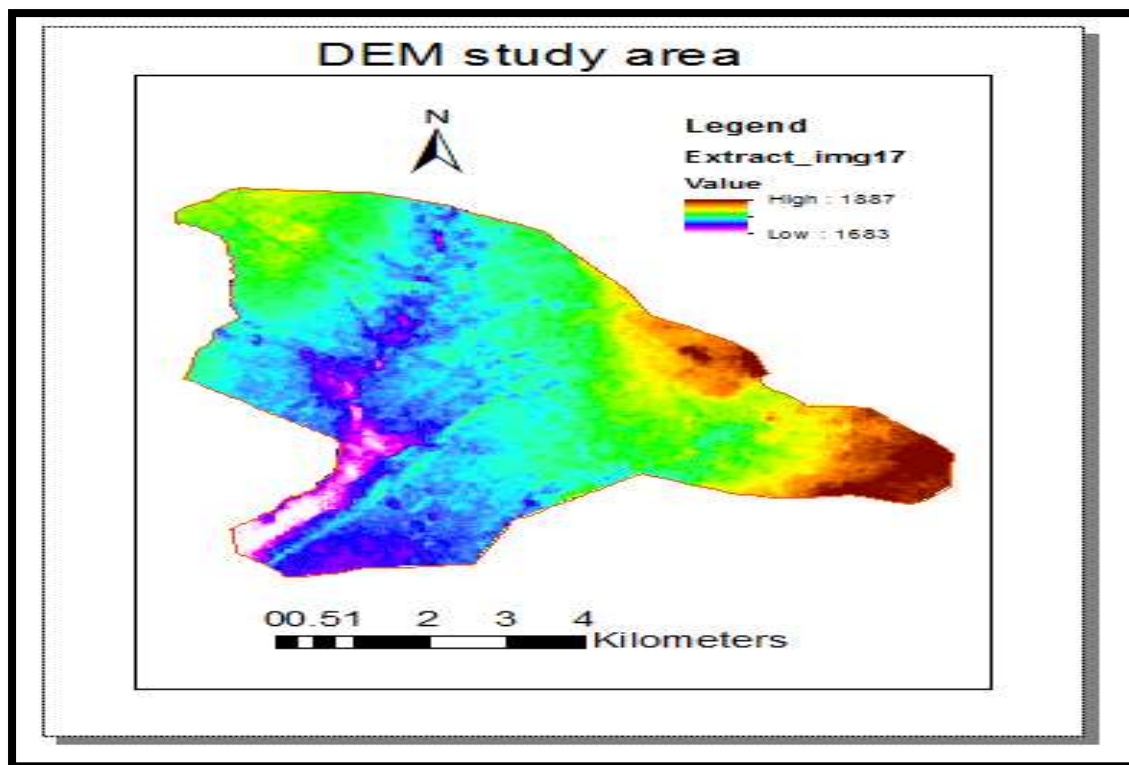
ID	POINT_X	POINT_Y	DESCRIPTION	ID	POINT_X	POINT_Y	DESCRIPTION
48	514338.8178	949443.8413	Agriculture	77	513764.5	948263.4	Agriculture
49	514572.7913	949424.0967	Vegetation	78	514448.2	948227.8	Built_up area
50	514581.3488	949234.6905	Agriculture	79	514769.1	948000	Built_up area
51	514645.0389	949231.7867	Built_up area	80	515373.5	947680.1	Barren land
52	514599.775	949049.5521	Agriculture	81	515414.4	947650.4	Agriculture
53	514221.7561	949702.7385	Built_up area	82	515374.7	947556.3	Agriculture
54	514061.8961	949966.4952	Vegetation	83	515869.6	947310.8	Agriculture
55	515087.4421	949791.8728	Barren land	84	517235.5	947154.7	Agriculture
56	515043.1823	950072.8633	Barren land	85	517489.5	947458.7	Agriculture
57	515136.7709	949447.1499	Barren land	86	516948.3	947913	Agriculture
58	515180.6034	949392.4111	Built_up area	87	518107.1	947098	Barren land
59	515445.9667	949404.9771	Barren land	88	518781.6	947147.4	Agriculture
60	516382.3126	949956.0839	Agriculture	89	518899.6	947272.4	Agriculture
61	516641.4637	950012.6583	Agriculture	90	518442.4	946855.9	Agriculture
62	513096.0726	952547.6913	Agriculture	91	518837.9	946617.4	Agriculture
63	515834.8121	949429.2829	Agriculture	92	517603.4	948442	Agriculture
64	516447.8246	948965.5814	Agriculture	93	514736.1	947017.4	Barren land
65	516751.7403	949221.1055	Agriculture	94	513667.2	947986	Barren land
66	515293.8152	948616.6064	Built_up area	95	512875	948062.7	Barren land
67	515561.3867	948022.7188	Barren land	96	512779.3	947645	Barren land
68	515748.8615	947804.6891	Built_up area	97	512536.8	947300.9	Barren land
69	516174.6666	948104.5124	Built_up area	98	512088.6	946571.3	Barren land
70	514918.272	948540.2527	Built_up area	99	511706.8	946184.5	Barren land
71	514633.7979	948486.2494	Built_up area	100	511372	945769.8	Built_up area
72	514705.1223	948819.7455	Built_up area	101	511487.5	945676.6	Built_up area
73	514296.7811	948729.7661	Built_up area	102	510894.5	945300.8	Barren land
74	514107.3741	948532.5277	Built_up area	103	510675.9	945059.1	Built_up area
75	514124.7098	948456.0829	Barren land	104	510610.8	944913.2	Agriculture
76	513852.2776	948671.4512	Barren land	105	510468.3	949095.6	Agriculture
77	513764.4932	948263.442	Agriculture	106	509925.5	949863.9	Agriculture



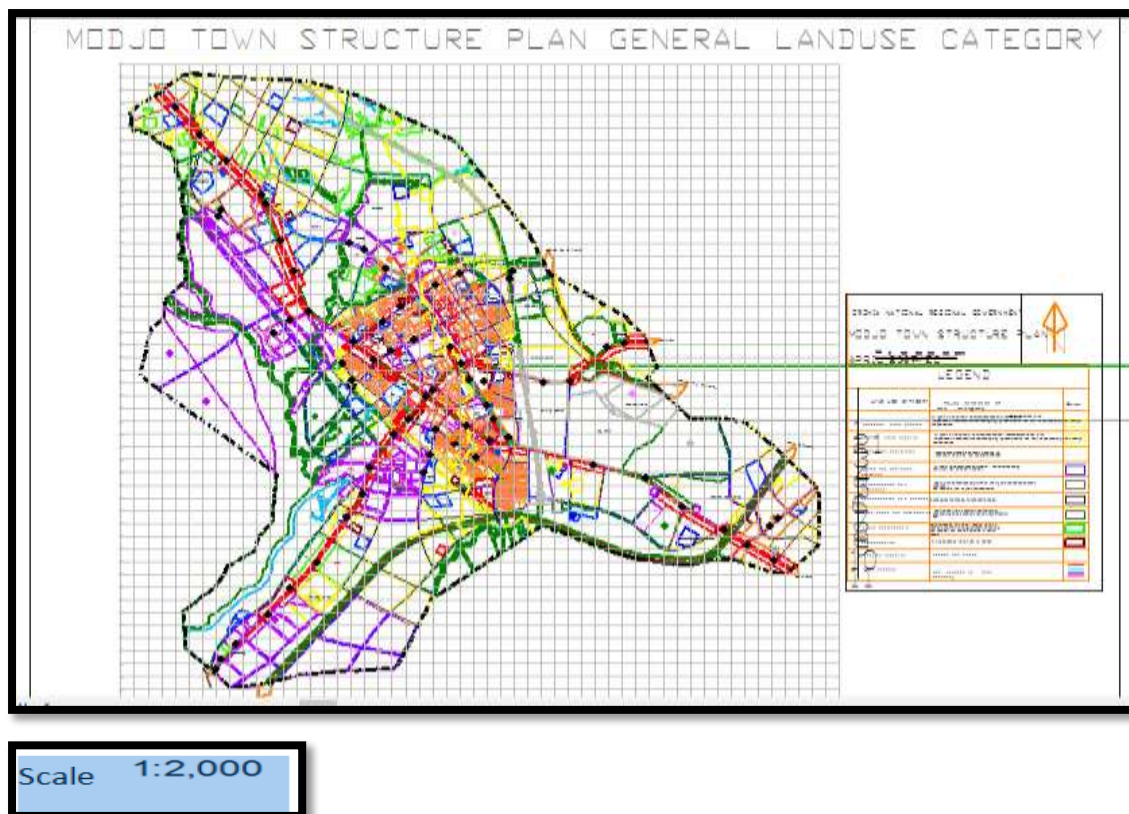
Randomly Selected Point data added for accuracy assessment on ACRGIS ENVIRONMENT for classified land sat 2019.

APPENDIX IV: SLOPE STUDY AREA, DEM AND STRUCTURAL PLAN





MODJO TOWN STRUCTURAL PLAN GENERAL LAND USE CATEGORY 2007.



APPENDIX V: Projected vs. actual/classified land use land cover 2019 obtained using LCM model

LULC classes	Projected 2019 LULC	Difference	Actual 2019 LULC
Built-up area	832.33	9.62	841.95
Agriculture	3516.41	12.35	3504.06
Vegetation	278.32	6.7	271.62
Barren land	655.04	9.43	664.47

LULC CLASSES	LULC 2030	2040	2050
Built-up area	1556.1	1731.6	1840.5
Agriculture	2523.1	2242.31	2004.61
Vegetation	377.64	397.44	411.84
Barren land	825.26	910.75	1025.15