# SPATIO-TEMPORAL URBAN GROWTH ANALYSIS AND MODELING USING THE CA-ANN MODEL: A CASE OF SHASHAMENE CITY, ETHIOPIA

Musa Gemeda Takasa

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

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

Office of Graduate Studies
Adama Science and Technology University

February, 2023
Adama, Ethiopia

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## Declaration

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

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## Recommendation

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled " Spatio-Temporal Urban Growth Analysis and Modeling Using the CA-ANN Model: A Case of Shashamene City, Ethiopia", prepared under my guidance by Musa Gemeda Takasa submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Geoinformatics Engineering Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

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**Approval Sheet**

I, the advisor of this thesis entitled, “Spatio-Temporal Urban Growth Analysis and Modeling Using the CA-ANN Model: A Case of Shashamene City, Ethiopia” and developed by Musa Gemeda Takasa, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Examiners of the thesis by Musa Gemeda have read and evaluated the thesis entitled “Spatio-Temporal Urban Growth Analysis And Modeling Using The CA-ANN Model: A Case Of Shashamene City, Ethiopia” and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geoinformatics Engineering.

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

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## THE LIST OF ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| ANN | Artificial Neural Network |
| CA | Cellular Automata |
| ERDAS | Earth Resource Data Analysis System |
| ETM | Enhanced Thematic Mapper |
| ENVI | Environment for Visualization of Image |
| FAO | Food and Agriculture Organization |
| GIS | Geographical Information System |
| GPS | Global Positioning System |
| LULC | Land Use and Land Cover |
| LPI | Largest Patch Index |
| MOLUSCE | Module Of Land Use Land Cover |
| NP | Number Of Patch |
| OA | Overall Accuracy |
| OK | Overall Kappa |
| PD | Patch Density |
| PLAND | Percentage Of Landscape |
| PA | Producer Accuracy |
| QGIS | Quantum Geographical Information System |
| SHDI | Shannon Diversity Index |
| SHEI | Shannon Evenness Index |
| SVM | Support Vector Machine |
| TM | Thematic Mapper |
| USGS | United States Geological Survey |
| UTM | Universal Transverse Mercator |
| UA | User Accuracy |
| WHO | World Health Organization |

## *ABSTRACT*

*Urbanization is a global trend with significant environmental effects, urging a clear policy at all levels. Analyzing the dynamics of urban growth on both spatial and temporal scales has been recognized as a critical step in understanding the consequences of urbanization and developing long-term planning strategies. In this study, Shashemene City, one of the rapidly growing cities in Ethiopia, is considered to analyze it's spatiotemporal growth from 1991 to 2021.Through supervised image classification using the support vector machine algorithm, LULC maps of the study area in 1991, 2006, 2013, and 2021 were prepared, and the spatiotemporal changes of LULC were investigated. Selected spatial metrics (number of patches, patch density, largest path index, class area, perimeter area fractional dimension) were used to examine the dynamics of landscape structure in the study area over time. The urban area of the city experienced a fragmented urban growth process. In order to simulate the spatiotemporal change transition potential and future LULC simulation in the Shashemene city, the five driving criteria, such as DEM, slope, aspect, distance from the road, and distance from the river, were integrated with CA-ANN technique within the MOLUSCE plugin of QGIS. The CA-ANN was then used to forecast changes in LULC for the years 2031 and 2041. The simulation result shows that almost 6900 ha of the total land was in the built up category of land use during 2021 and it would be further increased to 11191 ha in 2041. The Agricultural and vegetation area would be decreased for the next twenty years. This study would support planners and stakeholders to plan a new direction before negative outcomes become irreversible. The formulation of urban planning policies should also aim to create a balance between the sustainable use of limited resources and socio-economic needs.*

***Keyword****; spatial metrics, LULC, Urban growth, MOLUSCE.*

# CHAPTER I: INTRODUCTION

## 1.1. Background of the Study

Today, some 55% of the world's population 4.2 billion inhabitants live in cities. This trend is expected to continue. By 2050, with the urban population more than doubling its current size, nearly 7 of 10 people in the world will live in cities (World Bank, 2020).According to the World Urbanization report (2020), the level of urbanization in Africa is low (43.5%) when compared with developed countries like Europe (74.9%) and North America (83.6%). The urban population in Ethiopia is increasing rapidly. This is resulting in deterioration of infrastructure facilities, loss of agricultural lands, water bodies, open spaces, and diminution of ground water aquifer zones, water contamination, air pollution, health hazards and many micro-climatic changes.

Urban environment belongs to one of the most dynamic systems on the earth surface due to the heterogeneous nature of urban land uses. The major consequence of this nature of urban land use dynamics is rapid Land use Land cover Changes. One the critical concern of the world today is on land use/land cover changes because of the adverse consequences they have on weather and climate, surface run-off in relation to erosion and flooding, ecological biodiversity, socio-economic and health and the general state of environmental degradation. This is largely because land surface has considerable control on biophysical, biogeophysical, biogeochemical, hydro meteorological, processes (Srivastava, 2013).

Remote Sensing (RS) and Geographic Information System (GIS) are essential tools in obtaining accurate and timely spatial data of LU dynamics, as well as analyzing the changes in a study area (Pervez et al, 2016; Srivastava et al, 2013). RS and GIS approaches make it possible to effectively monitor and forecast the trends in LULC changes via the study of historical remotely sensed imagery. This could offer a foundation for systematic and effective land use planning, management and ecological restoration for socioeconomic development (Liping et al, 2018).

Several methods for urban dynamics study were widely available in literature. These methods differ based on purposes, methodologies, geographic areas of the analysis, assumptions and both the source and type of data employed (Michetti & Zampieri, 2014). Transition matrix has been widely used for in-depth analysis of land cover dynamics via the elements of gross gain, gross loss, vulnerability to gain/loss, net change, swap change and persistence area (Mincey et al, 2013).

Urban landscape structure is a complex variety of biological and physical patches within a matrix of infrastructure, human organizations, and social institutions characterized by composition and configuration (Tewolde & Cabral, 2011). Urban landscapes structure become increasingly disaggregated and complex with human invasion over time (McGarigal & Marks, 2015). According to (Zippered et al, 2000), understanding the change of patterns, processes and their interactions in heterogeneous Landscapes will help to accurately quantify the LULC pattern of the Landscape and its temporal dynamics. Spatial metrics provides configuration and composition of LULC.

The spatial patterns of landscape transformation over time are certainly related to changes in land use and land cover. Different regional regulations, intensifying agriculture, and urbanization all have an impact on the changing landscape(Ramachandra et al., 2012;Bharath et al., 2012).Temporal LULC studies using spatial metrics are helpful to quantify the spatial patterns of landscape dynamics and urbanization, which helps to understand the urban phenomena through properties like patch shape, contagion, epoch, edge, etc. This offers insightful information about the innate spatial structure across time and growth patterns. The modern urban environment can be described as dynamic and versatile. Landscape metrics are commonly used tools in the field of landscape ecology to understand landscape characteristics (pattern and structure), changes in landscape and complexity of landscape structure. Landscapes are dynamic systems, which are changing continuously due to increasing human interactions. In addition, in landscape metrics, landscape structure and changes are evaluated using different quantitative indices that are calculated based on shape, size, pattern and extent of landscape.

Modeling LULC change is becoming more important (Herold et al., 2010) as there will be time to address anticipated changes at various spatial and temporal scale (Daye & Healey, 2015) . Cellular Automata (Islam, 2018). Artificial Neural Network (ANN) (Schneider & Pontius, 2001), are used to model for the prediction and simulation of future LULC using MOLUSCE plugin in QGIS.

Numerous social, cultural, economic and political incentives have encouraged urban expansion as well as population growth. With the increased urban population, most of the land use changes have been dramatically changed in Shashemene city. Shashemene city is one of the fast growing city in Ethiopia and facing with urbanization problems. With the urbanization going on at a very fast, demand for land is very strong in the city. The land use/land cover change of a region is an outcome of natural and socio–economic factors and their utilization by man in time and space.

Information on LULC assists in monitoring the dynamics of land use resulting out of changing demands of increasing population and monitoring environmental changes. It is possible to quantify the LULC pattern of the landscape and its temporal dynamics by analyzing the urban landscape and structure and by comprehending how patterns, processes, and their interconnections change. Modeling and projecting land use land cover gives crucial information about urban dynamics, assisting planners and stakeholders in making decisions.

### 1.2. Statement of the Problem

Rapid urbanization, in the world is quite alarming (UNFPA, 2007), especially in developing countries. It has led to serious land use problems such as loss of agricultural land, unauthorized urban sprawl, high land values, speculation in land, and other related problems. The extent of urbanization or its growth is one phenomenon that drives the changes in land use pattern (Suraj, 2014).

Rapid urbanization, brought serious losses of agricultural land, forest land and water bodies. Urban growth, particularly the movement of residential and commercial land to rural areas at the edge of city areas, has long been considered a sign of regional economic vitality. However, its benefits is increasingly balanced against ecosystem impacts, including degradation of air and water quality and loss of farmland and forests, and socioeconomic effects of economic disparities, social fragmentation and infrastructure costs (Squires, 2002; Yuan et al., 2005). Because of the effects of the city's continual growth and expansion, productive farmlands and the farming population in the neighbor hoods and rural populations dwelling in the outlying areas have been subjected to increased eviction, and those living in the city have faced several problems. Unprecedented urbanization leads to rapid urban expansion, which can be harmful if not managed properly. The rapid growth of the city's population has put significant influence on the need for urban spaces, and the sprawl of the built-up region has drawn attention to the city being used as a case study.

Some studies have been attempted to analyze urban growth and its response to the landscape. For instance, (Sinha &Ayele, 2016) quantified the urban growth of Adama city using Landsat images from 1984 to 2015 and reported that the built-up area of the city increased rapidly. (Woldegerima &Yeshitela , 2017) characterized the urban structure of Addis Ababa through urban morphology types and reported that the rapid urban expansion had occurred in the green space. Getu & Bhat (2021) tried to assess and monitor the spatiotemporal dynamics of urban sprawl and its growth pattern in Bahir Dar and stated that the built-up area increased at the expanse of cropland and forest and existence of sprawl with high dispersion. Previous studies in shashemene city focused on urban sprawls. Gemeda, et al, (2019) studied the role of land speculators around the urban edge. Kemal,(2021) studied spatio-temporal urban pattern and growth .however, modeling of urban growth provides better understanding of causes and mechanisms governing urban growth and analyze to alternative urban growth consequences. The methods such as CA-Markov and Logistic Regression were primarily the focus of earlier studies for modeling the LULC dynamics but this study mainly based on the CA-ANN model via MOLUSCE plugin available in QGIS, which was not done in shashemene city and several Ethiopian city.

This study is significant because it gives vital information on urban growth, urban growth modeling and prediction for a complete local and regional environment change and sustainable development. It is also helpful for planners and stakeholders for decision-making. This research has an important role in filling the gap related to effect of urban dynamics in Shashemene city by analyzing urban growth dynamics from 1991-2021 years by using multydate remote sensing data and future predicting for 2031 and 2041 years using CA-ANN model via MOLUSCE plugin in QGIS and examine the urban landscape structure using landscape metrics. This research specifically addresses, analyzing the changes in LULC in the study area from 1991 to 2021, examine the urban landscape structure in the study area from 1991 to 2021 and predict future urban growth in the study area.

## 1.3. Objectives

### 1.3.1. General Objective

The general objective of this study is to analyze the spatiotemporal dynamics of urban growth in Shashemene City from 1991 to 2021 and predict its possible expansion up to 2041 using integrated CA-ANN model and MOLUSCE plugin in QGIS.

### 1.3.2. Specific Objectives

The specific objectives are to;

- analyze the changes in LULC in the study area from 1991 to 2021.
- examine the urban landscape structure in the study area from 1991 to 2021.
- predict future urban growth dynamics in the study area from 2031 to 2041.

## 1.4. Research Questions

This study answered some of the important research questions regarding the trend of LULC of shashemene city. The research questions are;

1. How has been LULC of Shashemene city changed from 1991- 2021 years?
2. What is the dynamics of urban landscape structure in shashemene city between 1991 and 2021?
3. What will be the future extent of the predicted LULC of shashemene city from 2021-2041?

## 1.5. Significance of the Study

This research will have significant in that;

- the expected results of this research may help urban planners and policy makers in building and adopting the planning and promoting better decision-making.
- the results will provide an analyzing method for other city and make it possible in comparing with them
- this study is to analyze the spatiotemporal urban and predict its possible expansion ,hence it offers vital information for comprehensive countrywide and local environment change and sustainable development, and useful for planning and management for decision-makers.

## 1.6. Scope of the Study

The scope of this study was to analyze the spatiotemporal dynamics of urban growth in Shashemene City from for the last thirty years and the future urban growth is modeled using the geospatial technology and CA-ANN model for the year 2041, Because of available time, resources and in order to make the study more detail manageable the scope of the study was limited to only shashemene city.

## 1.7. Limitation of the Study

This study has following limitations: data quality like Lack of high-resolution satellite data. In addition to this, there is no Empirical study on urban growth modeling for the study area (published).

## 1.8. Organization of the Study

The study has organized in to five chapters. The first chapter contains brief description of introduction. The second chapter deals with literature review and addresses the relevant literature that was associated with the study. The third chapter has described the materials and methods. The fourth chapter was concerned with results and discussion of the study. Finally, the fifth chapter covers the conclusion and recommendations.

# CHAPTER II: LITERATURE REVIEW

## 2.1. Introduction

This chapter reviews the literature regarding urbanization and urban growth, land-use/land cover changes, advances in remote sensing technology in analyzing urban growth, classification methods, geospatial tools, and their application in monitoring urban growth patterns and driving factors of urban growth and urban modeling techniques. After that, the related methods in the analysis and modeling urban growths also assessed.

## 2.2 Urbanization, Urban Expansion and urban growths

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). Urbanization is simply defined as "the movement of people from rural to urban areas with population growth equating to urban migration" (United Nation, 2005). Urbanization is also a social process, which involves the changes of behavior and social relationships as a result of people living in urban area (Bhatta, 2010). Nowadays however, urbanization is commonly used in more broad sense and it refers to much more than simple urban population growth; it involves the physical growth of urban areas as well as the changes in the socioeconomic and political structure of a region as a result of population immigration to an urban area (Deng, 2015).

The process of urban growth can be described as either a change in the area of urban (a measure of extent) or the pace at which non- urban land is converted to urban uses (a measure of rate) (Seto & Fragkias, 2005).

Urban growth is a spatial and demographic process that refers to the increased importance of towns and cities as a concentration of people within a particular economy and society (Bhatta et al., 2010). Three urban growth types. Infilling growth which occurs within urbanized open space and increases contiguity of built-up area by filling in that space; Edge expansion which refers to non-infill development intersecting the urban footprint and extending outward from previous development; and Spontaneous growth which neither intersects the urban footprint nor is contiguous with previously developed areas and has greatest effect on fragmentation of open lands.

### 2.3. Urban Land use/Land Cover Dynamics

Land cover change refers to the conversion of one land cover category to a new cover category or modification of one land cover category. Whereas, land-use change refers to a conversion of land use due to human activities for different purposes such as for settlement, infrastructural development, agriculture, and recreational use. Another definition of LULC change is the human modification and conversion of the earth‘s terrestrial surface. Modification happens when the change affects only the properties of the land cover without causing a complete shift from one LULC category to the other or completely replaced by another (Meyfroidt & Lambin, 2013).Land-use change is not static in nature but dynamic with a cause-response behavior involving multiple variables. A parcel of land may change from one category of land-use to another, depending on multiple variables. (Zhang, 2009)

### 2.4. Causes of Land Use-Land Cover Change

Land use-land cover changes were caused by multiple interacting factors and these causes vary in time and space according to specific humans' environmental conditions. Although LULC changes are the result of human influences, biophysical drivers, and natural processes (Lambin &Geist, 2008). The drivers noted above were also confirmed as common phenomenon in the whole of Ethiopia (Sishaw, 2018).

### 2.5. Trends of Urbanization

#### 2.5.1. The speed of urbanization around the world

In recent decades, the world has been urbanizing rapidly. In 1950, only 30 percent of the world's population lived in urban areas, a proportion that grew to 55% by 2018. The global urbanization rate masks important differences in urbanization levels across geographic regions. Northern America is the most urbanized region, with 82% of its population residing in urban areas, whereas Asia is approximately 50 percent urban, and Africa remains mostly rural with 43 % of its population living in urban areas in 2018 (United Nations, 2018).

#### 2.5.2. Urbanization in Africa

Africa is projected to have the fastest urban growth rate in the world: by 2050, Africa's cities will be home to an additional 950 million people. Urban planning and management are therefore key development issues. Understanding urbanization, its drivers, dynamics and impacts is essential for designing targeted, inclusive and forward-looking policies at local, national and continental levels.(OECD/SWAC ,2020).The current rates of urbanization in

Africa, exceeding 4% to 5 % per annum in most countries, are close to those of western cities at the end of the nineteenth century (UN-habitat, 2005).

### 2.5.3. Urbanization in Ethiopia

Like most African countries, in Ethiopia large-scale urbanization is fairly a recent phenomenon. However, the history of town dwelling in the country extends back to the Axumite Kingdoms of fourth century. The urban population in Ethiopia is increasing rapidly. Estimated at only 17.3 percent in 2012, Ethiopia's urban population share is one of the lowest in the world, well below the Sub-Saharan Africa average of 37 percent. However, this is set to change dramatically. According to official figures from the Ethiopian Central Statistics Agency, the urban population is projected to nearly triple from 15.2 million in 2012 to 42.3 million in 2037, growing at 3.8 % a year. Analysis for this report indicates that the rate of urbanization will be even faster, at about 5.4 percent a year. That would mean a tripling of the urban population even earlier by 2034, with 30 percent of the country's people in urban areas by 2028.

## 2.6. Application of Geospatial technology on urban land use dynamics

### 2.6.1 Use of Remote Sensing and GIS for Land use Land cover Change

Remote sensing and GIS are being increasingly used in combination spatial analysis. GIS databases are used to improve the extraction of relevant information from remote sensing imagery, whereas remote sensing data provide periodic pictures of geometric and thematic characteristics of terrain objects, improving our ability to detect changes and update GIS databases. Both remote sensing (RS) and geographic information systems (GIS) have been widely applied and recognized as powerful and effective tools in detecting the spatiotemporal dynamics of land use and land cover (LULC). Remote sensing can provide researchers with valuable multi temporal data for monitoring land-use patterns and processes and GIS techniques make possible the analysis and mapping of these patterns (Netsanet, 2007).The information derived from remote sensing can help describe and model the urban environment, leading to an improved understanding that benefits applied urban planning and management (Longley & Mesev, 2000; Longley et al., 2001).

### 2.6.2. Image Pre-processing

Preprocessing function involves operations that are normally required before data analysis and extraction of data. These are grouped into radiometric and geometric corrections. Radiometric correction includes correcting the data for sensor irregularities and unwanted sensor or atmospheric noise (Dadras et al., 2014) while geometric correction algorithms conduct the correction sequentially and use the ground control points in higher-level processing.

### 2.6.3. 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). Each image was classified into a set of spectral classes using the Support Vector Machine (SVM) algorithm in ENVI software. SVM is a non-parametric classifier. Unlike parametric classifiers such as maximum likelihood, which assumes that the data is normally distributed, non-parametric classifiers do not base classification on a normality assumption or statistical parameters (Bulti, 2019). Training samples for each class were collected from each image. Because highly heterogeneous land covers data (e.g., urban areas) are unlikely normally distributed; the distribution of land cover surfaces is associated with various uncertainties that 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. There are various image classification methods that can be applied to extract land cover information from remotely sensed images (Lu & Weng, 2007). Support vector machine and maximum likelihood are example of supervised classification.

### 2. 6.4.Post Classification Techniques

The process by which variation in an object at different times or changes that occur in LULC are checked and identified over a certain number of years is known as change detection (Duda et al., 2001; Tewolde & Cabral, 2011). The post-classification technique is one of the best types of change detection, which involves the independent production, and subsequent comparison of spectral classifications for the same area at two different time's .Tewolde & Cabral. (2011), detected LULC changes using spatiotemporal data.

### 2.6.5. Accuracy Assessment

Accuracy assessment methods evaluate the performance of classifiers (Huang et al., 2010). This was done through a comparison of kappa coefficients and the computation of overall accuracy assessment through a confusion matrix. Accuracy assessment and Kappa coefficient are common measurements used to determine the efficiency of the classification of images (Belay et al., 2019). A couple of methods that quantitatively evaluate separability of training areas are in use.

### 2.6.6. Land use Change Detection Analysis

The main objective of change detection is to compare spatial representation of two points in time frame by controlling all the variances due to differences in non-target variables and to quantify the changes due to differences in the variables of interest (Lu et al, 2004). 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.

## 2.7. Processes of urban land change

### 2.7.1. Urban expansion

According to (Eshetu, 2018) the process of urban expansion was listed as under. Annual average rate of change (AARC), Annual average urban expansion intensity index (UEII) & urban expansion types (UET).

### 2.7.2. Urban land transition matrix

Analyzing the expansion of urban area to different cover types and its conversion to others is important for change detection and is of interest to land use manager for sustainable planning. This is quantified from the transition matrix as. Gross gain, Gross loss &Net change that was obtained by cross-tabulating land cover statistics of different years (Pontius et al. 2004).

## 2.8. FRAGSTATS Analysis

### 2.8.1. Urban landscape metrics

Urban landscape configuration was quantified using selected landscape metrics as these methods are the most popular easily comparable result (Uuemaa et al. 2013).Also, they show the pattern that would not be clear for visual interpretation (Shrestha et al. 2012). The use of several landscape metrics is vital for a better understanding of land cover pattern (Neel et al. 2004) instead of using few and less interpretative indices (Li &Wu 2004). Landscape metrics are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics (Huang et al., 2009).

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

Class level, which uses data of the patches that belong to the same land-use type. Class indices individually quantify the quantity and spatial configuration of each patch type and thus provide a means to quantify the level and fragmentation of each patch type in the landscape (Garical, 2012).

Landscape-level data defines the entire landscape, encompassing the entire scope of the data. The mosaic pattern of the landscape, as well as the spatial characteristics and patch distribution, are of particular significance (Garigal, 2012). Because they quantify the entire landscape pattern, landscape metrics can also be understood as landscape heterogeneity indices. Landscape metrics can be divided into two broad categories: those that quantify the composition of the map without reference to spatial qualities, and those that quantify the spatial arrangement of the map and need spatial information to calculate them (Gustafson, 1998; Garigal & Marks, 1995).Without taking into account the spatial character, positioning, or location of patches, the composition is categorically measured and refers to attributes connected to the variety and abundance of patch types within the landscape.

Choosing metrics involves a number of considerations. Firstly, the objectives of the study, spatial characteristics of the system and ecological processes under investigation determine which metrics to use (Garigal& Marks, 2015). Secondly, landscape metrics were chosen based on the literature review. Similarly, (Garigal, 2015) studied in Quantifying land use/land cover spatio-temporal and landscape pattern dynamics from Hyperion using SVMs classifier and FRAGSTATS in central Greece covering between 2001 and 2009.

### 2.9. Land use Change Modeling

Land is utilized for multiple purposes and it is critical that land cover change be monitored and modeled to analysis changes. A number of land use land cover models have been developed (Wu & Webster 2000; Chang, 2006). Among the numbers of land use modeling tools and techniques the commonly used models are Land Change Modeler (LCM), Cellular Automata (Sinha et al., 2015),markov Chain Analysis (MCA) or Markov Model (Sivakumar, 2014), Cellular Automata-Markov Model (CA-Markov) (Subedi et al., 2013) and Artificial Neural Network (ANN) (Schneider& Pontius, 2001), CA operates on a grid based cells and transition rules that are applied to determine the state of a cell. Whereas, Markov Chain analyzes two qualitative land cover images from different dates and produces a transition matrix, a transition areas matrix, and a set of conditional probability images (Thomas & Laurence, 2006).The CA-Markov is a combination of both CA and Markov chain. These two are termed as the geosimulation techniques used to produce land use predictions (Sunet.et al, 2007).

ANN is a machine-learning technique which is capable of capturing non-linear relationships among different land use transformations through formulating the relationships between input and output variables (Azari et al., 2016) ANN is also known as Multi-Layer Perceptron (MLP) that undertakes the classification of remotely sensed imagery through a Multi-Layer Perceptron neural network classifier using the Back Propagation (BP) algorithm. The driver variables were inserted as the independent variables and land use change image as the dependent variable. The explanatory power of driver variables is tested using Pearson correlation value.

CA is the most widely used urban growth modeling approach due mainly to its flexibility, visualization, and capability to integrate spatial and temporal processes and simulate complex dynamic systems .In addition, CA models can directly use raster data and this allows easy integration with remote sensing and GIS technologies.

CA-ANN Model; CA-ANN model is a nonlinear tool that has been applied successfully in LULC modelling and prediction (Mahajan.et al, 2009). Cellular Automata (CA) consist of a simulation environment (gridded cells) in which the new state is determined based on its previous state and that of its immediate neighbors according to specific transition rule (Khalid.et al, 2013). Artificial Neural Network (ANN) is a system, which consist the piece of a computing system used to simulate the way the human brain analyzes and processes information (Ujjwalkaran, 2016). The main reason to integrate the CA with ANN is; CA has open space model so can be easily integrated but dependent on spatial data and not appropriate to make a realistic simulation whereas ANN can detect potential interdependencies through the implied driving forces. Thus, to get effective modelling and simulation result the both models are combined; CA and ANN (Gharaibeh et al, 2020).

MOLUSCE stands for Modules for Land Use Change Evaluation. This plugin is used to analyze the model and simulate land use changes in QGIS. MOLUSCE incorporates well-known algorithms, which can be used in land use/ land cover change analysis as well as forestry applications. MOLUSCE (Modules of Land Use Change Evaluation), a new QGIS plugin that can estimate potential LULC changes, is built with the CA model and includes a transition probability matrix used by most researchers (NEXTgis 2017). Four well-known algorithm models are employed in this plugin: Multilayer Perceptron-Artificial Neural

Networks (MLP-ANN), Logistic Regression (LR), Multi-Criteria Evaluation (MCE), and Weights of Evidence.

### 2.10 Empirical Literature Review.

Different researchers have conducted research on land use land cover classifications and urban growth. Extraction of LULC is important (Sinha & Ayele, 2016).Woldegerima, &Yeshitela, (2017) studied LULC classification to characterized the urban structure of Addis. LULC is classified by using remote sensing data and using different algorithm .Support Vector Machine and Maximum likelihood are very popular in land cover classification. They have higher accuracy compared to other algorithms in identifying land cover (Schneider, 2012).A Number of literature used Maximum likelihood Supervised classification in ERDAS software. Gebremedhin &Biruh,(2019) conducted research in Axum town. Terfa, (2019) urban expansion in Addis Ababa, Adama &Hawassa. Getu, & Bhat, (2021) used supervised maximum likelihood technique to assess and monitor the spatiotemporal dynamics of urban sprawl and its growth pattern in Bahir Dar. Moreover, support vector machine supervised classification in ENVI software is far better than Maximum likelihood supervised classification. In particular, SVM yields better accurate land cover classification due to its nonparametric nature (Rimal & Rijal, 2020). SVM reduces the misclassification of land cover from hidden information or controls the level of certain misclassifications. SVM and maximum likelihood are very popular in land cover classification because they have higher accuracy compared to other algorithms in identifying land cover classes in watersheds and others (Kavzoglu & Colkesen, 2009).

There are also attempts to use different indices to analyses spatio temporal urban growth dynamics. Some literature used (i.e,Han Li & Ye,2014) used NDVI to study urban expansion in Shanghai.Nautiyal & Maithani,(2019), Shannon's entropy for the Analysis of Spatio-Temporal Urban Growth Dynamics in Dehradun.in the same way national literature(i.e Terfa, 2019) in three Ethiopian city Addis Ababa , Adama & Hawassa and globally Sapena & Luis ,(2018) in Srinagar city and surrounding china. Anees, (2020) used landscape metrics along with other indices. Li et al, (2008) used spatial statistical analysis in Nanjing city, china. Urban landscape configuration was quantified using selected landscape metrics as these methods are the most popular to get the easily comparable result (Uuemaa et al, 2013). In addition, they show the pattern that would not be clear for visual interpretation (Shrestha et al, 2012). The use of several landscape metrics is vital for better understanding of land cover pattern (Neel et al, 2004) .The combined use of remote sensing based land cover classification and landscape metrics has provided a positive step toward gaining a comprehensive understanding of the features of landscape structure. Remote sensing coupled with landscape pattern analysis provides a framework within which landscape structure could be quantified and studied (Fan & Myint, 2014).

Modeling of land use land cover plays a significant role to understand impacts of the changes that occur through time. This has become more efficient with the advancement of geospatial tools, which provide us the capability to integrate, and processed spatial data and various other modeling factors. A number of authors in the field of urban studies have stated several modeling advantages. Among the numbers of land use modeling tools and techniques, the commonly used models are Land Change Modeler (LCM), Cellular Automata (CA), Markov Chain, CA-Markov, ANN,(Eastman, 2006) .MOLUSCE plugin incorporates well known algorithms, which can be used in land use/ land cover change analysis as well as forestry applications. MOLUSCE plugin is used to analyze the model and simulate land use changes in QGIS.

### 2.11. Conceptual Framework

This study uses multyremote sensing data, spatial metrics and CA-ANN model integrated with MOLUSCE plugin to get an understanding of spatiotemporal urban growth process, modeling, and predicting. The conceptual framework is composed of three major elements interacting at different stages of the study. Those are remote sensing data, spatial metrics and CA-ANN model via MOLUSCE plugin in QGIS .The first one shows the potential use of classified temporal remote sensing image to detect the LULC change of the study area. The second shows interaction between urban remote sensing and spatial metrics computation in FRAGSTAT to quantify urban landscape fragmentation patterns. Following the LULC analysis, landscape metrics for each time series maps were calculated. This metrics were computed to quantify the spatial configuration and composition of urban landscape. The third one is CA-ANN model, which was used along with MOLUSCE plugin in QGIS to model and predict future land use.

## CHAPTER II: MATERIALS AND METHODS

### 3.1. Introduction

In this chapter the available data, the overall methods, techniques, approaches and materials that have been used to achieve the research objectives were addressed. It mainly explains the data sources and types; methods of data collection, image classification technique employed, and change detection method, accuracy assessment, MOLUSCE model selection of spatial metrics and list of software packages were used.

### 3.1.1 Description of the Study Area

Shashemene city is in the southern part of the Regional State of Oromia, about 250 km from Addis Ababa .Shashemene city is the headquarter of West Arsi Zone and has “A” grade level city regional status with a surface area of about 17, 174(ha) . Geographically the city is located between $7^{0}8'50''$N to $7^{0}18'17''$N latitude and $38^{0}32'43''$E to $38^{0}40'58''$E longitude. The city has eight urban Kebele administration units and recently added seven rural kebele to the city administration.

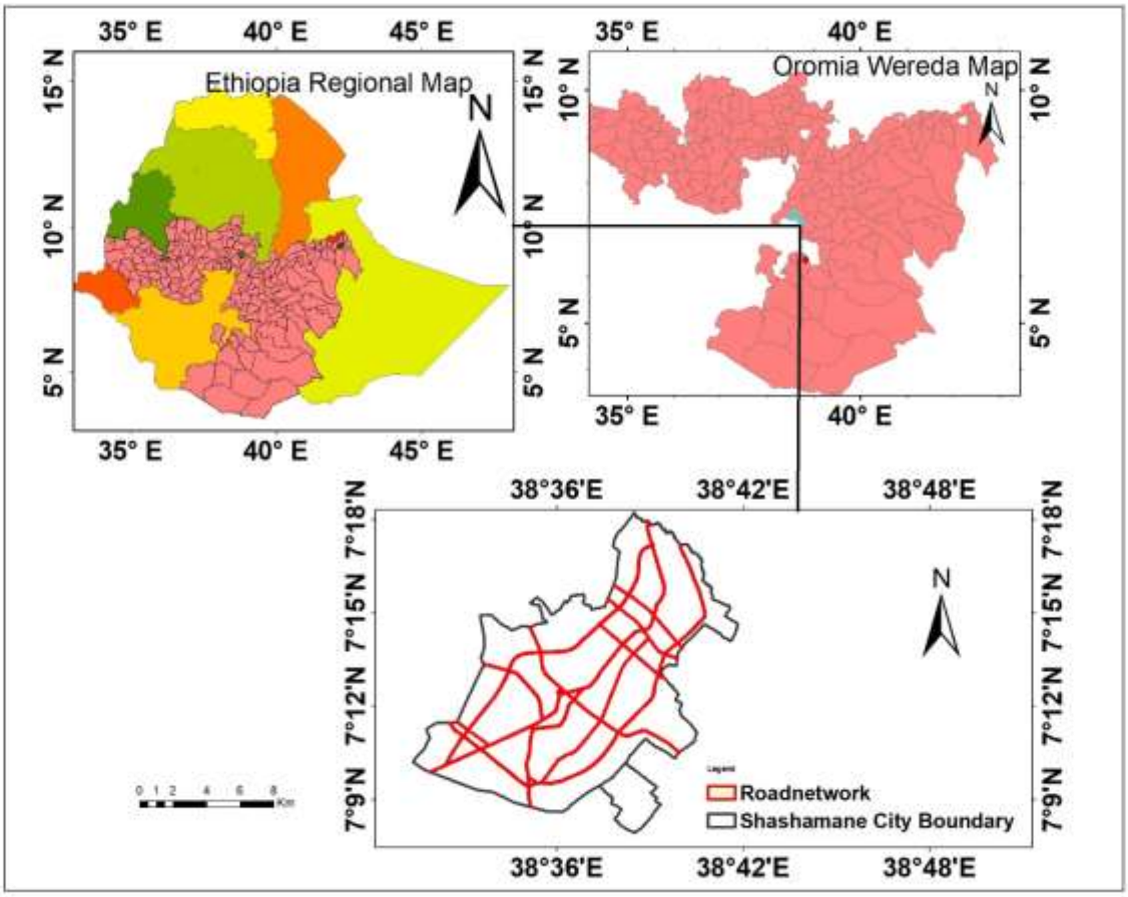



Figure 3. 1. Location of study area map

### 3.1.2 Topography

Shashamene extends to the southeastern escarpment of the Rift Valley. The town is located on a plateau with an elevation ranging about from 1,826 to 2,247 meters above mean sea level .The city is situated at the upper great East African Rift valley.

### 3.1.3. Population

Evidences from the available literature show that the fast growth of Shashamene's population has been observed since the 1990s .The 2007 national census reported a total population for this town of 100,454, of whom 50,654 were men and 49,800 were women. Because of demographic uncertainties, such as high net migration, and natural population increment, currently, the exact number of inhabitants is not really known. However, when projected using 6% annual growth rate, the City's total population as stated in the structure plan was 240,540 in 2011. This figure includes 13,946 residents from the former Kuyera Town (now sub-city of Shashemene) and 85,693 occupants from peasant administrations adjacent to the urban periphery. According to the projection by OUPI, Shashemene is expected to host 295,898 inhabitants by 2020 (OUPI 2010).

### 3.1. 4.Climate

The climate in Shashamene is characterized by the average maximum and minimum temperature of 24.3°C in May and 7.5°C in December, respectively. The average annual rainfall in Shashamene amounts to 1200mm. The main wet season takes place from June to September, causing about 70% of annual rainfall with the highest peak in August. Another small peak of rainfall is observed in April (OUPI, 2010). The annual amount of precipitation in Shashemene is 879mm.

## 3.2. Data Source

To achieve the study goals, the related data have to be collected from different sources. Preprocessing such as mosaicking, coordinate transformation (projection), resampling, and sub-setting was performed on each raster and vector data to prepare the data for further analysis.

### 3.2.1. Data Source and Purpose

Collecting accurate and reliable data is the most determinant factor for any research as it determines the quality of the research. The main sources of the data in this study were primary data and secondary data sources as listed in the table 3.1. The time of the satellite image was purposely chosen based on fundamental remarks and changes in the city. The

1991 first urban land lease system is a basic turning point in peri-urban land intervention processes in the country. The 2006 was selected purposely considering the time new master plan was formulated and the 2013 years was selected considering when the city became the capital of west Arsi zone.

Table 3.1.Data sources

| Types of data | Source | Formats | Resolution | Purpose/year |
|---|---|---|---|---|
| Shashemene master plan | Shashemene land administration office | Dwg | - | 2021 To generate boundary |
| Land sat 5 TM<br>Land sat 7 ETM+<br>Land sat 8 OLI | USGS | TIFF | 30m | 1991,2006 ,2013,2021 LULC classification |
| Google earth image | GPS data | Vector | - | For accuracy assessment |

### 3.2.2 Software used

For the purpose of this study different software were used as shown in table 3.2.

Table3.2.Software used

| Software | Version | Purpose |
|---|---|---|
| ArcGIS | 10.8 | Storing and analyzing spatial information and produce map |
| Microsoft word | 2016 | To produce documents |
| ENVI | 5.3 | For image processing and classification |
| FRAGSTATS | 4.2 | spatial metrics calculation |
| QGIS | 2.8.8 | Prediction & modeling of LULC |

## 3.3. Methods of data analysis

This study's analyses were carried out to map urban built-up areas utilizing satellite photos and other supplementary data. By delineating with the city boundaries, the spatial patterns of urban growth trends were analyzed and quantified using landscape metrics. The future urban growth trends also predicted with the help of CA-ANN model in MOLUSCE plugin QGIS. Overall, methodological flowchart is indicated in figure 3.3.

### 3.3.1. Image Pre-processing

Pre-processing is very important when it comes to analyzing LULC change, as errors attributed to imaging sensors, atmospheric effects and curvature of the Earth, if not corrected, can lead to false results (Parsa et al.,2016). In this study, Landsat imageries of TM and ETM+ and OLI acquired in the same season and the same level of resolution for the periods 1991, 2006, 2013 and 2021. Thus, it was conducive for comparison of changes and patterns occurred in within given time. The images were downloaded from the United States Geological Survey (USGS).the images were spatially referenced in the Universal Transverse Mercator (UTM) projection with datum World Geodetic System (WGS) 1984 UTM zone 37N. First, image analysis and processing, image clipping and composite and atmospheric correction and rectification of the image were carried out with ENVI 5.3 software. Second, Landsat images were preprocessed in ENVI 5.3 for layer stacking (stacking is the method used to produce a multiband image from discrete bands and sub setting (after stacking, the study area was extracted) of the image based on Area of Interest (AOI). All satellite data were studied by assigning per-pixel signatures. Training sites selections for the years 1991, 2006, 2013, and 2021 were determined, and spectral signature files of selected LULC classes such as vegetation, buildup area, bare soil, and waterbodies (Table 3.3) were created for uses in the classifications using ENVI software. The classified images were compared with ground truth of the study area.

### 3.3.2. LULC Scheme

In order to make sample collection and classification easy, land cover nomenclatures are required to create and define the possible LULC classes. The LULC classes applied in this study were adopted from the classification used by European Environment Agency (EEA), Co-ordination of Information on the Environment (CORINE) , which describes land cover (and partly land use) according to a nomenclature of 44 classes organized hierarchically in different levels (EUROPA,2008). Moreover, due to the geographical location of the study area in Tropics, the CORINE land classes adopted was not entirely applied. It is a LULC class, which is more applicable for Temperate and cold Polar Regions. In order to solve this challenge, AFRICOVER land cover classification system that is widely applied at East African Countries (AFRICOVER, 2002) was integrated. For this research, major LULC nomenclatures (Built up area, Agricultural land, Vegetated area, Water body and bare lands) were used.

Table 3.3. Land use land cover classification scheme

| Land use category | Descriptions |
|---|---|
| Built up area | Comprises areas with all types of artificial surfaces, including buildings and transportation infrastructure (asphalt, gravel). |
| Agriculture | Includes all areas employed for agricultural activities farmland |
| Vegetation | Refers to areas covered by vegetation of any type, Open and green area .open spaces with little or sparse vegetation, including artificially vegetated green areas |
| Water body | River |
| Bare land | Refers to open spaces without any function, bare soils, and open areas in side vegetation. |

### 3.3.3. Image Classification

Landsat preprocessed with radiometric calibrations, atmospheric correction, topographic correction and image to map registration. The coordinate system used for registration was WGS84, UTM zone 37N. For atmospheric correction, the FLAASH module used. Lastly, the radiance converted to surface reflectance value. Then sample area were collected to classify using SVM algorithm.

### 3.3.4 Classification Algorithms

Each image was classified into a set of spectral classes using the Support Vector Machine (SVM) algorithm in ENVI software. For this study, supervised classification by using support vector machine algorithm was used. Support Vector Machine (SVM) is one of the most popular Supervised Learning algorithms. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category. For instance, this algorithm was selected for this research.

### 3.3.5. Process of Urban Expansion

LULC change detection was analyzed using post-classification technique comparison in the Arc GIS software environment by overlaying two land use and land cover classes based up on the classified images between the three-period ranges. To calculate the annual rate of LULC change, the following equation according to ( (Eshetu, 2018) was adopted:

1. Annual average rate of change (AARC)

This is the method to understand temporal dynamics of the urban area during the study period and to predict its change.

$$\text{AARC} = \frac{A2-A1}{A1} * \frac{1}{N} * 100.$$

Where A1 and A2 are the urban areas at the beginning and end of a certain period, respectively, and N is the number of years between them.

AARC brings the relative dynamic rate of the urban area that is easy for comparison of the changes. This index is one of the easiest ways of measuring urban sprawl by normalizing the growth rate from the initial urban area (Kasanko et al, 2010)

2. Annual average urban expansion intensity index (UEII).

It is used to describe the intensity or speed of urban expansion in different periods. Higher UEII implies fast urban expansion. The UEII can be divided into very low, low, moderate, rapid and highly rapid with corresponding values of <0.1, [0.1–0.2), [0.2–0.4), [0.4–0.7) and ≥0.7, respectively (Qiuying et al, 2015).

$$\text{UEII} = \frac{A2-A1}{N} * \frac{100}{TA}$$

3. Rate of land use dynamics

The rate of land use change during 1991-2021will be determined using the formula obtained from (Pham & Yamaguchi, 2011). The annual rate of change was calculated using the following formula:

$$r = \frac{1}{t2-t1}(ln\frac{At2}{At1})$$

Where At2 and At1 are the built up land area in the year t2 and year t1, respectively. This equation has been widely used to calculate the annual growth rate because the method assumes urban growth is an exponential to the annual rate of compound interest (Pham & Yamaguchi, 2011).

### 3.3.6. Accuracy Assessment

The accuracy assessment was done based on ground truth data and visual interpretation using GCP points (Butt et al. 2015). Statistical error matrices together with nonparametric Kappa index were used for comparison of reference data and classification result (Robertson & King, 2011; Dabboor et al., 2014). The producer accuracy, user accuracy, overall accuracy, and Kappa coefficient were calculated for the classified map selected times periods, based on the formula given by (Congalton &Green ,2009).The formula for computing Kappa index coefficient is given as follows:

$$\text{Over all accuracy} \qquad K=\frac{N\sum Xii-\sum(Xi*Xj}{(N*N)-\sum(Xi*Xj)}$$

K=kappa coefficient, N=total number of pixel points, xii=correctly classified points in column i, xi=sum of row points, xj=sum of column points.

Table 3.4. Kappa coefficient interpretation

| Kappa statistics | <0.00 | 0.01 - 0.20 | 0.21 - 0.40 | 0.41 - 0.60 | 0.61 - 0.80 | 0.81 - 1. |
|---|---|---|---|---|---|---|
| Strength of agreement | Poor | Slight | Fair | Moderate | Substantial | almost perfect |

Source: Congalton and Green (2009)

### 3.3.7. LULC Change Detection Analysis and Matrix

The LULC changes were detected between two pairs of LULC maps between each study periods. Change detection is the process of identifying differences in the states of an object by observing it at different times. Image differencing, principal component analysis and post classification detection are the most widely used methods for change detection (Lu et al., 2004). The detections were held between the years (1991 – 2006, 2006 – 2013, and 2013 – 2021). Using post-classification comparison techniques, the area of each LULCs were identified. Gain is the amount of land use class i that was added between time t1 and time t2, whereas loss is the amount of land use class j that was lost from time t1 to time t2. The land use category's total change is the sum of the net change and the swap or the total sum of the gains and losses. In addition, the net change is the difference between the gain and losses during the study period. Net gains or losses in hectares (ha) and percentages (%) for each land-cover category; Contributors to the net change and Change matrices were analyzed.

### 3.4. Quantifying Urban patterns Using Spatial Metrics.

### 3.5. 1.Urban landscape metrics

Spatial metrics are an analytical method for quantifying the spatial shape and pattern of an area through categorization and interpretation in patch, class, and landscape. Selected metrics measures were used to quantify urban landscape configuration. The use of several landscape metrics is vital for better understanding of land cover pattern (Mcgarigal, 2015). FRAGSTATS 4.2 is a spatial pattern analysis program for quantifying the structure (i.e., composition and configuration) of landscapes. The landscape subject to analysis is user-defined and can represent any spatial phenomenon. Metrics are grouped into patch, class, and landscape indices. Landscape metrics are algorithms that quantify the spatial structure of land cover patterns within a defined geographic area. Class metrics are computed for every patch type or class in the landscape.

### 3.5.2. Selection of spatial indices

The FRAGSTATS 4.2 software package was used to quantify landscape metrics and their changes for the study area. Description and computation of each spatial metrics was described in table 3.5.

Table 3.5 the landscape metrics used in this study area

| Spatial metrics | Description | Range |
|---|---|---|
| Largest Patch Index (LPI) | $LPI = \frac{Maxaij}{A}(100)$<br>LPI equals the area (m2) of the largest patches of the corresponding patch type divided by the total landscape area (m2), multiplied by 100 (to convert to a percentage) | $0 < LPI \leq 100$ |
| Percentage of Landscape (PLAND) | PLAD = Pi= $\sum aij\ n\ J=1\ A$ (100) (2)<br>Where, aii = number of like adjacencies (joins) between pixels of patch type gik = number of adjacencies between pixels of patch types i and k. PLAND quantifies the proportional ratio of each patch type in the landscape. It equals the sum of the area (m2) of all patches of the corresponding patch type, divided by the total landscape area (m2), and multiplied by 100 (to convert to percentage) | 0<=PLADJ≤100 |
| Landscape Shape Index (LSI) | $LSI = \frac{\sum Ei}{\mathbf{Ei}_{min}}$<br>Where, Ei =total length of the edge (or perimeter) of class i in terms of a number of cell surfaces; includes all landscape boundary and background edge segments involving class i. min Ei=minimum total length of the edge (or perimeter) of class i in terms of number of cell surfaces. | LSI>1, Without Limit |
| Patch density (PD) | $PD = \frac{\text{Number of patches}}{\text{Total area of the landscape}}(1000000)$<br>It is one more measure of landscape fragmentation of the patches of a land cover | PD > 0, without limit. |

| | | |
|---|---|---|
| | class, which specifies the density of the fragmented urban units within a quantified area. Values of this indicator are affected by the size of the pixel and also the minimum mapping unit since this is the significant factor for describing individual patches. This usually expresses number of patches on a per unit area basis that facilitates comparisons among landscapes of the varying size | |
| Number of Patches (NP) | NP = $\sum ni$<br>NP equals the number of patches in the landscape. It is the measure of discontinuous urban areas or individual units in the landscape (Gezahegn Awake Abebe, 2013). Due to the rapid core development, the number of patches is expected to increase due to the emergence of new fragmented patches around the cores. Number of patches indicates the diversity or richness of the landscape. In other word it gives a simple measure of the extent of subdivision or fragmentation of the patch type | NP $\geq$ 1, without limit. |

| | | |
|---|---|---|
| Perimeter-Area Fractal Dimension (PAFRAC) | aij = area (m2) of patch ij. pij=perimeter (m) of patch ij. N= total number of patches in the landscape .<br><br>is a 'Shape metric'. It describes the patch complexity of the landscape while being scale independent. This means that increasing the patch size while not changing the patch form will not change the metric. However, it is only meaningful if the relationship between the area and perimeter is linear on a logarithmic scale. Furthermore, if there are less than 10 patches in the landscape, the metric returns NA because of the small-sample issue. | $1 \le PAFRAC \le 2$ |
| Shannon's Diversity Index (SHDI) | SHDI = $-\sum_{i=1}^{m}(\boldsymbol{Pi} * \boldsymbol{lnPi})$<br>Where Pi is the proportion of class i.<br>is a way to measure the diversity | SHDI $\ge 0$, without limit |

Source: McGarigal, K. (2015)

### 3.6 LULC modeling and Future Prediction

#### 3.6.1. CA-ANN Model

CA-ANN model is a nonlinear tool that has been applied successfully in LULC modelling and prediction (Mahajan et.al, 2009). The main reason to integrate CA with ANN is; CA has open space model so can be easily integrated but dependent on spatial data and not appropriate to make a realistic simulation whereas ANN can detect potential interdependencies through the implied driving forces. Thus, to get effective modelling and simulation result the both models are combined; CA and ANN (Gharaibeh et al, 2020). CA-ANN composed of various essential elements. In CA, cells, array dimension, transition rule are major parts whereas neurons, weights, input, hidden and output layer are major components of ANN (Gharaibeh, et al, 2020). Similarly, the neurons are the basic unit in an

ANN, which receives input from some other nodes, or an external source and computes an output (Ujjwalkaran, 2016).

### 3.6.2. MOLUSCE plugin

MOLUSCE (Modules of Land Use Change Evaluation), a new QGIS plugin that can estimate potential LULC changes, is built with the CA model and includes a transition probability matrix used by most researchers (Kamaraj & Rangarajan,2022). A CA-ANN model in MOLUSCE is a reliable tool for predicting future LULC that may be utilized in land use planning and management. MOLUSCE is also used to investigate temporal LULC shifts and predict future land use (Rahman et al. 2017; Saputra & Lee 2019; Aneesha et al. 2020). This model predicts the spatial LULC shift by estimating the pixel's current condition based on its initial situation, adjacent neighborhoods eventuality, and changeover laws. Moreover, this accurately depicts nonlinear spatial stochastic LULC change processes and produce complex patterns (Saputra & Lee, 2019).

**MOLUSCE Procedures**

Inputs data; the initial and final land use/land cover maps, as well as spatial variables like elevation, slope, DEM, Distance from road and distance from rivers are loaded within it.

Evaluation Correlation; For evaluating this there are three options i.e. Pearson's Correlation, Crammer's Coefficient and Joint Information Uncertainty. These techniques are used to check the correlation among the spatial but in this research Pearson's Correlation method have been used. In this part try to compute the area change, which can be seen in initial raster and final raster. The area change is calculated and the percent of change is calculated.

Transition Potential Modelling; For calculating and charting land use/land cover changes, , artificial neural networks (ANN) require spatial variables and information on land use/land cover change as their inputs to represent transition potential.

Cellular Automata; Simulation Result is going to simulate the results of land use/land cover maps after completing learning models.

Validation; Validation method computing the Kappa Statistics i.e. Kappa Histogram, Kappa Locations. Inputs were Reference LULC and Simulated LULC. Then proceed for map comparison between these maps. As a result, determine correctness percentage, total kappa, histogram kappa, and position kappa

### 3.6.3. Driving factors for LULC

To achieve the requisite accuracy, the modelling criteria have to select. Many researchers for LULC studies took into account the distance from the road, the distance from the built-up area, the distance from the river, the DEM, the aspect, and the slope (Alam et al. 2021; Ashaolu et al. 2019; Guan et al. 2011; Hakim et al. 2019; Nugroho et al. 2018; Saputra and Lee(2019). Along with the thematic LULC maps. DEM obtained from website (https://earthexplorer.usgs.gov)then imported into the ARC GIS 10.8 software. Clipped by study area boundary then slope and aspect was computed and distance from road and distance from rivers were exported from master plan of shashemene city converted to raster format using Euclidean distance tool available in spatial analyst to get the distance from the road and distance from the rivers. Overall, methodological flowchart is indicated in figure 3.2.

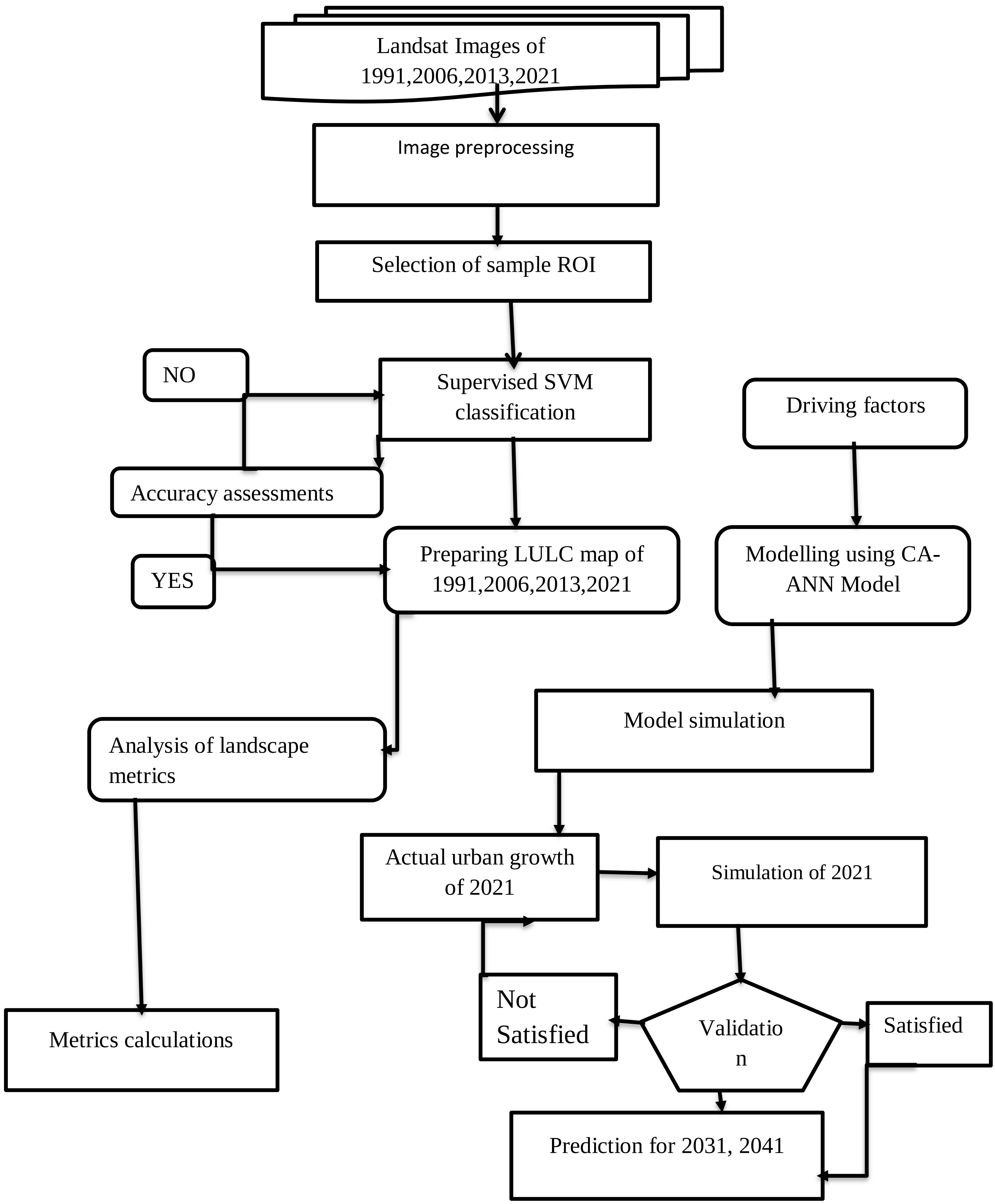



Figure 3. 2. Methodological framework

## CHAPTER IV: RESULTS AND DISCUSSIONS

### 4.1. Introduction

In this chapter, based on the satellite imagery data gathered, data analysis was performed. The output images of LULC images developed for the years 1991, 2006, 2013, and 2021.Table 4.2 shows the statistical change analysis of LULC between the years 1991 and 2021.The spatial metrics was calculated using FRAGSATS 4.2 Software. Prediction of LULC for the next twenty years were performed using CA-ANN model.

### 4.2. Accuracy assessment.

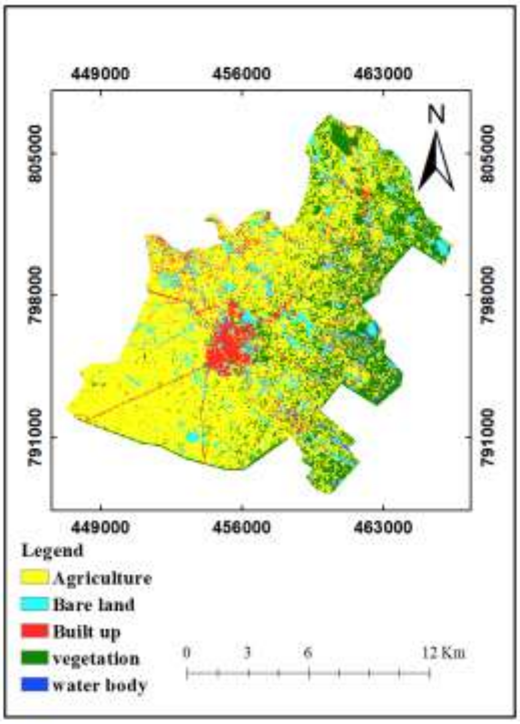
Accuracy assessment of the study area revealed the overall accuracies of 88.8%, 90.2% 91.12% and 92.02% were calculated for the 1991, 2006, 2013, and 2021, respectively. This implies that all classifications are in acceptable range because an overall accuracy of each year is greater than 85% is an indicator for a strong accuracy. The table 4.1 shows the user accuracy, producer accuracy, overall accuracy and overall kappa of each study years. Ground truth were used for verification (see appendix 1). Note: PA, AU, OA and OK-producers accuracy, Users accuracy, overall accuracy and overall kappa respectively

Table 4.1.accuracy assessment of the satellite images of the 1991,2006,20013 &2021.

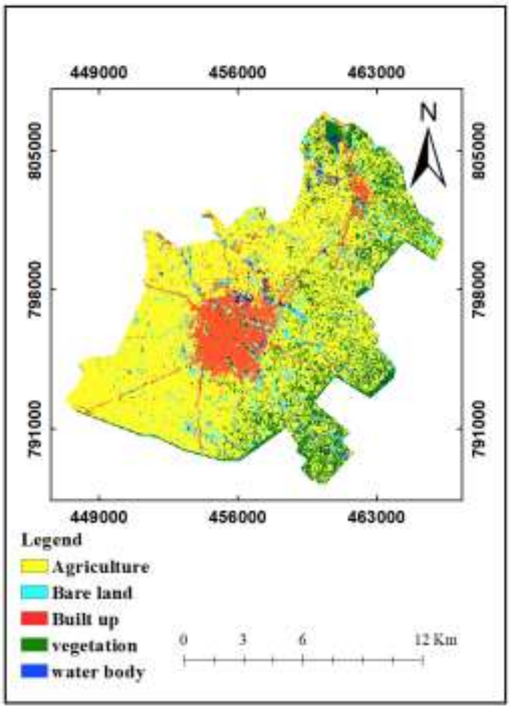
| LULC | 1991 | | 2006 | | 2013 | | 2021 | |
|---|---|---|---|---|---|---|---|---|
| | UA% | PA% | UA% | PA% | UA% | PA% | UA% | PA% |
| Built up | 81.6 | 96 | 100 | 94 | 91.3 | 84 | 98.2 | 98.2 |
| Water body | 100 | 80 | 86.2 | 88 | 94.3 | 94 | 92.8 | 100 |
| vegetation | 93.8 | 92.2 | 90.2 | 92 | 80.1 | 89.5 | 91.8 | 83.3 |
| agriculture | 91 | 97.7 | 84.9 | 90.5 | 100 | 92 | 88.7 | 88.7 |
| Bare land | 85 | 75.4 | 95.8 | 92.3 | 94.2 | 98 | 89.83 | 92.9 |
| OA% | 88.8 | | 90.2 | | 91.12 | | 92.02 | |
| OK% | 86 | | 88.9 | | 89.4 | | 89.9 | |

### 4.3. Spatio - temporal land use land covers (LULC) change.

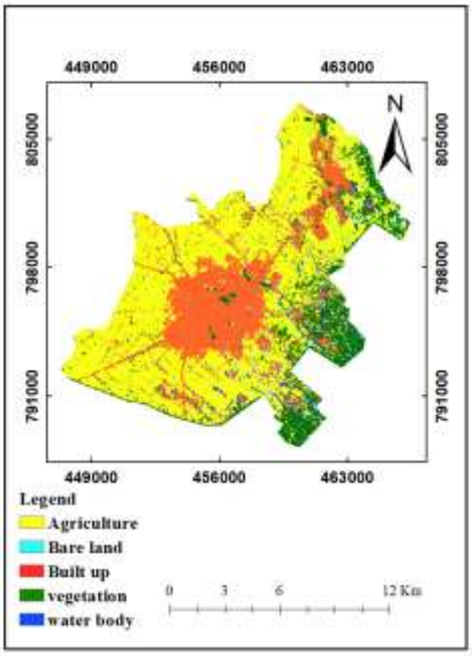
After generation of land use maps, each land cover's changes during the studied periods were identified. The LULC changes were divided into four times: 1991–2006 (the first period), 2006–2013 (the second period), 2013–2021 (the third period), and 1991–2021 (the whole period). The results of the LULC change analysis show the historical LULC and the dynamics of change in each land cover class. The support vector machine LULC Classification in ENVI 5.3 software used. The classified land use/land cover maps for the years 1991, 2006, 2013, and 2021 were produced in ArcGIS 10.8. The results show that the land use and land cover of Shashemenne City have changed between 1991 and 2021 .five LULC classes defined in the study region for the specified timeframe of 1991–2021. Training sites for each class were collected from each satellite image. In the year 1991, the study area was dominated by Agriculture 62.75% followed by vegetation land covering 19.12%, of the study area. Built-up, water body and bare land shared 7.24%, 2.68 %, and 8.21% of the total area respectively. In the 2006 the agricultural area was 61.15%, vegetation is 16.95%, water body 2.57% and bare land was 7.81 and built up increased to 11.5%.In the year 2013 agricultural land was 57.03%, water body, vegetation and bare land covers 2.48%, 12.96% and 7.81% respectively. Built up area cover 24.28% of total area. Built up increased in large amount in this year. Similarly built up area doubled in 2021 but all other class were decreased. Water body, vegetation, agriculture and bare land 1.99%, 11.40%, 45.89% and 0.54% respectively. From this statistics, the built up are increased throughout the study period while the other LULC area were fallen. Land use land cover map of 1991, 2006, 2013 and 2021 were addressed in Figure 4.1.



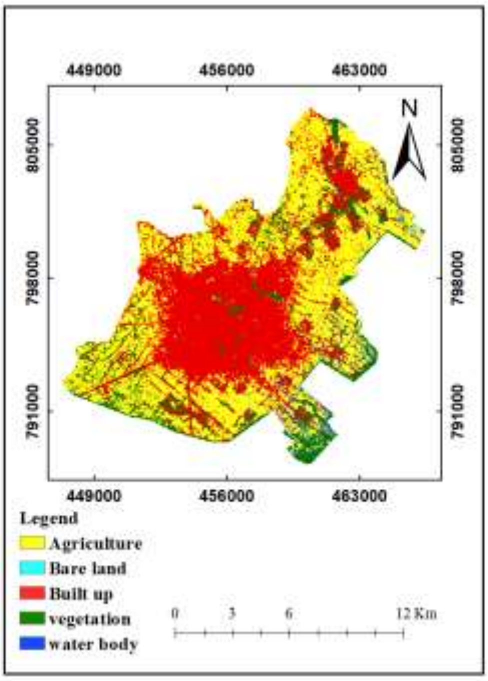

a)




**b** )




**c)**




**d)**

Figure 4.1. Land use land cover map of 1991 (a), 2006(b), 2013(c) &2021(d)

Quantitative analysist of satellite images reveals that in the year 1991 built up covered only 7.24%(1243.54ha), agricultural is the dominant one it covers 62.75%(10777.04ha ) vegetation was the second dominant it covers 19.12%(3283.57ha).the other land use land cover vegetation, bare land, and water body cover. Built up area increased in each study years by 11.51%, 24.28% and 40.18% in 2006, 2013 &2021 respectively but the agricultural area decreased in 2006 which is 61.15% and declined to 57.03% and 45.89% in 2013 and 2021 respectively.

Table 4.2: Quantitative Distribution of LULC, in 1991, 2006, 2013 and 2021.

| LULC | 1991 | | 2006 | | 2013 | | 2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area ha | % | Area ha | % ha | Area ha | % | Area ha | % |
| Built up | 1243.5 | 7.2 | 1976.8 | 11.5 | 4169.5 | 24.3 | 6900.8 | 40.1 |
| Water | 459.6 | 2.7 | 442.2 | 2.6 | 426.5 | 2.5 | 342.1 | 1.9 |
| Vegetation | 3283.5 | 19.1 | 2910.7 | 16.9 | 2225.7 | 12.9 | 1957.9 | 11.4 |
| Agriculture | 10777.0 | 62.8 | 10502.3 | 61.1 | 9795.1 | 57.1 | 7880.5 | 45.9 |
| Bare land | 1409.8 | 8.2 | 1341.8 | 7.8 | 557.1 | 3.2 | 92.7 | 0.5 |
| | 17173.5 | 100 | 17173.5 | 100 | 17173.5 | 100 | 17173.5 | 100 |

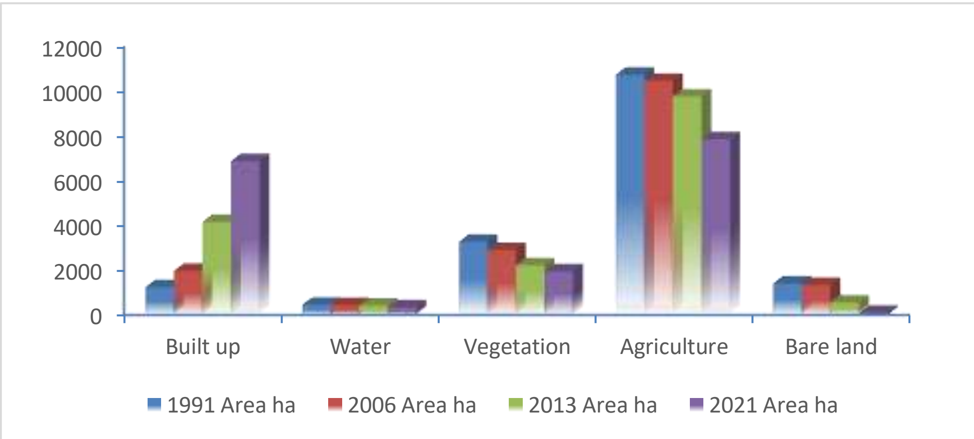



Figure 4.2 Historical Change Trends of LULC from 1991-2021.

Table 4.3.Overall Amounts and Percentage of Land Cover Change1991-2021.

| LULC | 1991-2006 | | 2006-2013 | | 2013-2021 | | 1991-2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area ha | % | Area ha | % | Area ha | % | Area ha | % |
| Built up | 733.3 | 4.28 | 2192.6 | 12.8 | 2730.9 | 15.9 | 5656.8 | 32.9 |
| Water | -17.5 | -0.10 | -15.7 | -0.09 | -84.3 | -0.5 | -117.5 | -0.6 |
| Vegetation | -372.9 | -2.2 | -684.9 | -3.99 | -267.8 | -1.6 | -1325.7 | -7.7 |
| agriculture | -274.8 | -1.6 | -707.2 | -4.12 | -1914.6 | -11.1 | -2896.6 | -16.9 |
| Bare land | -68.0 | -0.4 | -784.7 | -4.57 | -464.5 | -2.70 | -1317.12 | -7.7 |

The overall amounts and Percentage of LULC for the entire study area was shown in the table 4.3.indicate that the built up area increased while other LULC were decreased.

### 4.3.1. LULC Change between 1991-2006

The study observed that during the first period various LULC type changed into other land cover types. For instance, The LULC net change of 1991-2006 shows that built up area was changed positively by 4.26%. The other land use land cover, waterbody, vegetation and bare land and agriculture were decreased by -0.1%, -2.17%, -0.39% & -1.6% respectively for the last 15 years (see figure 4.3).

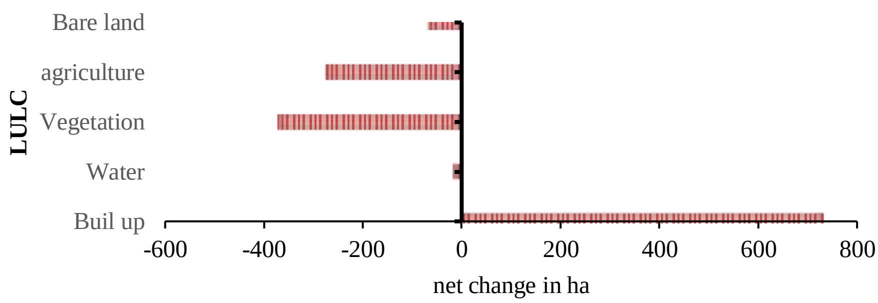



Figure 4.3 Net Change in LULC from 1991-2006

### 4.3.2. LULC Change between 2006-2013

The second period witnessed the conversion of LULC types to different land covers. The area of agriculture declined in huge amount 707.2ha (-4.12%) in the 2006-2013.On the other hand, like first period built up area showed an increment of 2192.64 (12.78%).the net change of vegetation was -684.96(-3.96).the result indicate that the built up area increased in huge amount while vegetation and agriculture area declined rapidly. The first and second period reveals the rapid expansion of the urban area while losing agricultural valuable area and degradation of vegetation (see figure 4.4)

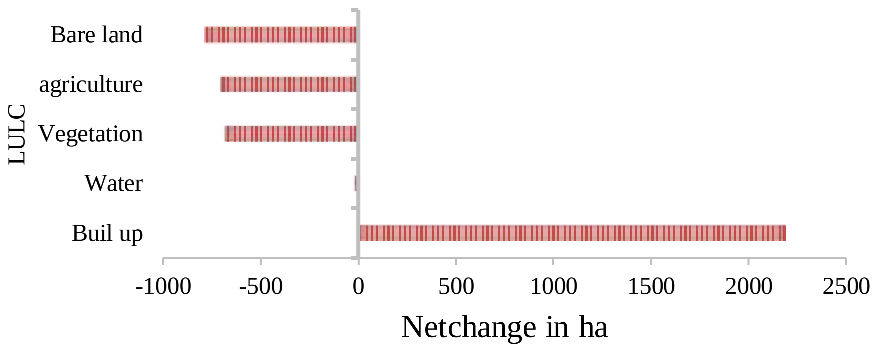



Figure 4.4. LULC net change of 2006-2013.

### 4.3.3. LULC Change between 2013-2021

The third period characterized by advanced LULC dynamics where land cover classes such as vegetation, declined net change by -267.84( -1.56%) and agricultural area reduced by net change -11.1%.The built-up area reveals rapid change with a net positive increase of 2730.94ha (15.9%). Hence, the expansion of built-up areas had resulted in a negative change of agricultural land. When compared with first and second period agricultural area experiences rapid decline and built-up area showed rapid increments (see figure 4.5)

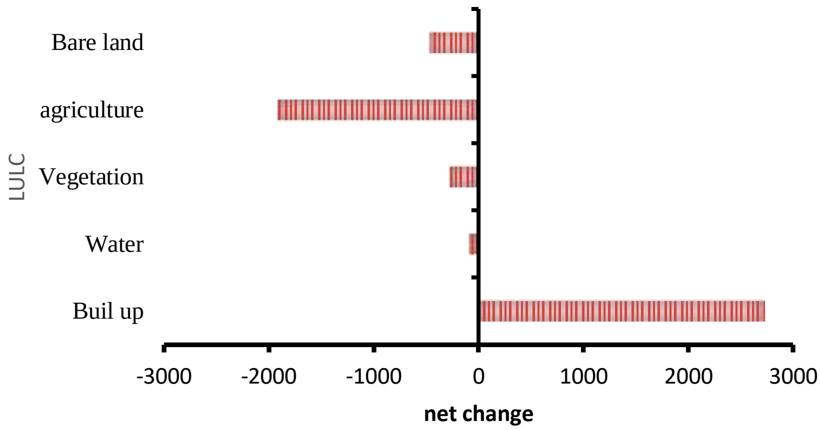



Figure 4.5 net LULC of 2013-2021.

### 4.3.4. Land Use Land Cover Change during 1991–2021

As shown in Figure 4.6 the change in the area experienced by each land cover class from 1991–2021, the agricultural area net decreased to(-2896.58)-16.87% while the net built up area increased to 32.41% over the past 30 years. Therefore, the change in LULC can negatively affect the potential characteristics of the area mainly in agricultural valuable land.

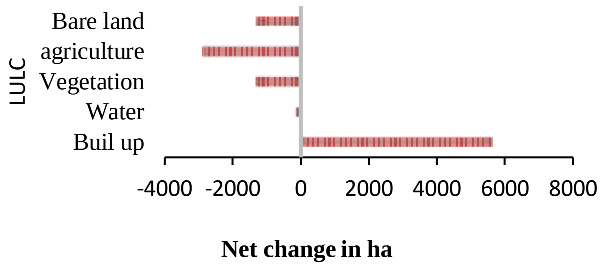


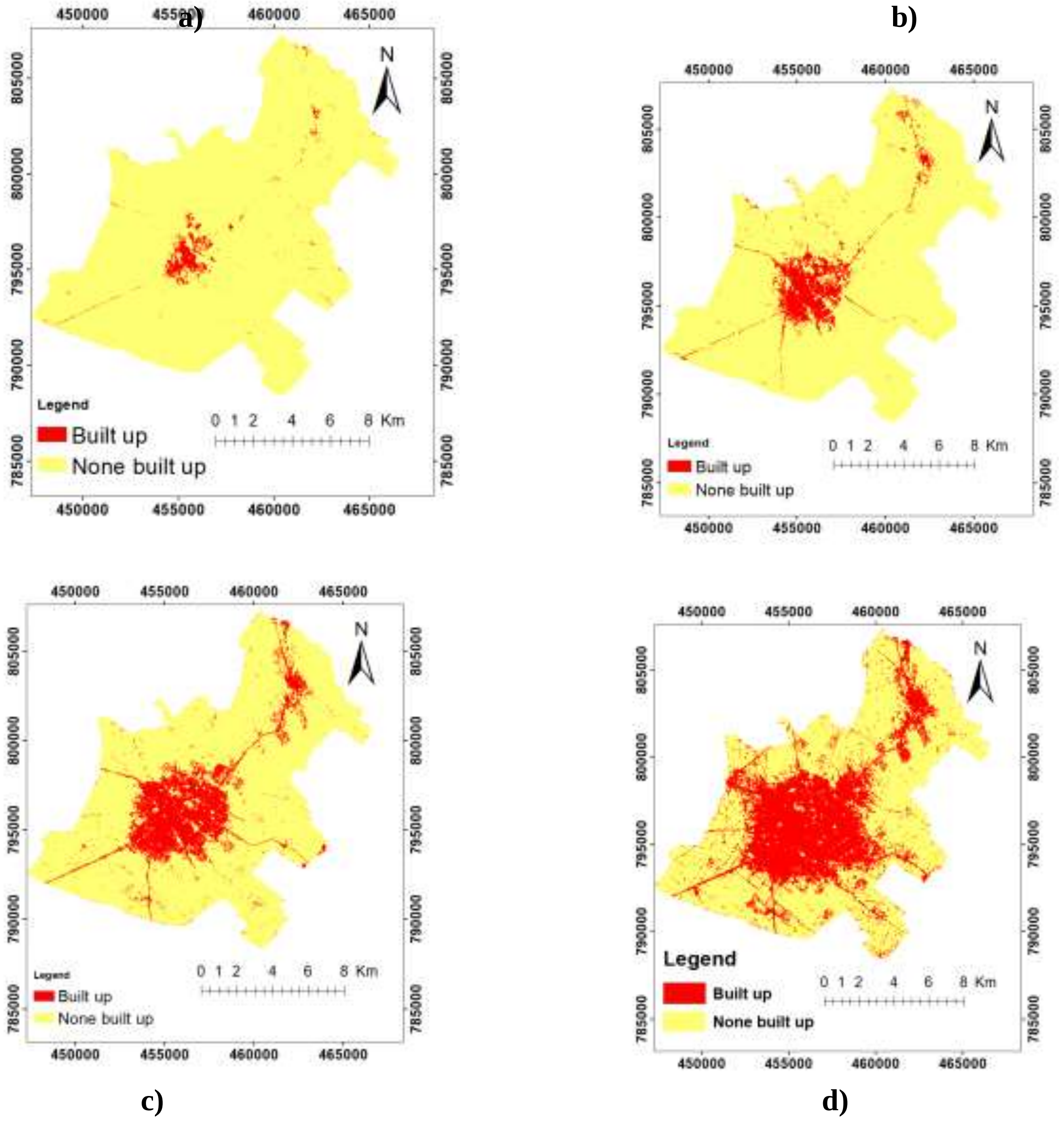

Figure 4.6.the net change of LULC of 1991-2021

## 4.4. Urban extent of Shashemene city

The study reveals that steady growth in the shashemene city‘s built-up area and significant changes in other LULC classes. In order to visualize and examine the spatial expansion of the built up areas during the four time periods, the LULC map was reclassified into built up and non-built up area (Figure 4.7). These maps show a clear pattern of increased urban expansion prolonging both from urban center to adjoining non-built up areas along transportation corridors. The maps show the spatiotemporal urban growth in the study area. As clearly seen in table 4.4, It indicates an increased in built-up area from 1243ha in 1991 to 1976ha in 2006 to 4169 ha in 2013 and further increased to 6900 ha in 2021,this is an increased from 7.24% to 11.51% to 24.28% to 40.18% of the total area during 1991, 2006, 2013 and 2021 respectively.

Table 4.4. Built up and none built up area expansions

| Land cover class | 1991 | | 2006 | | 2013 | | 2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area(ha) | % | Area(ha) | % | Area(ha) | % | Area(ha) | % |
| Built-up area | 1243 | 7.2 | 1976.8 | 11.5 | 4169.4 | 23.6 | 6900.3 | 40.1 |
| Other LULC | 15,930 | 92.8 | 15196.2 | 88.5 | 13003.6 | 76.4 | 10273.2 | 59.8 |




Figures 4.7.built up extent for the 1991(a), 2006(b), 2013(c), & 2021(d) years

As shown in the figure 4.8 the built up area increased dramatically in each study periods. From the 2013-2021 the amount of built-up area increased highly.

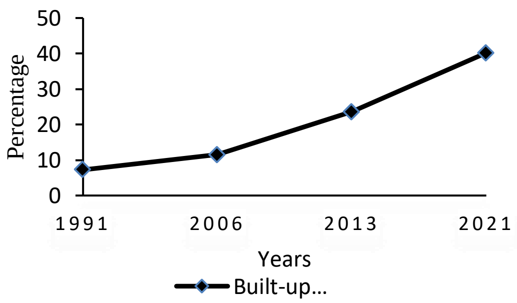



Figure 4.8. Built-up extent

### 4.5. Processes of urban land change

### 4.5.1 Urban expansion

Rapid urban expansion in Ethiopia has happened blindly and out of control .Likewise, shashemenne has experienced rapid urban expansion over the last three decades from 7.24% (1991) to 40.1% (2021) at a rate of 5.71% as shown in the table 4.4.The annual average rate of change 3.93%, 15.85% and 8.18% of 1991-2006, 2006-2013 and 2013-2021 respectively. During the entire period of the study, the average annual rate of change in urban area of shashemenne city was 15.5% during 1991–2021. This fast urban expansion was also evidence with the positive values of annual average rate of change and its expansion intensity index in all periods. Annual growth rate of the city over the last 30 years was 5.71% indicating the rapid expansion of the city. Urban expansion intensity indices (UEII) in shashemene were in the category of moderate urban expansion in 1991-2006, and highly rapid from 2006-2013, 2013-2021 and 1991-2021 as shown in the table 4.5).

Table 4.5. Rate of urban expansion and its intensity

| | Periods | | | |
|---|---|---|---|---|
| | 1991-2006 | 2006-2013 | 2013-2021 | 1991-2021 |
| The annual average rate of change (AARC %) | 3.9 | 15.85 | 8.2 | 15.5 |
| The annual growth rate(r)% | 3.0 | 10.7 | 6.3 | 5.7 |
| Annual average urban expansion intensity index (UEII) | 0.3 | 1.82 | 1.9 | 1.0 |
| Category of UEII | Moderate | Highly rapid | Highly rapid | Highly rapid |

### 4.5.2. LULC Change Matrix

Using a post-classification comparison approach, the changes in LULC that had taken place over the study period were discovered. Post classification comparison methods were preferred in this study for the number of reasons. Firstly, using this method minimizes the problems associated with multytemporal images recorded under different atmospheric and environmental conditions and by different sensors. Secondly, this methods provide the extent and nature of ‘from-to’ change information .Based on this, five LULC maps were compiled to display the type of LULC classes and compare between the classified images. Then the whole study period (1991–2021) was classified into four sub-periods (1991 to 2006; 2006 to 2013; 2013 to 2021; and 1991 to 2021), which includes the entire 30 years of study periods). Then, paired overlay was performed through spatial analysis in GIS in order to detect, compare, and analyze patterns and directions of changes and to quantify gains, losses, net change, and total change. LULC change matrix was prepared in ArcGIS 10.8.The image of the initial year and final year was processed by using geo-processing tool. The intersection of the two images was analyzed to check for the conversion of LULC.

Agricultural area was the maximum that changed to built-up area during first period (1991-2006) by 862.42 ha. Bare land, vegetation and waterbody contributed to urban area by 244.78ha, 162.84ha and 42.16 ha respectively as shown in the table 4.6

Table 4.6. LULC change matrix from 1991-2006

| LULC | | 2006 | | | | |
|---|---|---|---|---|---|---|
| | | Agriculture | Bare Land | Built up | Vegetation | Water body |
| 1991 | Agriculture | 8111.36 | 602.65 | 862.42 | 1009.08 | 187.21 |
| | Bare land | 514.18 | 470.10 | 244.78 | 77.83 | 101.77 |
| | Built up | 406.43 | 79.53 | 663.91 | 56.49 | 36.32 |
| | Vegetation | 1730.14 | 110.41 | 162.84 | 1190.92 | 85.58 |
| | Water body | 234.86 | 78.18 | 42.16 | 73.08 | 30.99 |

The result of LULC change matrix from 2006-2013 was shown in table 4.7 indicate that Agricultural area changed to built-up area was 1501.92ha.It showed increment when compared to first period indicating the large amount of agricultural area conversion to built -up area. Bare land, vegetation and water body converted to built-up area were 627.70ha, 189.96ha and 39.10ha respectively .in this period Agricultural area and vegetation area were the highest conversions to built-up area. Vegetation was converted to agricultural area in large amount (1106.86) ha.

Table 4.7. LULC change matrix of 2006-2013

| LULC | | 2013 | | | | |
|---|---|---|---|---|---|---|
| | | Agriculture | Bare land | Built up | Vegetation | Water body |
| 2006 | Agriculture | 7910.7 | 205.7 | 1501.9 | 1096.5 | 282.8 |
| | Bare Land | 375.8 | 175.4 | 627.7 | 69.2 | 92.6 |
| | Built up | 249.9 | 11.1 | 1676.1 | 31.5 | 7.4 |
| | Vegetation | 1106.7 | 60.8 | 189.9 | 985.8 | 64.3 |
| | Water body | 146.3 | 44.5 | 172.9 | 39.1 | 38.9 |

During the third period (2013-2021) built up area gained 2586.15 ha from agriculture, 236.27ha from bare land, 253.7.ha from vegetation and 192.82ha from waterbody. Agricultural area contributed large amount to built-up area. This indicates the continuous loss of agricultural area as shown in the table 4.7.

Table 4.8. LULC change matrix from 2013-2021

0

| LULC | | 2021 | | | | | |
|---|---|---|---|---|---|---|---|
| | | Agriculture | Bare land | Built up | Vegetation | Water body | Grand Total |
| 2013 | Agriculture | 6538.2 | 24.07 | 2586.15 | 563.9 | 76.4 | 9788.6 |
| | Bare land | 128.9 | 37.1 | 236.3 | 65.7 | 29.8 | 497.8 |
| | Built up | 152.6 | 20.3 | 3629.59 | 323.4 | 42.3 | 4168.7 |
| | Vegetation | 994.6 | 7.6 | 253.7 | 810.0 | 156.8 | 2222.8 |
| | Water body | 62.2 | 3.5 | 192.8 | 191.8 | 35.8 | 486.2 |
| | Grand Total | 7876.5 | 92.6 | 6898.6 | 1955.2 | 341.4 | 17164.2 |

As shown in the table 4.9 the agricultural area of 4264.84ha was converted to built-up area over the last 30 years. During the entire study period (1991-2021), the conversion of vegetation area into agricultural land accounted for 1736.82Ha. In the same period, bare land and waterbody accounted for 340.52ha and 175.28ha area for agriculture respectively.

During the entire study period (1991 - 2021), bare land, vegetation water body and agricultural area contribute to built-up area by 849.71ha, 737.32ha, 172.71ha and4264.84 respectively from 1991-2021 entire study periods. During the overall period (1991-2021), the conversion of vegetation and waterbody into barren land accounted for 16.38and 6.13.52ha respectively.

Table 4.9. LULC Change Matrix of Whole Study Periods.

| LULC | | 2021 | | | | |
|---|---|---|---|---|---|---|
| | | Agriculture | Bare land | Built up | Vegetation | Water body |
| 1991 | Agriculture | 5322.1 | 24.2 | 4264.8 | 1013.6 | 146.4 |
| | Bare land | 340.5 | 43.2 | 849.7 | 153.6 | 21.6 |
| | Built up | 299.4 | 2.7 | 873.9 | 54.8 | 11.8 |
| | Vegetation | 1736.8 | 16.4 | 737.3 | 653.2 | 136.4 |
| | Water body | 175.2 | 6.1 | 172.7 | 79.8 | 25.1 |

**4.7. Spatio-temporal analyzes of urban growth using spatial metrics.**

Spatial metrics provide quantitative description of the composition and configuration of urban landscape. A single spatial metric cannot capture all the aspects of landscape characteristics; therefore, a suite of selected metrics may be useful in the interpretation of landscape change (Ayele et al, 2017).FRAGSTATS is a spatial pattern analysis program for quantifying the structure (i.e., composition and configuration) of landscapes. The landscape subject to analysis is user-defined and can represent any spatial phenomenon. FRAGSTATS simply quantifies the either spatial heterogeneity of the landscape as represented in a categorical map (i.e., landscape mosaic) or continuous surface (i.e., landscape gradient, expected in version 4.4); it is incumbent upon the user to establish a sound basis for defining and scaling the landscape in terms of thematic content and resolution and spatial grain and grain.

Landscape metrics were selected on the basis of different outlooks (size, shape and edge) to measure characteristics of urban landscape. The specific choices of metrics vary depending on the selected scale (i.e., patch, class, or landscape). FRAGSTATS divides metrics into 5 groups, including area and edge, shape, core area, contrast, and aggregation. For the purpose of this study class level and landscape, level metrics were selected. The satellite Image was clipped in to four direction, Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE).The use of more landscape metrics is important to overcome the limitation of one another.

### 4.7.1. Landscape Metrics at the Landscape Level.

Landscape metrics also known as spatial pattern metrics, spatial pattern indices, or landscape pattern metrics are algorithms that quantify the spatial structure of land cover patterns within a defined geographic area (Frazier. 2019). Landscape level indices represent the spatial pattern of the entire landscape mosaic, considering all patch types simultaneously. At the landscape level six landscape metrics were used (i.e. number of patches (NP), patch density (PD), largest patch index (LPI),Shannon‟s diversity index (SHDI and Shannon‟s evineness index( SHEI).The outputs presented in table 4.10 were generated for the selected metrics in the form of numeric values for the whole study area in FRAGSTATS 4.2

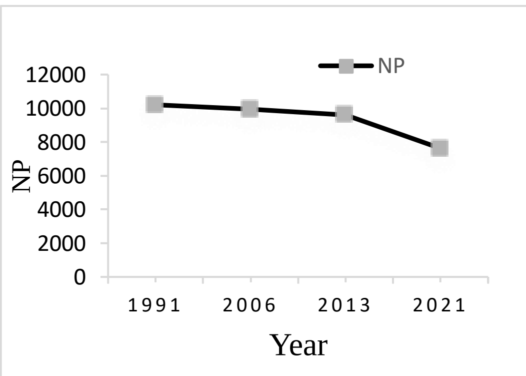
The change in metrics for landscape pattern between 1991 and 2021 is shown in Table 4.10. From 1991 to 2006, the number of patches (NP) declined (10206 to 9941).and it also decreased to 9611 in 2013.similarly the NP declined in 2021 to 7621.Patch density (PD) declined from 59.40% in 1991 to 57.86% in 2006, similarly the PD value decreased to 55.44% and 44.36% in 2013 and 2021 respectively. Landscape shape index (LSI) decreased from 57.16% in 1991 to 56.46% in 2006 This is characterized by the appearance of new, dispersed settlements (Araya and Cabral, 2010) and decreased to 44.59% in 2013 and increased to 48.61% in 2021.

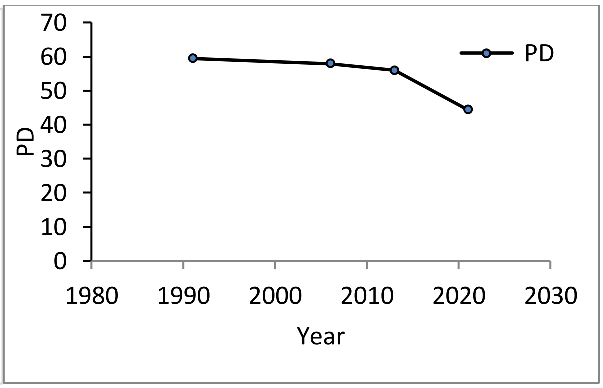
Shannon Diversity Index; SHDI value is zero when the landscape contains only one patch (no diversity). SHDI increases as the number of different patch types (patch richness, PR) increases, and/or the proportional distribution of area among patch types becomes more equitable. In order to assess if urban area expansion was compact or divergent, the Shannon's entropy was calculated for each directions. SHDI value for the year 1991 to 2006 was almost similar, but as shown in Table 4.10, SHDI value increased in 2013(1.15) and declined in 2021(1.1) . This indicates that the city has varied patch richness is dispersed. Shannon’s Evenness Index(SHEI); SHEI is zero when the landscape contains only one patch (no diversity) and approaches zero as the distribution of area among the different patch types becomes increasingly uneven (dominated by 1 type). SHEI value is one when distribution of area among patch types is perfectly even (proportional abundances are the same). SHEI increased slightly in 1991 to 2006 as shown in the table 4.10. This value increased slightly in 2013 and decreased slightly in 2021.figure 4.9 shows six selected Landscape composition at landscape level between 1991 and 2021. LSI indicates decrement during study the periods except 2021. PAFRAC shown up and down that it describes the patch complexity of the landscape.

The increase in SHEI indicates that the patches were not distributed evenly. The increase in landscape pattern metrics during the study period because of the fact that fragmentation of the landscape tended to strengthen (Huang et al., 2010) and spatial variability of the landscape increased in shashemene city in the last three decades. Moreover, the landscape pattern structure became more complex, as discerned in the following landscape metric changes from 1991 to 2021. Human activities, including urban expansion can result in landscape pattern fragmentation and more complex landscape structure. Shannon's diversity index (SHDI) also confirms the landscape is getting more diversified and rich with different patches over time.

Table 4.10. Selected landscape composition at landscape level between 1991 and 2021

| year | NP | PD | LSI | PAFRAC | SHDI | SHEI |
|---|---|---|---|---|---|---|
| 1991 | 10206 | 59.41 | 57.161 | 1.486 | 1.123 | 0.698 |
| 2006 | 9941 | 57.86 | 56.465 | 1.507 | 1.127 | 0.7 |
| 2013 | 9611 | 55.945 | 44.59 | 1.486 | 1.148 | 0.713 |
| 2021 | 7621 | 44.36 | 48.612 | 1.494 | 1.089 | 0.677 |



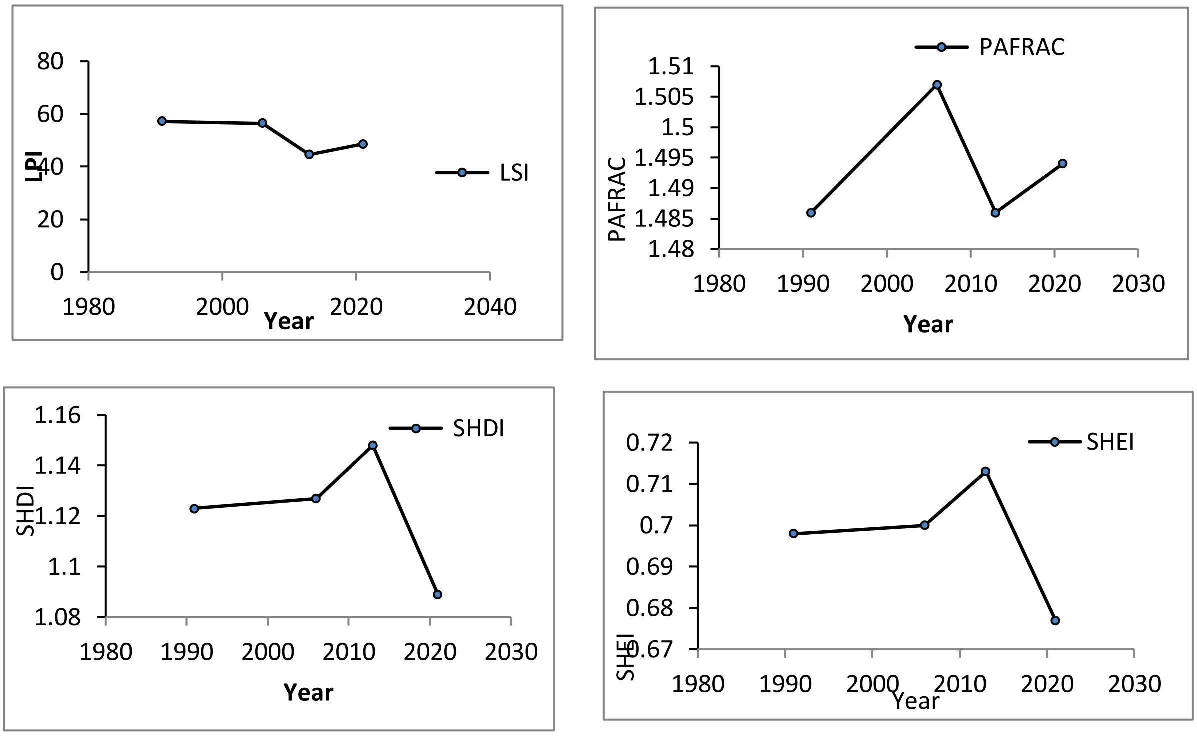



Figure 4.9. Landscape composition at landscape level between 1991 and 2021

### 4.7.2 Landscape Metrics at Class level

Class-level metrics; Class metrics are integrated over all the patches of a given type (class). These may be integrated by simple averaging, or through some sort of weighted-averaging scheme to bias the estimate to reflect the greater contribution of large patches to the overall index. There are additional aggregate properties at the class level that result from the unique configuration of patches across the landscape. In many applications, the primary interest is in the amount and distribution of a particular patch type. A good example is in the study of habitat fragmentation. Habitat fragmentation is a landscape-level process in which contiguous habitat is progressively sub-divided into smaller, geometrically more complex (initially, but not necessarily ultimately), and more isolated habitat fragments as a result of both natural processes and human land use activities (Garigal and Comb 1999).

The class-level indices have a spatial feature to represent the spatial distribution and pattern as they measure the configuration of a particular patch type. The class level indices act as fragmentation indices because class level metrics provided more comprehensive information on the comparative contributions of individual configuration of a particular patch type (Ramachandra et al, 2013). Class indices separately quantify the amount and spatial configuration of each patch type and thus provide a means to quantify the extent and fragmentation of each patch type in the landscape. The followings are some important indices selected to study their relative performance with varied parameters in this research. These are class area (CA), number of patch (NP), Patch density (PD), largest shape index (LPI), and Shannon evenness' index (SHEI) and Shannon diversity index (SHDI).

The pattern of urbanization has not been consistent everywhere. Hence the area has been separated into 4 zones based on directions, Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE), correspondingly (see Figure 4.10), based on the Central pixel, to better understand the pattern of urban growth in relation to  Centre of the city ). Based on the results of the field visit and experience of the area, the assumed city centers were identified and chosen. Linings drawn with ArcGIS 10.8 was use to classify the orientation. The line was divide into fourth sections, each of which was $90^0$ from the origin. The outcomes of this division should answer the questions of where and in which direction the changes mostly occurred from the city core and what patterns the city should followed. Northeast direction is along Addis Ababa, road direction. The city expanded along the road in this direction, Kuyyara sub city was included in this direction. South East direction is along Kofale-Bale-Robe road direction. South West Direction is along Hawasa road direction. North West Direction; is along Hajje-Alaba road direction.

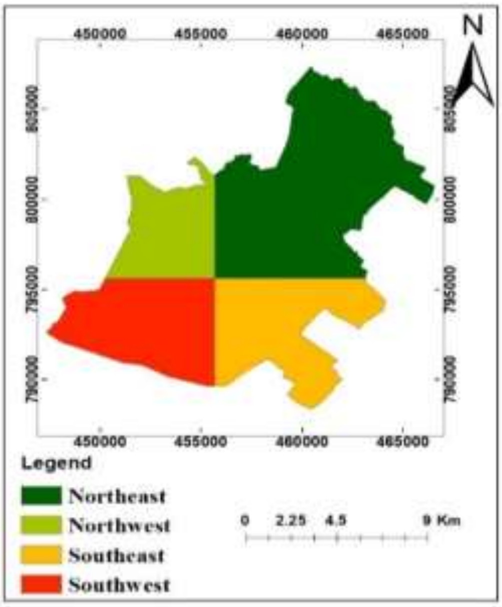



Figure 4.10. Directional division of spatial metrics.

Class Area (CA) ;The Class Area sometimes referred as total Area, CA, in this context, refers to the spatial extent of the urban land use obtained using the metrics. According to the CA, calculated, urban land use has greatly changed over the study period. Large extent of land use change during the study period was characterized by replacement of agricultural areas, vegetated land with urban areas.

Amount of built up area in each four direction shows the increments, however amount of built up in each four direction were different. Similarly in the Northeast (along Addis Ababa road) the built up area CA increased from 505.8 to 1382.32 in 1991 to 2021 respectively agricultural area CA raised from 3898.8 to 4387.3ha in 1991 to 2006 respectively however it declined from 2006 to 2021 year as clearly shown in the figure 4.11.

In Northwest direction CA of built up area increased from 371.34 to 475.47 in 1991 to 2006 similarly Ca for built up area increased in 2013(651.96) and 2021(1382.31) .however agriculture, shows increments up to 2013 years but it declined in 2013-2021 years. Waterbody and vegetation showed up and down while bare land decreased at each study periods. The CA value built up area of southeast and southwest increased in each study periods however, CA of agriculture shows decrease in each study periods. Other LULC shows up and down in each study period in these directions.

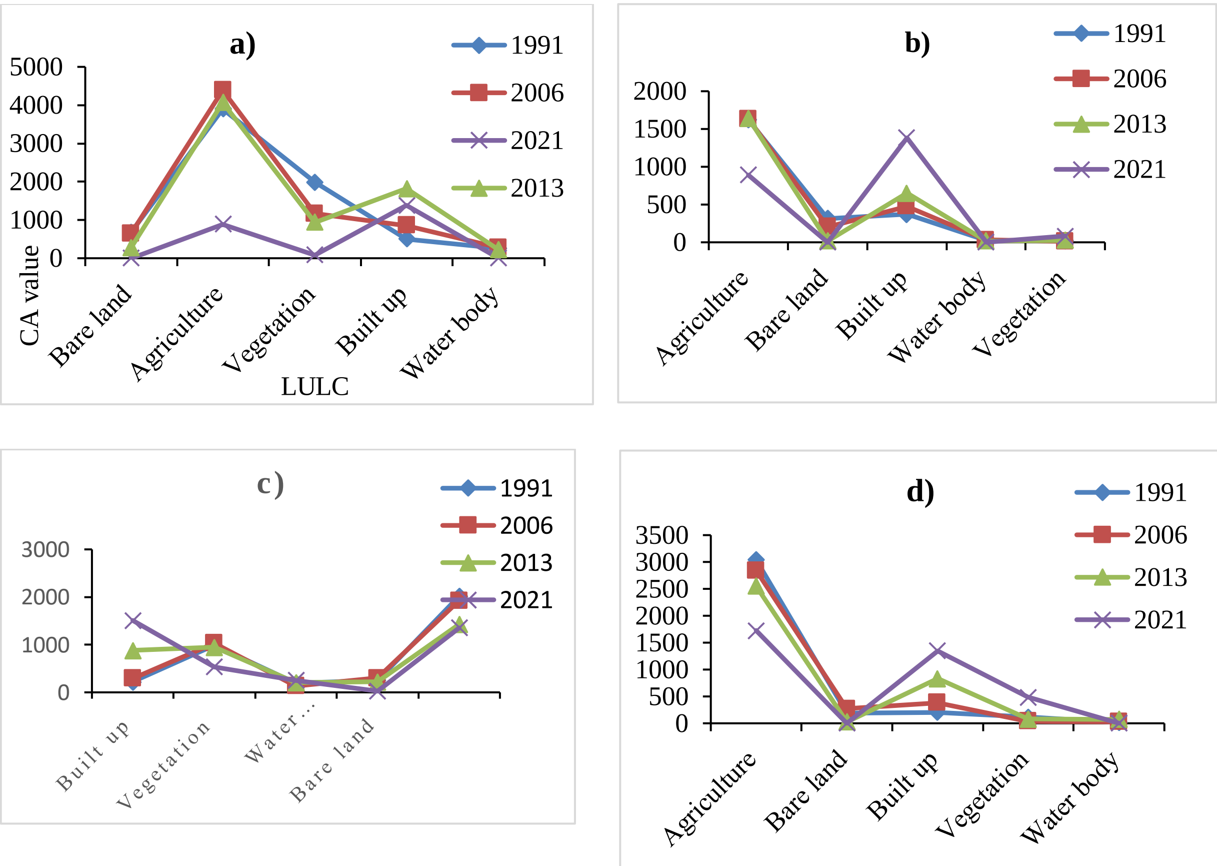



Figure 4.11. CA value NE (a), NW (b), SE(c) &SW (d)

Number of Patch (NP) Number of patches is an indication of the diversity of the landscape. This index can be calculated and interpreted very easily. NP is a type of metrics that describes the growth of particular patches whether in an aggregated or fragmented growth in the region and explains the underlying urbanization. In general, when the number of patches increase the level of fragmentation also increase (refer figure 4.12).

The number of patches for built-up areas decreased from 1309 in 1991 to 233 in 2021 in the northeast direction, similarly the NP decreased from 1991 to 2021 in the northwest direction. Indicating that he aggregated urban growth in both directions. The NP value for built-up area in the Southwest direction was increased from 130 in 1991 to 301 in 2006 and increased to 357 in 2013 and to 458 in 2021. The NP value of built up area in the Southeast was 574 in 1991 and it decreased to 214 in 2006,however it decreased to 625 in 2013 and 499 in 2021. The maximum number of patches for the built up area was found to be 1358Northeast direction in 2006 year (see figure 4.12a) .This up and dawn of NP for built up area showed the aggregation and fragmentation of urban growths.

The number of patches for agricultural increased northeast direction from in the year 1991, 2006 and 2013 but it declined in the year 2021 indicating the formation of new patch in this direction. In Northwest direction the number, patch of agricultural area increased throughout study periods however, the number patch in this direction was less compared to Northeast direction. The NP in the southeast and southwest direction increased each study periods.The NP value for vegetation decreased in the year 1991 to 2006 then increased from 2006-2013 then declined in 2021 year in the North East direction as shown in (see figure 4.12a).Indicating the fragmentation in this direction. The NP of vegetation in Northwest increased throughout the study period except 2021 (refer figure 4.12b) but in the South East NP for vegetation showed decrement in 1991 -2006 but raised from 2006-2013 declined from 2013-2021 years. The maximum Np value for vegetation was 1648 in 2013 and the minimum one is 1021in 2021in Northeast direction indicating the NP less fragmented in this direction. In the southwest direction NP value for vegetation increased indicating the fragmentations due to urban sprawls. The NP value for each direction was shown Figure 4.12.

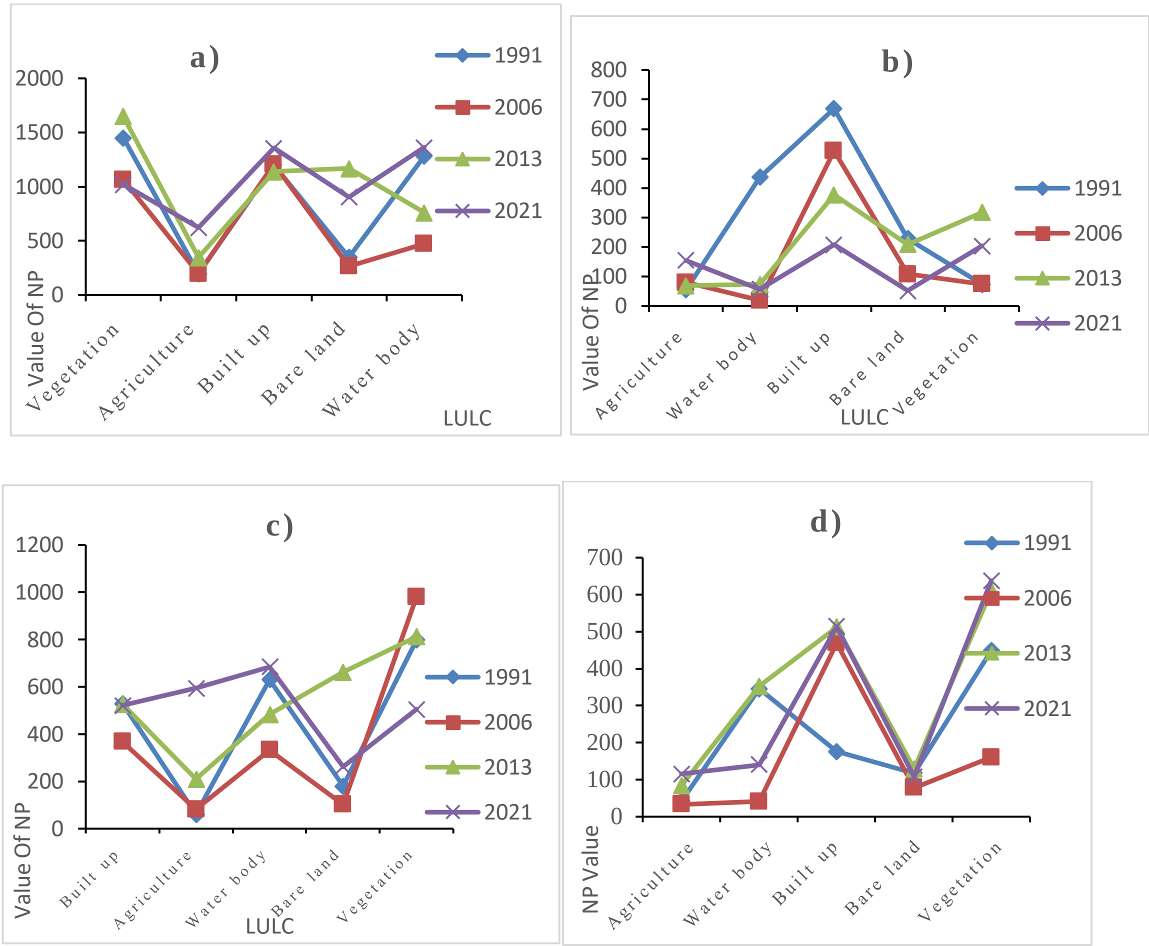



Figure 4.12. NP value in NE (a), NW (b), SE(c) &SW (d)

Patch density (PD); A patch represents an area, which is covered by single land cover class. The patch density (PD) expresses the number of patches within the entire reference unit on a per area basis. PD for built up area in the Northeast and northwest direction have decreased each study periods indicating the varying patch sizes and dispersion between the patches (see figure 4.13 a &b) .PD value in southeast direction for built up area was decreased in 2006, however it increased in 2013 but declined in 2021.

PD value for agriculture for northwest and northeast were declined in the first period however raised second and third periods. In the Southeast direction it increased first and second periods but declined in the third periods, however it showed increments in southwest direction through study periods. Hence, PD value for agriculture indicates the separation of large patch and variation of pach sizes. PD value for vegetation in northeast and south east direction increased in 1991,2006 and 2021 but declined in 2013 years however in Northwest direction and Southwest direction it showed decrement in 2006 but increased in 1991,2013 and 2021 years.in general the PD value indicates the aggregation of agriculture and vegetation in all directions.

Largest Patch Index (LPI); LPI approaches zero when the largest patch in the landscape is increasingly small. LPI = 100 when the entire landscape consists of a single patch; that is, when the largest patch comprises 100% of the landscape. Largest patch index quantifies the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance.

LPI for built up area increased for the last thirty years in all four directions .The maximum LPI was 52.05% in Northwest &Northeast direction in 2021 year and the minimum occurred was 1.07% in 1991 in northeast direction. This was related to the connection of small and isolated urban patches into the largest patch and development of built up areas around the existing largest patch. In other word it means that most of the small isolated and fragmented urban sprawl and associated built ups were connected with the core and main urban (see figure 4.13).

LPI value for vegetation's was small in each directions except Northeast direction. LPI value of vegetation for all the study period was less than one similarly in the southwest direction except the final years, which is 1.55% in 2021. Small LPI value was occurred when large patches decreased and development of other patches. LPI for agricultural area was maximum in 1991 in southwest direction and it declined in the all four directions at each study periods. Similarly, LPI value for water and bare land decreased throughout study periods and was less than one for water at each study periods showing the connection of small area to other patches.

Largest Shape Index; LSI $\geq 1$, without limit. LSI is one when the landscape consists of a single square patch of the corresponding type; LSI increases without limit as landscape shape becomes more irregular and/or as the length of edge within the landscape of the corresponding patch type increases. LSI for built up area in Northeast and Northwest direction declined throughout the study periods however, it increased in Southwest direction throughout study periods and showed up and down in southeast direction. For agriculture decreased in Northeast, Northwest, and Southeast direction. However, it increased in Southwest direction. Vegetation increased in 1991-2006 years in Northeast, Northwest and southeast direction however it decreased in 2013-2021 in Northeast direction. The increase of LSI shows the landscape shape becomes more irregular. The value for built up area indicate the irregularity of the patches indicating the growth of urban area and decline of agriculture and vegetation area (see Figure.4.13).

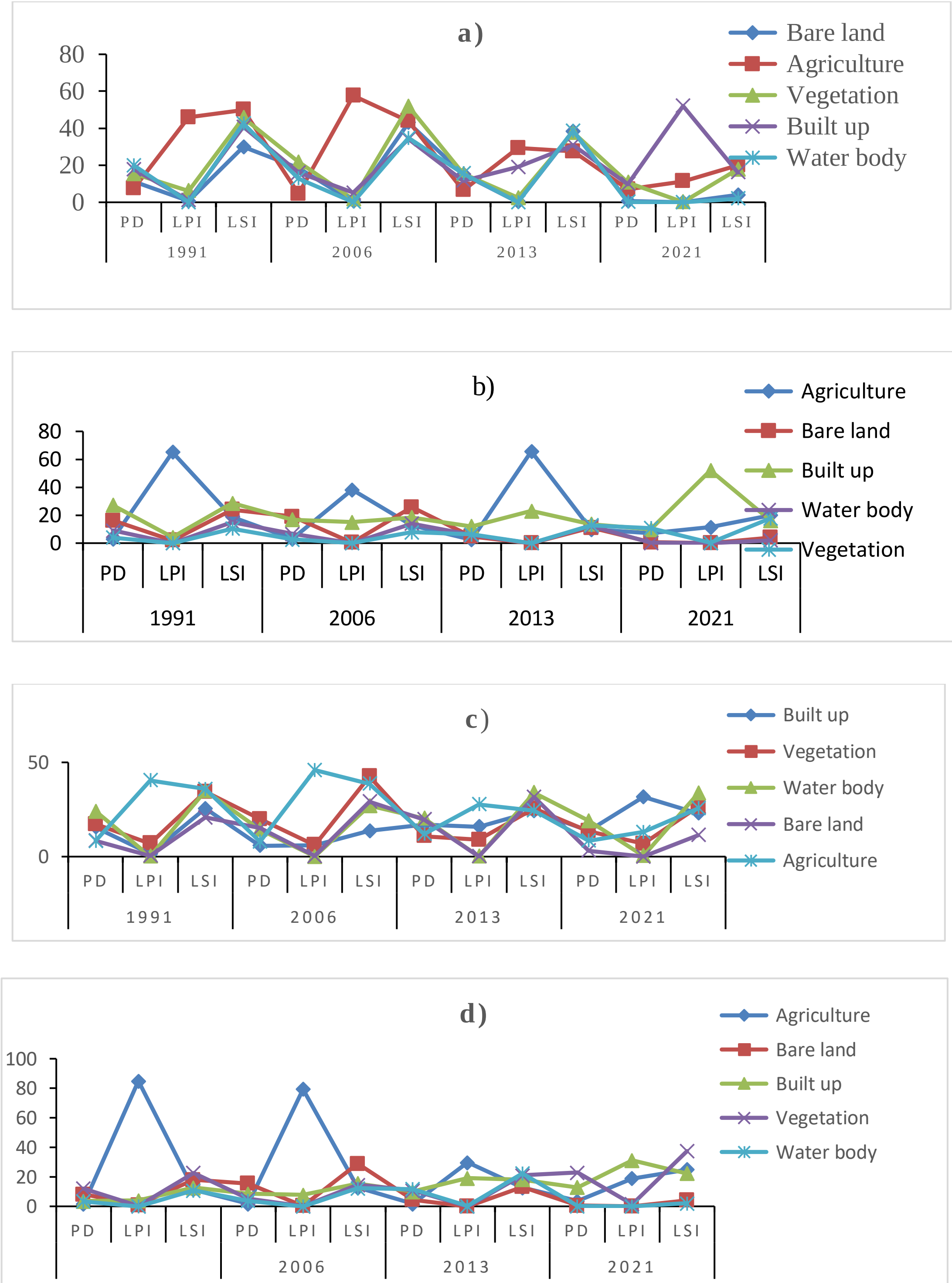



Figure 4.13. PD, LPI&LSI value in NE (a), NW (b), SE(c) &SW (d)

### 4.7.3. Forms of urban growth

It was feasible to quantify the trends and patterns of urban dynamics at the city level using the results of spatial metrics analysis. The spatio-temporal analysis of spatial metrics over the entire study area here described indicates that the urbanization has substantially changed the land cover of the study area, with a significant land conversion. In all research periods, the built-up area has been expanding significantly, although the growth process has been fragmented. This may be an indicator of urban sprawl. In addition to this which can be witnessed from, patch density and the largest patch index also revealed that the city is experiencing infill and edge expansion around the urban core (refer figure 4.9).

## 4.8. LULC Modeling and Future Prediction

Many models on simulations are continuously being created for LULC change modelling from the last 2 decades at the global level (Han et al, 2015). In this study LULC, change simulation has been done in MOLUSCE tool given in open-source QGIS software of 2.8.1 version using cellular automata (CA) simulation to predict LULC pattern of shashemene city in 2031 and 2041. In QGIS, Cellular Automata function is Markovian in nature because it depends on the current state of land use and not of previous. This function works by giving inputs of past and present land use maps with spatial variables like road network, slope aspect, and waters to generate the output in the form of maps and tables. According to that MOLUSCE plugin trains model is given inputs with algorithms. For transitional potential modelling of LULC, ANN algorithms have been applied because of its maximum accuracy than other algorithms (Molusce 2018; Al-Rubkhi et al, 2017).

### 4.8.1. Drivers for LULC Changes

In order to understand the process of the LULC changes and predict future LULC, the drivers should be properly studied and analyzed. The impact of each driver on LULC change differ in their own way. In case of biophysical factors, the land classes having flatland has high possibility to change into built-up compare to the steep land. Similarly, the fertile land has high possibility to change into agriculture compare to the bare land. Similarly, proximate factors such as distance from rivers and distance from roads plays crucial role in the LULC change pattern significantly. The distance from the road, and the distance from the river, the DEM, the aspect, and the slope were factors that considered for LULC investigations as shown in figure 4.14). Digital Elevation Model (DEM) was downloaded from United States Geological Survey (USGS). The DEM was clipped to the project extent. The slope layer was derived from Digital Elevation Model (DEM). Distance from road and distance from river were derived from city masterplan.

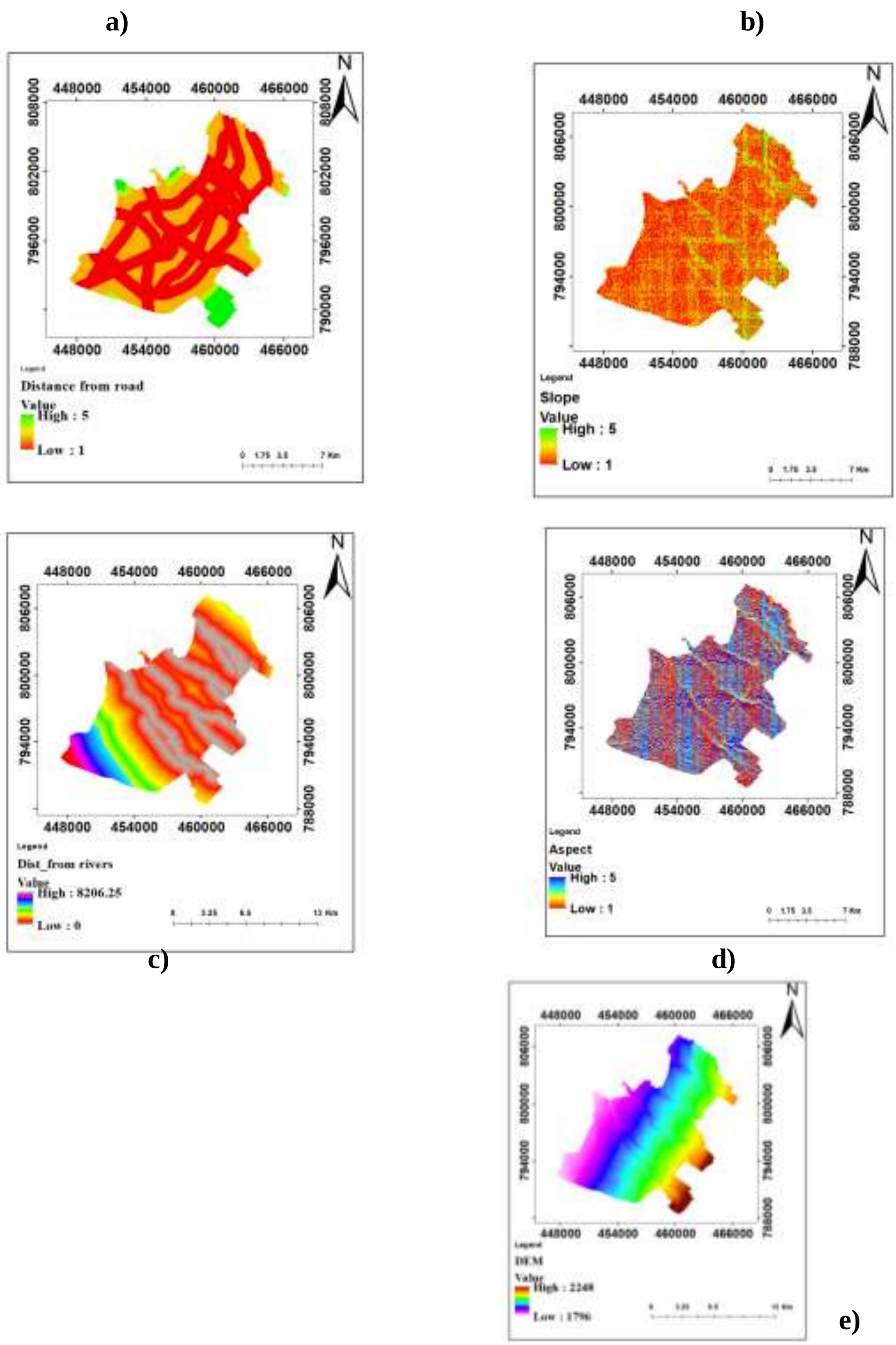



Figure 4.14. LULC Drivers; distance from road (a),slope(b), distance from river(c) aspect (d), and DEM (e)

### 4.8.2. Transition Potential Modeling

CA-ANN composed of various essential elements. In CA; cells, array dimension, transition rule are major parts whereas neurons, weights, input, hidden and output layer are major components of ANN. Similarly, the neurons are the basic unit in an ANN, which receives input from some other nodes, or an external source and computes an output.

The accuracy assessment of image classification and simulation results is slightly different because in the latter case the accuracy is assessed by using the maps, not the specific points that are indicating the real category information (Rossiter, 2004). In many studies, kappa statistical measurements have been used for the accuracy assessment .The aim was to observe the main changes between 2021 classified and then comparing the results with the predicted map, to understand if the overall changes have been predicted correctly or not. The method used for the accuracy assessment, calculating kappa values related to the location and the quantity to observe the accuracy in each class. These are Klocation and Khisto which demonstrate the source of error, whether it is location or quantity. Klocation shows the similarity in the spatial distribution of classes but does not differentiate between classes that are close or distant and it is independent of the total number of cells per class. Khisto measures quantitative similarity between two maps, in other words, it checks the similarity in the amount of the cells in the testing map and reference map.

The MOLUSCE plugin integrates some well-known algorithms for transition potential modeling, such as the ANN, (multilayer perception. Learning algorithm analyses the reached accuracy on training and validation sets of samples and stores the best neural net in memory. The training process finishes when the best accuracy is reached. Neighborhood pixels kept it as 1px because minimum is most efficient. Performed 100 iterations for the Multi-Layer Perceptron. Chosen 10 Hidden Layers and kept the learning rate and momentum as low as 0.001.Current Validation Kappa came to be 0.9012.The spatial variables for model calibration were chosen based on their relatively strong association with LULC, as measured by Pearson’s correlation. The study used the CA-ANN approach for transition potential modeling and prediction. LULC data from 2006–2013 employed along with spatial variables to projected LULC for 2021 and obtained a validation kappa value of 0.9012.

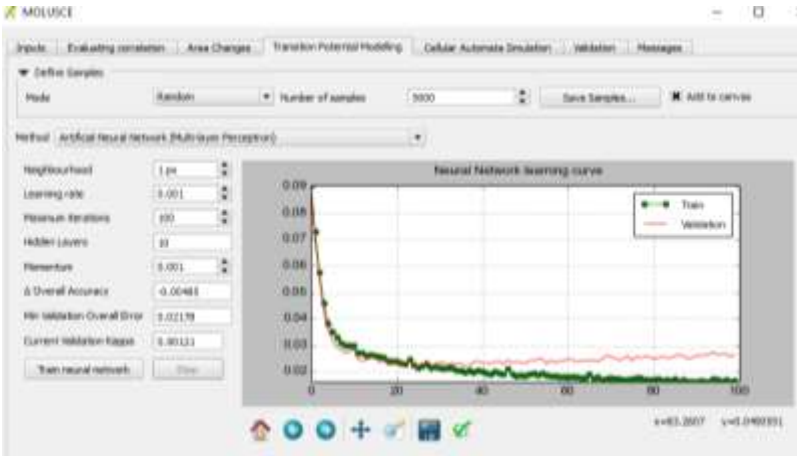


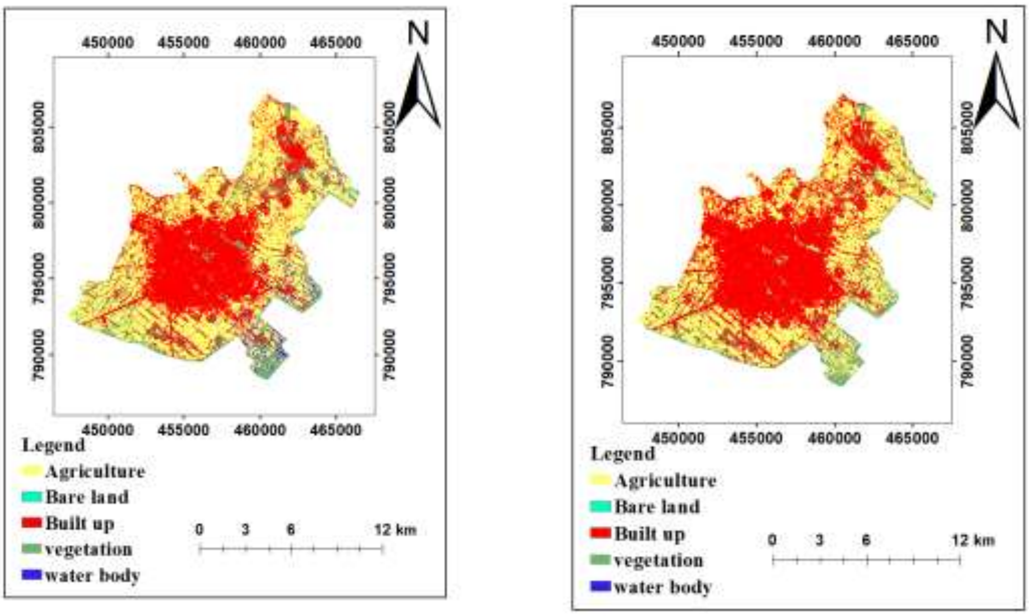

Figure 4.15. Graph showing ANN modeling training.

4.9. Urban growth Predication

Existing urban areas are expected to expand based on the previous growth pattern. The quantitative demand for land use is mainly based on the urban change from 1991 to 2021, and the drivers (see figure4.14) with the CA-ANN Model is used to predict the land use change in 2031& 2041 (refer figure 4.18a & b).

### 4.9.1. Cellular automata simulation fort the year 2031 and 2041

Cellular automata (CA) are a type of discrete model commonly used in modeling spatio-temporal processes. In this study, the LULC data and related variables were transformed into raster datasets, which can be modeled in a CA. With the transitional rules derived by the ANN. The CA is able to simulate the LULC dynamics at different time steps in a raster format. The percentage of correctness shows the percentage of the predicted area that is precisely the same as the real area in the same year. The Kappa value shows the degree of accuracy and reliability in a statistical classification. After comparing predicted and actual LULC of 2021 and obtained a current validation kappa value of 0.9. After obtaining satisfactory results from model validation, predicted the LULC for 2031 and 2041 was started. Figure 4.16(a) shows the simulate LULC of 2021 and figure 4.16(b) shows actual LULC of 2021.as clearly shown in the figures 4.16 and the validation kappa values possible to predict future LULC of 2031 and 2041.




a) b)

Figure 4.16. Actual (a) and simulated (b) LULC of 2021

### 4.9.3. Model Validation

The kappa statistics includes kappa histogram (86.79%) that is an estimation of the frequency distribution of the simulation, Kappa location (86.87%) that is the simulation ability to perfectly specify location between the reference map and the simulated map, and Kappa overall (75.39%) that is the total accuracy of the number pixel correctly classified between the reference map and simulated map. Accordingly, the results of the analysis indicate that the variables employed were found to be effective and simulation result is relatively reliable in predicting the future change in LULC .Figure 4. 17-shows the output graph generated by running validates using the 2021 LULC map as the reference map and the 2021 simulated map as the comparison map. As explained above, this comparison method is of main interest since it indicates the accuracy of the model at simulating LULC changes.

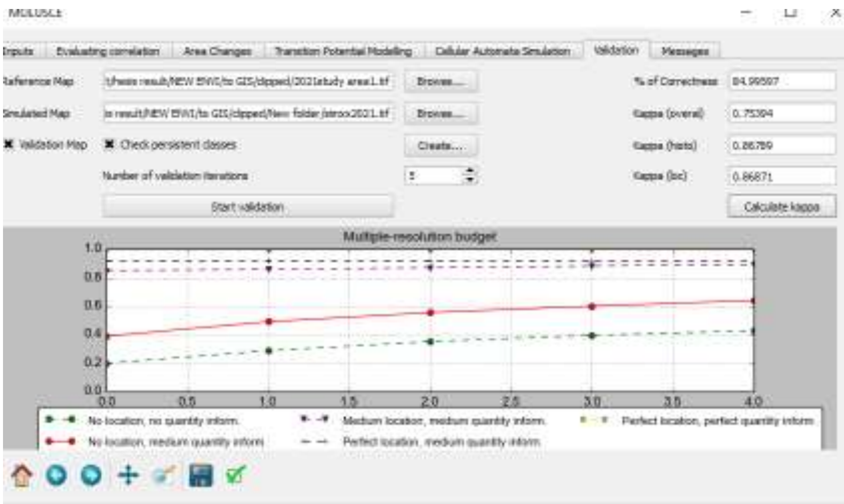
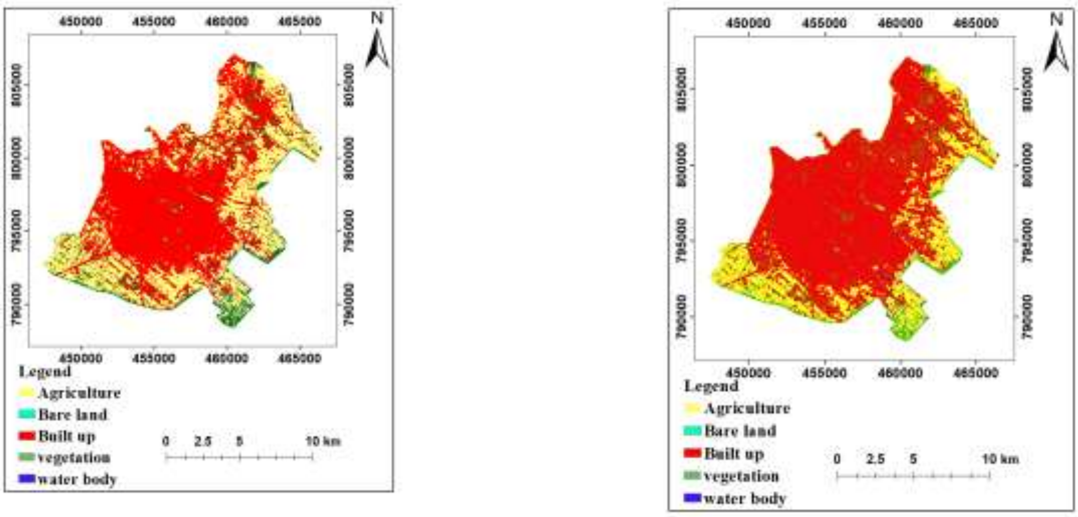



Figure 4.17.the output graph generated by running validates.

The statistical value of LULC change of 2021,2031 and 2041 were shown in the table 4.11.the built up area increased by 55.77% in 2031 and it further increased to 65.17% in 2041.this shows that amount of land covered by built up area are more than have of the other all LULC classes. Agriculture area was 45.89% in 2021. however, it declined to 35.68% in 2031 and it would decreased to 27.49% in 2041(see table 4.11).Vegetation was at 11.4% in 2021 and it would be decreased to 7.55% , and 6.6% in 2031 and 2041 indicating the rapid expansion of the city resulted the declination of the vegetation area and agriculturally valuable area which would be serious environmental problems unless necessary measurement is taken.




**a)** **b)**

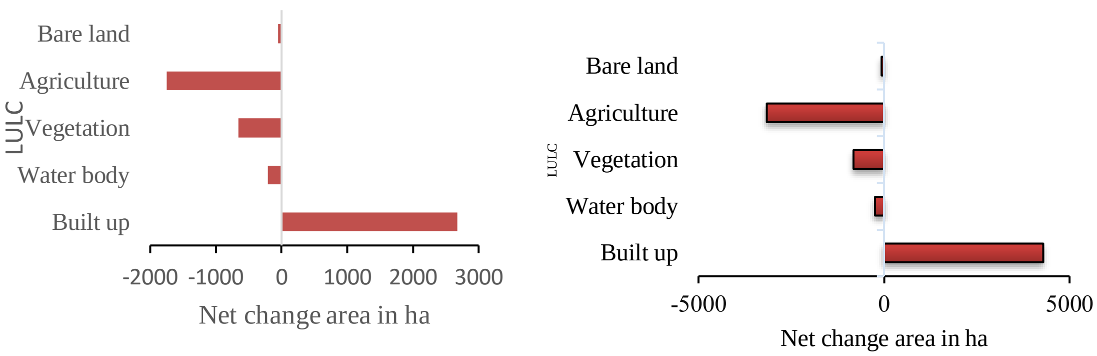
Figure 4.18. LUC of 2031 (a) and 2041(b)

Table 4.11. Amount and percentage of projected LULC of 2031 and 2041.

| LULC | 2021 | | 2031 | | 2041 | |
|---|---|---|---|---|---|---|
| | Area in ha | % | Area in ha | % | Area in ha | % |
| Built up | 6900 | 40.18 | 9578 | 55.77 | 11191 | 65.17 |
| Water body | 342 | 1.99 | 131 | 0.76 | 100 | 0.58 |
| Vegetation | 1958 | 11.40 | 1296 | 7.55 | 1135 | 6.61 |
| Agriculture | 7880 | 45.89 | 6127 | 35.68 | 4720 | 27.49 |
| Bare land | 93 | 0.54 | 41 | 0.24 | 27 | 0.16 |
| Total | 17173.00 | 100.00 | 17173.00 | 100.00 | 17173.00 | 100.00 |

### 4.9.4. LULC Change between 2021-2031 and 2031-2041

LULC net change for the year 2021–2031 was shown figure 4.16, the built-up area will change positively by 15.6%(2677.6250ha) For the next ten years, the other land uses land cover, waterbodies, vegetation, and bare land would drop by negatively -0.12%, -3.8%, -0.3%, and 10.21%, respectively. The net change during the next 10 years, from 2021 to 2031, is shown in figure 4.15 (a &b). The chart makes it quite evident that during the next ten years, the net built-up area will expand while agriculture, vegetation, bare land, and water bodies will all decrease. Similarly the net change of LULC of 2031-2041 will indicate the expansion of built-up area while the decline of agriculture, water body, bare land and vegetation as shown in the figure 4.17 (b).these projected future land use land cover of shashemene city indicate the expansion of the city without control due to population expansion and illegal built up area.




a) b)

Figure 4.19. LULC net change between 2021-2031(a) and 2031-2041(b)

## 4.10. Discussion

The current study performs the analysis of LULC change and landscape structure in 1991 to 2021 years. It also predicted future land cover that provides an answer to the research question of LULC change trend in the past three decades and where LULC changes are expected to occur in 2041 using CA-ANN model of MOLUSCE plugin in QGIS .Spatial metrics was used to analyses urban land configuration and composition.

To classify Landsat image, ENVI 5.3 along with SVM algorithm were used. SVM is a non-parametric classifier. Unlike parametric classifiers such as maximum likelihood that assumes that the data is normally distributed, non-parametric classifiers do not base classification on a normality assumption or statistical parameters (Bulti, 2019).Arc GIS 10.8 was used to prepare LULC maps. The findings in the study area shows that a significant decrease in agricultural area occurred from 1991 to 20021, which showed a negative change in all of the LULC categories except built up area. Built up area increased each study period by 7.24%, 11.51%, 24.28% and 40.18% in 1991, 2006, 2013 and 2021 respectively. Niaz et al, (2017) studied urban expansion dynamics in Dhaka and reported rapidly urban growth resulted in a substantial decrease in natural vegetation cover and agricultural land. This is due to the development of residential areas for commercial, academic, and business purposes in all the three-time periods in unplanned manner. Other LULC showed continuous decline through each study periods. LULC change matrix also shows the conversion of agricultural area and vegetation to urban area.

The annual average rate of change 3.93%, 15.85% and 8.18% & 15.16 % of 1991-2006, 2006-2013, 2013-2021 and 1991-2021 respectively. This fast urban expansion was also evidence with the positive values of annual average rate of change of 15.16% .Annual growth rate of the city over the last 30 years was 5.71% indicating the rapid expansion of the city. Similarly (GebreMedhin, & Biruh, 2019) studied urban dynamics in Axum town and reported that the rate of urbanization is going faster. Urban expansion intensity indices (UEII) in shashemene city shows the highly rapid expansion of the city especially in the second and third periods. Shifaw et al, (2018) Studied spatio-temporal urban dynamics and modeling in Nepal and reported the same result. Land transition matrices provide better information, about the spatiotemporal variability of persistent areas and susceptibility to gain/loss of the area exchange among land cover types.

Analyzing the spatial extent and rate of urban growth and identifying the growth direction alone does not give sufficient insight in to the patterns of urban growth processes, which are important to better understand urban growth. To bridge this gap according to (Fan, & Myint, 2014) Remote sensing data coupled with landscape pattern analysis provides a framework within which landscape structure can be quantified and studied. The outputs presented in table 4.10 were generated for the selected metrics in the form of numeric values for the whole study area in FRAGSTATS 4.2. This metrics shows increments and decrements shown in the figure 4.9**,** indicating the fragmentation and composition of urban growth through study periods. SHDI index shows the city's varied patch richness is dispersed. In the past thirty years, processes for disaggregating landscapes have been fostered and their shape complexity has increased. This finding is consistent with research conducted in China, the Phoenix metropolitan area, and Arizona (Huang et al., 2010). Class level metrics at four-selected cardinal direction (region based) for each study year shows the dynamics of study area over study period. Urban landscape configuration was quantified using selected landscape metrics as these methods are the most popular to get the easily comparable result this is supported research conducted in Estonia (Uuemaa et al, 2013).

Modelling and prediction will depend upon given inputs; image datasets, driving factors and model parameters (Bhandari et al.2021).Modeling and predicting are important to understand urban growth. CA-ANN integration with MOLUSCE model predicts future urban growth of 2031 and 2041.Actual map of 2021 and simulated map of 2021 were compared to predict. Then the prediction was carried out indicating that the built up area increased at an alarming ratee. According to the expected outcome, over 6900 ha of the total amount of land was used for built-up area in 2021, and that number would rise to 11191 ha in 2041. In 2021, the agricultural and vegetative areas would be 7880 ha and 1958 ha, 61 respectively, while in 2041, they would be 4720 ha and 1135 ha. Similarly, a research conducted in City of Banepa and Dhulikhel, Nepal using MOLUSCE reported (Bhandari et al 2021) the built-up area expanded while other land use land cover declined..

# 5. CONCLUSIONS AND RECOMMENDATIONS

## 5.1. Conclusion

In order to analyzing the dynamics of urban growth on both spatial and temporal scale, Understanding the effects of urbanization and developing long-term planning strategies has been regarded as a vital steps. Because of the effects and influences, urbanization has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and their drivers over space and time is important to predict future urban developments and set decision-making mechanisms. Hence, this study was aimed to analyze the spatiotemporal dynamics of urban growth and predict its possible expansion using the CA-ANN Model via MOLUSCE plugin in QGIS. Four years of Landsat images were interpreted to obtain land-use Landover changes and to model and predict urban land use change for 2031 and 2041years. Through supervised image classification using the support vector machine algorithm, LULC maps of the study area in 1991, 2006, 2013, and 2021 were prepared. The Classification results of LULC show a reduction in agricultural, vegetation, waterbody and bare land while increase with built-up area between 1991 from 7.24% to 40.18% in 2021 year. The study has shown that urban land change has profound impact on urban Landscape and human activities, including urban expansion can result in landscape pattern fragmentation. The results show that the built-up area has undergone about 5.71 % expansion annually in the past 30 years, indicating highly rapid urban growth. In the first period, the city expands moderately but after 2013, the city expanded highly rapidly.

Urban spatial configuration was captured with landscape metrics. Landscape metrics both at landscape level and at class level were selected. Six metrics at landscape level namely number of patch(NP),patch density(PD),largest shape index(LSI), Perimeter-Area Fractal Dimension( PAFRAC),shannon diversity index(SHDI) and Shannon evenness index(SHEI) were selected. The increase and decrease in landscape metrics during the study period was because of the fact that fragmentation of the landscape tended to strengthen and the spatial variability of the city. The built-up area has significantly increased over all selected years despite the fragmented growth approach. Urban sprawl may be indicated by this. Patch density and the largest patch index also highlighted that the city is experiencing infill and edge development surrounding the urban Centre, in addition to urban sprawl.

The results of prediction indicate the capability of MOLUSCE plugin in open source QGIS to predict future land cover using the CA-ANN model. Driving criteria, such as DEM, slope, aspect, distance from the road, and distance from the river, and LULC map of 2013 and 2021 are integrated with CA-ANN technique within the MOLUSCE plugin of QGIS. The overall accuracy of prediction using ANN is 86.78%, which is satisfactory .The simulation result shows that almost 65.17% area will cover by built up area for the next twenty years. The Agricultural and vegetation area would be decreased to 4720 ha and 1135 ha in 2041 respectively. In order to prepare a new action plan before adverse effects become irreversible, planners and stakeholders would benefit from the findings of this study. The creation of urban planning policy should also work to achieve a healthy balance between socioeconomic needs and the sustainable use of limited resources.

## 5.2. Recommendations

Based on the findings of this study, the following recommendations have been drawn.

- The quality of image classification depend on the quality of satellite images. Landsat time series data is challenging because of significant intra-urban heterogeneity and spectral confusion between other land cover types; hence, other high spatial resolution satellite images are required.
- LULC prediction provide essential information on future urban growth, currently urbanization is growing rapidly and shows variation even within a year. The prediction years have to be within a short time interval may be five years.
- For precise prediction, major responsible drivers for LULC changes such as plan and policy, climatic conditions, temperature, ecological degradation, hydrological variation and soil erosion are recommended to consider for future research.
- The city is growing at an alarming rate, therefore planning is important, particularly in collaboration with the regional urban planning institutes and stakeholders.

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# APPENDICES

Appendix 1 GCP used for accuracy assessments

| Easting | Northing | Land _type | Easting | Northing | Land _type | Easting | Northing | Land _type |
|---|---|---|---|---|---|---|---|---|
| 453367 | 795912 | Bare land | 456661 | 795953 | Vegetation | 453223 | 794876 | Built-up area |
| 454553 | 795922 | Bare land | 456025 | 795987 | Vegetation | 453030 | 794875 | Built-up area |
| 455674 | 797524 | Bare land | 453018 | 795990 | Vegetation | 453021 | 794762 | Built-up area |
| 451234 | 797585 | Bare land | 453035 | 795676 | Vegetation | 453029 | 794567 | Built-up area |
| 451286 | 797590 | Bare land | 453026 | 795641 | Vegetation | 453147 | 794978 | Agricultural area |
| 452134 | 795960 | Bare land | 453012 | 795675 | Vegetation | 453175 | 794978 | Agricultural area |
| 452765 | 796075 | Bare land | 453079 | 795543 | Vegetation | 453198 | 794765 | Agricultural area |
| 452465 | 796563 | Bare land | 453065 | 795456 | water body | 454045 | 794869 | Agricultural area |
| 457864 | 796555 | Bare land | 453044 | 795543 | water body | 454087 | 794854 | Agricultural area |
| 454567 | 796870 | Bare land | 453037 | 795789 | water body | 454078 | 794876 | Agricultural area |
| 453567 | 796892 | Bare land | 453042 | 795356 | water body | 454097 | 794863 | Agricultural area |
| 453876 | 796899 | Bare land | 453010 | 795912 | water body | 454245 | 794328 | Agricultural area |
| 458765 | 796878 | Bare land | 453021 | 795345 | Vegetation | 454567 | 794367 | Agricultural area |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 458732 | 796667 | water body | 456038 | 795349 | Vegetation | 454678 | 795985 | Agricultural area |
| 458714 | 796544 | water body | 455033 | 795678 | Vegetation | 454767 | 795999 | Agricultural area |
| 455767 | 796785 | water body | 456012 | 797898 | Vegetation | 454432 | 797506 | Agricultural area |
| 455678 | 796772 | water body | 456028 | 797134 | Built-up area | 453432 | 797800 | Agricultural area |
| 454778 | 796787 | water body | 453038 | 797987 | Built-up area | 456789 | 797815 | Agricultural area |
| 454667 | 797981 | water body | 456032 | 797238 | Built-up area | 453675 | 796544 | Agricultural area |
| 454867 | 799776 | water body | 455037 | 797865 | Built-up area | 445678 | 796585 | Bare land |
| 456234 | 799787 | water body | 455028 | 798769 | Built-up area | 453563 | 796590 | Bare land |

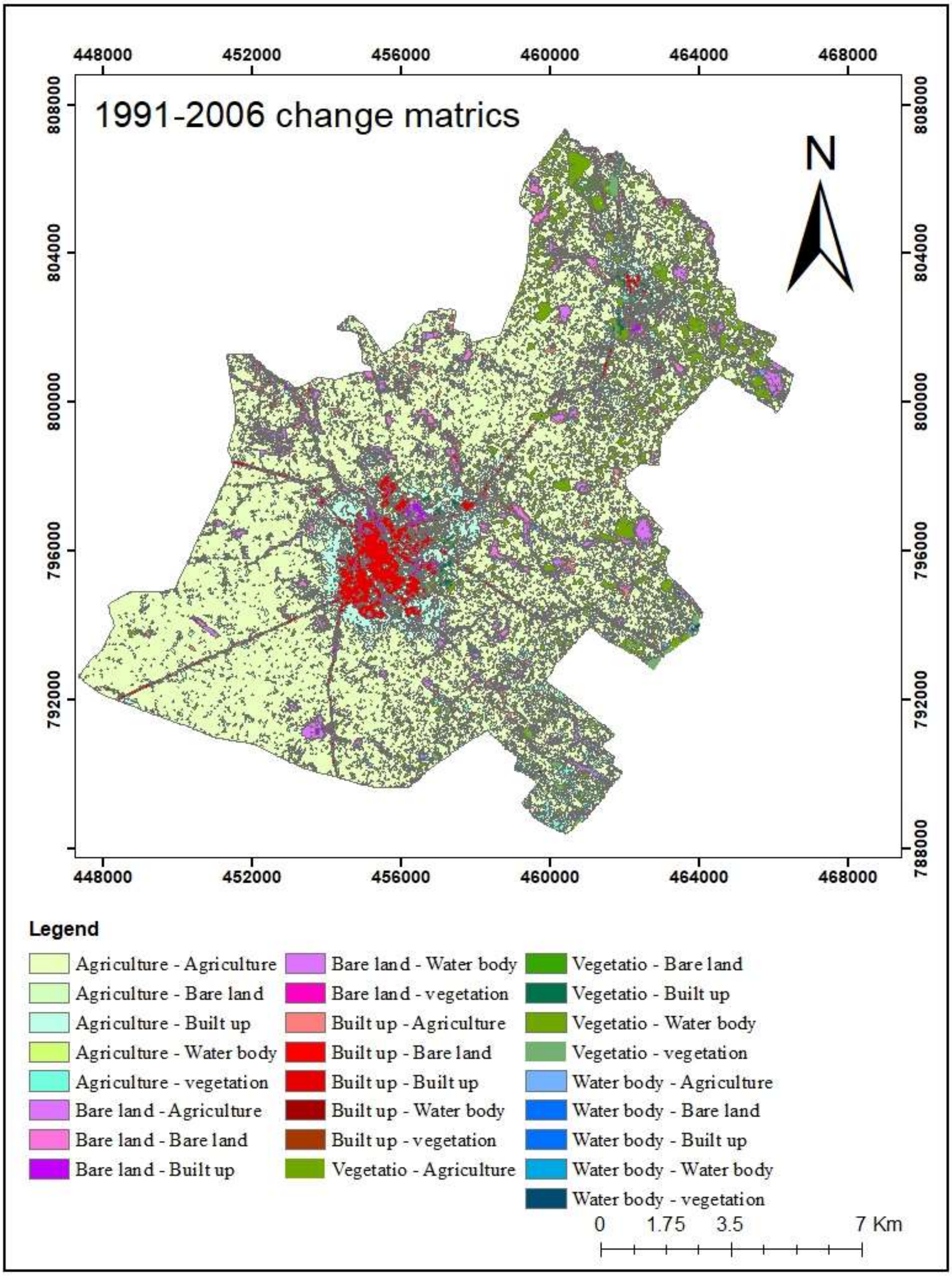
Appendix 2. Confusion Metrix Of 2021

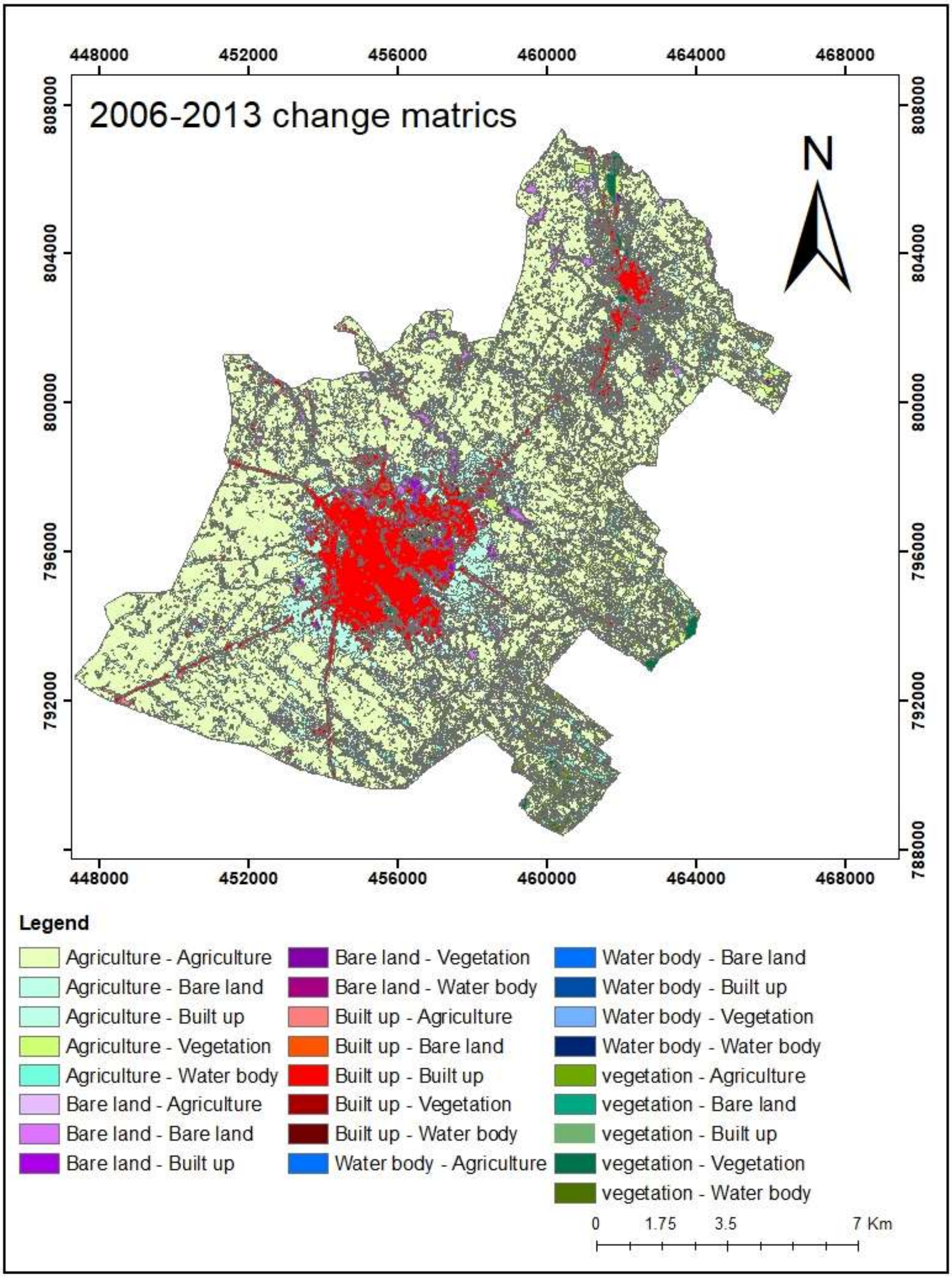
| LULC 2021 | Built up | Water | Vegetation | Agriculture | Bare land | Total user | user accuracy % |
|---|---|---|---|---|---|---|---|
| Built up | 54 | 0 | 0 | 1 | 0 | 55 | 98.2 |
| Water body | 0 | 35 | 3 | 0 | 0 | 38 | 92.1 |
| Vegetation | 0 | 0 | 45 | 2 | 2 | 49 | 91.8 |
| Agriculture | 1 | 0 | 4 | 55 | 2 | 62 | 88.7 |
| Bare land | | 0 | 2 | 4 | 53 | 59 | 89.8 |
| Total producer | 55 | 35 | 54 | 62 | 57 | 263 | |
| producers accuracy % | 98.2 | 100. | 83.3 | 88.7 | 92.9 | | |

Overall accuracy;- 92.02%

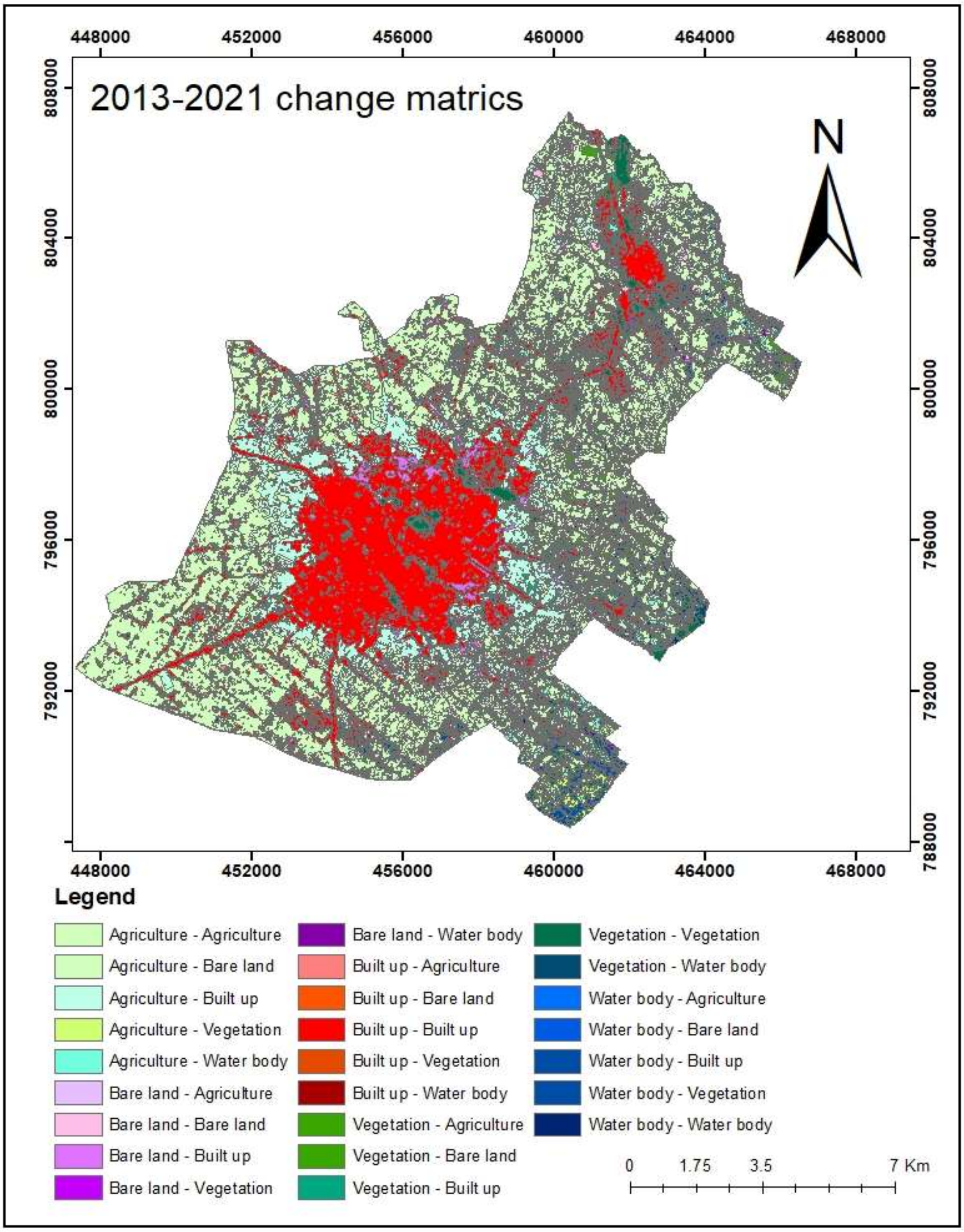
Overall kappa statistics ;- 89.95%

Appendix 3.LULC change matrix





2006-2013 change matrics
N
448000
452000
456000
460000
464000
468000
808000
804000
800000
796000
792000
788000
Legend
Agriculture - Agriculture
Agriculture - Bare land
Agriculture - Built up
Agriculture - Vegetation
Agriculture - Water body
Bare land - Agriculture
Bare land - Bare land
Bare land - Built up
Bare land - Vegetation
Bare land - Water body
Built up - Agriculture
Built up - Bare land
Built up - Built up
Built up - Vegetation
Built up - Water body
Water body - Agriculture
Water body - Bare land
Water body - Built up
Water body - Vegetation
Water body - Water body
vegetation - Agriculture
vegetation - Bare land
vegetation - Built up
vegetation - Vegetation
vegetation - Water body
0 1.75 3.5 7 Km



2013-2021 change matrics
N
448000
452000
456000
460000
464000
468000
808000
804000
800000
796000
792000
788000
Legend
Agriculture - Agriculture
Agriculture - Bare land
Agriculture - Built up
Agriculture - Vegetation
Agriculture - Water body
Bare land - Agriculture
Bare land - Bare land
Bare land - Built up
Bare land - Vegetation
Bare land - Water body
Built up - Agriculture
Built up - Bare land
Built up - Built up
Built up - Vegetation
Built up - Water body
Vegetation - Agriculture
Vegetation - Bare land
Vegetation - Built up
Vegetation - Vegetation
Vegetation - Water body
Water body - Agriculture
Water body - Bare land
Water body - Built up
Water body - Vegetation
Water body - Water body
0 1.75 3.5 7 Km