

QUANTIFYING THE RATE OF SPATIO-TEMPORAL URBAN GROWTH PATTERN
USING REMOTE SENSING AND SPATIAL METRICS:
(A Case of Shashemanne Town)

By:
Kemal Jado Tufa



A Thesis Submitted to
The department of Geomatics Engineering
School of Civil Engineering and Architecture
Presented in Partial Fulfillment of the Requirement for the Degree of Master's of
Science in Geoinformatics Engineering.

Office of Postgraduates
Adama Science and Technology University

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Advisor:

Getachew B/Meskel (PHD.)



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We, the undersigned, members of the Board of Examiners of the final open defense by **Kemal Jado Tufa** have read and evaluated his thesis entitled “QUANTIFYING THE RATE OF SPATIO-TEMPORAL URBAN GROWTH PATTERN USING REMOTE SENSING AND SPATIAL METRICS IN SHASHEMANNE TOWN” and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Master’s of Science in Geoinformatics Engineering.

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Date

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LIST OF ACRONYMS

ASTER	Advance Space –Borne Thermal Emission Reflection Radiometer
CA	Class Area
CBD	Central Business District
ER	Eastern Region
ETM+	Enhanced Thematic Mapper-Plus
GIS	Geographical Information System
LCM	Land Change Modeling
NIR	Near Infra- Red
NP	Number of Patch
NR	Northern Region
PCP	Percentage Correct Prediction
PD	Patch Density
SPSS	Statistical Package for Social Sciences
SR	Southern Region
TM	Thematic Mapper
UN	United Nation
USGS	United State Geological Survey
VHR	Very High Resolution
VIF	Variance Inflation Factor
WGS	World Geodetic System
WR	Western Region

ABSTRACT

The spatio-temporal patterns and processes of urban growth of Shashemanne town and its drivers were investigated from the year 1990 to 2019 by using remote sensing and spatial metrics by Logistic Regression Model (LRM). Four different land cover maps derived from Landsat TM image of 1990, Landsat ETM+ 2000, 2010 and Landsat OLI/TIR of 2019 were used to evaluate a set of five selected spatial metrics to reveal patterns and dynamics of urban growth in the study area. The computation of spatial metrics was conducted at two spatial scales. First, the summary descriptors of landscape heterogeneity at the town level are evaluated. Secondly, in order to better link the metric analysis to more specific locations, the study area is broken into five smaller individual regions on the basis of administrative boundaries. Then the changing patterns of urban growths over time were linked to the major physical driving forces in the study area with binary logistic regression modeling. Therefore three models were built for 1990-2000, 2000-2010 and 2010-2019 time periods. The growth was prolonging both from urban center to adjoining non-built up areas in all direction, but mainly to the east, north and west direction along major road corridors. The total built-up area in the town has grown from 305 ha in 1990 to 2500 ha in 2019 at an average growth rate of 2.65%, 5.29% and 7.19% per annum during 1990-2000, 2000-2010 and 2010-2019 study periods respectively. The analysis of spatial metrics at the town level revealed that the urban landscape has experienced a process of sprawling and fragmented development pattern particularly in the fringe areas while, the town center under went in fill and edge expansion development processes. The results of binary logistic regression model revealed that proportion of built up cell distance to (major roads, town centers, higher institution, CBD and satellite towns) and slope were the major driving forces of urban growth at different time periods with varying level of significance and correlation.

KEYWORDS: REMOTE SENSING, URBAN GROWTH, SPATIAL METRICS, LAND USE AND LAND COVER CHANGE, LOGISTIC REGRESSION MODEL.

CHAPTER-1: INTRODUCTION

1.1 Background.

Urbanization has been a global and important social and economic phenomenon taking place all around the world. This process, with no sign of slowing down, could be the most powerful and visible anthropogenic force that has brought about fundamental changes in land cover, land use change and landscape pattern around the globe. Rapid urbanization and urban growth, especially in the developing world, is continuing to be one of the crucial issues of global change in the 21st century affecting the physical dimensions cities/towns.

The rate of urbanization is very fast in developing countries. This can be more explained when we compare the current rate of growth with the historical trends and the urbanization rate of developing countries with that of developed countries to note their difference in rate of growth (Wondmu, 2011). For instance, the urban population in developing country is estimated to increase from 2.5 billion in 2009 to 5.2 billion in 2050 while urban population in developed country will only show a moderate increases from 0.9 billion in 2009 to 1.1 billion in 2050 (UN,2010). Forty years ago Gamst characterized Ethiopian civilization as “Peasantries and Elites without Urbanism”. He was referring to a presence of a social organization and high culture civilization in which cities were absent (Gamst, 1970).

Thirty years later, researchers were still talking about “urban deserts” in Ethiopia, despite the acceleration of urbanization, with an average growth rate between 4.4 and 5.6 percent a year (Golini, 2001). A recent urbanization study that used an agglomeration index as a methodology concluded that “a large share of the population still resides more than 10 hours travel time from an urban center” (Schmidt, 2009). Even though the background to the state of urban growth and urbanization is related to the predatory nature of the Ethiopian state (Teg,1996). Infrastructure and service delivery are already undermined in many cities by growing urban extents and by stretched municipal budgets, while formal labor markets are failing to keep up with demand for jobs.

Ethiopian cities run the risk of becoming less attractive places for people and economic activity. Moreover, constraints on rural–urban migration - including the loss of land rights for those who leave rural areas reduce incentives to move to cities, which in the long run could slow agglomeration, reducing productivity and economic growth. Shashemanne is among the fast growing urban centers in the country. The town has attractive potential that contributed for its accelerated growth. Hence the expansion of the city is becoming irregular, uncontrolled and often resulting in creation of slums (Daniel, 2005). Shashemanne, being one of the Towns in the developing countries has never been in a position to escape the forgoing undesired realities of rapid urbanization.

Principles and guidelines fundamental to ensure healthy urban growth have never been put in place. Like in many other cities in the developing countries, the majority of the urban poor in Shashemanne live in informal and illegal settlement either as owner-occupiers or as Renters. Recently increasing concerns about sustainable development have fostered a new interest of the international literature on the physical dimension of cities and particularly on the issues of urban growth pattern and urban form (J. Huang et al., 2007; 3Vande Voorde et al., 2009). Numerous studies have been conducted focusing on the phenomenon of urban sprawl and informal settlement and their adverse environmental and socio-economic consequences as opposed to the concept of compact and formal development (Dubovyk et al., 2011; A. Schneider & Woodcock, 2008). However, following the growing demand for empirical data and systematic analysis of urban growth processes patterns, and factors which promote urban growth. There is an increasing interest on the development of quantitative methods of urban analysis. This method is significant to provide very use full information to help local and regional land use planners to better understand the urban growth process and make informed decision.

1.2 Statement of the problem

Shashemanne is among the fast growing urban centers in Ethiopia. The town has attractive Potential that contributed for its accelerated growth. Hence the expansion of the town is becoming irregular, uncontrolled and often resulting in creation of slums. Due to effects of continuous growth and expansion of the town productive farmlands and the farming population in the neighbor hoods and rural communities residing in the outlying areas have been subjected to increasing eviction and people live in cite

experienced many problem. Acute problems of drinking water, noise and air pollution, disposal of waste, traffic congestion and housing rent increasing from time to time and informal transaction of land and housing also observed around the cite.

Basically, planning and management of urban spaces requires a comprehensive knowledge of the development process and physical dimension of town (Klosterman, 1999). To do this some research were conducted on urban expansion of Adama city. Urban expansion and modeling of land use/land cover change in Adama city using remote sensing and GIS (Regassa, 2014) and urban expansion and suitability analysis for housing of Adama city using remote sensing and GIS (Seid, 2007); however both researcher highlight the value of spatial metrics on the analysis of the spatial characteristics of cites growths in the study of urban landscapes.

Combined with remote sensing, spatial metrics can give better result than using either of them gives separately (Herold et al., 2003). This is particularly true for less developed towns like Shashemanne where the availability of spatial data is very limited. Therefore; this study investigating the spatio-temporal patterns of Shashemanne town urban growth and quantifies the underlying spatial pattern of the urban landscape. Remote sensing and spatial metrics tools were utilized to accomplish this task. The combined use of these tools is believed to lead to new levels of understanding of urban development process which can assist city planners and policy makers to make informed decision (Herold et al., 2005).

Justification

As discussed earlier, there are many reasons why urbanization processes have been a hot research area for several decades. One of the most important reasons for such an interest is that, the size and spatial configuration of an urban area directly impacts energy and material flows such as carbon emissions and infrastructure demands, and thus has direct or indirect consequences on the proper functioning of Earth as a system and on the quality of life of urban inhabitants. To do so city planners, policy makers and resource managers need more advanced and quick techniques to acquire quantitative information on urban growth processes and patterns. It can facilitate the urgent establishment of management mechanisms and relevant policy interventions for proper allocation of resources and urban

infrastructures based on empirical evidences. However, the available information on the city growth and evolution is insufficient and out-dated. Therefore, quantifying urban growth processes and patterns is crucial to monitor urbanization and its impact on environment over time.

However, they give insufficient information about spatial patterns of urbanization processes that characterize urban areas. Remote sensing data can provide time series land-cover maps explicitly exhibiting the dynamics of urban growth; yet some underlying patterns and characteristics could not be visualized clearly. Moreover, spatial metrics provides a linkage to structure, pattern, processes and functionality in urban studies (Luck & Wu, 2002). Thus, remote sensing and spatial metrics are valuable tools to analyze urbanization processes and patterns empirically. Therefore, assuming that urbanization will continue to be one of the major global environmental and social challenges in the foreseeable future, understanding and quantifying the changing patterns of urban growth is critical to put forward appropriate policies and monitoring mechanisms on urban growth.

1.3 Research questions

1. What is the physical spatial rate of urban growth?
2. How did the spatial pattern of urban growth change is more fragmented over time?
3. What are the major physical driving factors of urban growths in the study area?

1.4 Research objectives

1.4.1 General objective:

The general objective of the study is quantifying the spatio- temporal of urban growth patterns in one of fast developing town of Ethiopia which is shashemane using remote sensing and spatial metrics.

1.4.2 Specific objectives:

The specific objectives of this research are to:

- ✓ Analyze the rate of spatio-temporal urban growth using multi-temporal satellite images.
- ✓ Quantify the spatio-temporal urban growth pattern of landscape fragmentation using spatial metrics.
- ✓ Identify the main major physical driving factors of urban growth pattern.

1.5 Significance of the Study

This study quantifies urban growth pattern and process of the major physical driving factors of urban growth of Shashemanne town. Therefore it is expected to provide basic information on the status and dynamics of the urban land cover of the area and the potential of remote sensing data and spatial metrics for such purpose. It is also expected to identify the rate of urban growth, the direction of growth, the physical driving factor and urban land cover changes in different times and provide greater importance to the research community, urban planners, stake holders as well as decision making groups in terms of understanding how and where Shashemanne town was going to grow.

1.6 Scope of the Study

This study was an urban level study and thus focused/limited mainly on issues within the Town of Shashemanne: The study was emphasized on spatial expansion of the Town, pattern of expansion, the physical driving force for expansion and its direction of expansion.

1.7 Conceptual framework

This study makes use of both remote sensing and spatial metrics methods to get a deeper insight into spatio-temporal urban growth processes and the underlying patterns. The conceptual frame work is composed of three major elements interacting at different stages of the research. These are: remote sensing, spatial metrics & urban growth. The arrow no.1 shows the potential use of classified temporal remote sensing images to quantify urban growth.

Whereas the arrow no. 2 shows interaction between urban remote sensing and spatial metrics, in which the output of classified remote sensing image is used as an input for spatial metrics computation (e.g. in FRAGSTATS) to quantify urban landscape fragmentation processes and patterns (arrow no. 3). Selected metrics are used to quantify urban growth pattern. These metrics are computed to quantify the spatial configuration of the urban landscape (e.g. size, shape, edge length, patch, density, fractal dimension) and the composition of the landscape, (Gustafson, 1998). Finally, (arrow no. 4) binary logistic regression modelling is used to identify factors responsible for the changing patterns of urban landscape.

The results of the entire analysis are used to discuss on how these methods can improve the better understanding of urban growth processes and patterns and can help urban planners and policy makers to put forward informed decision.

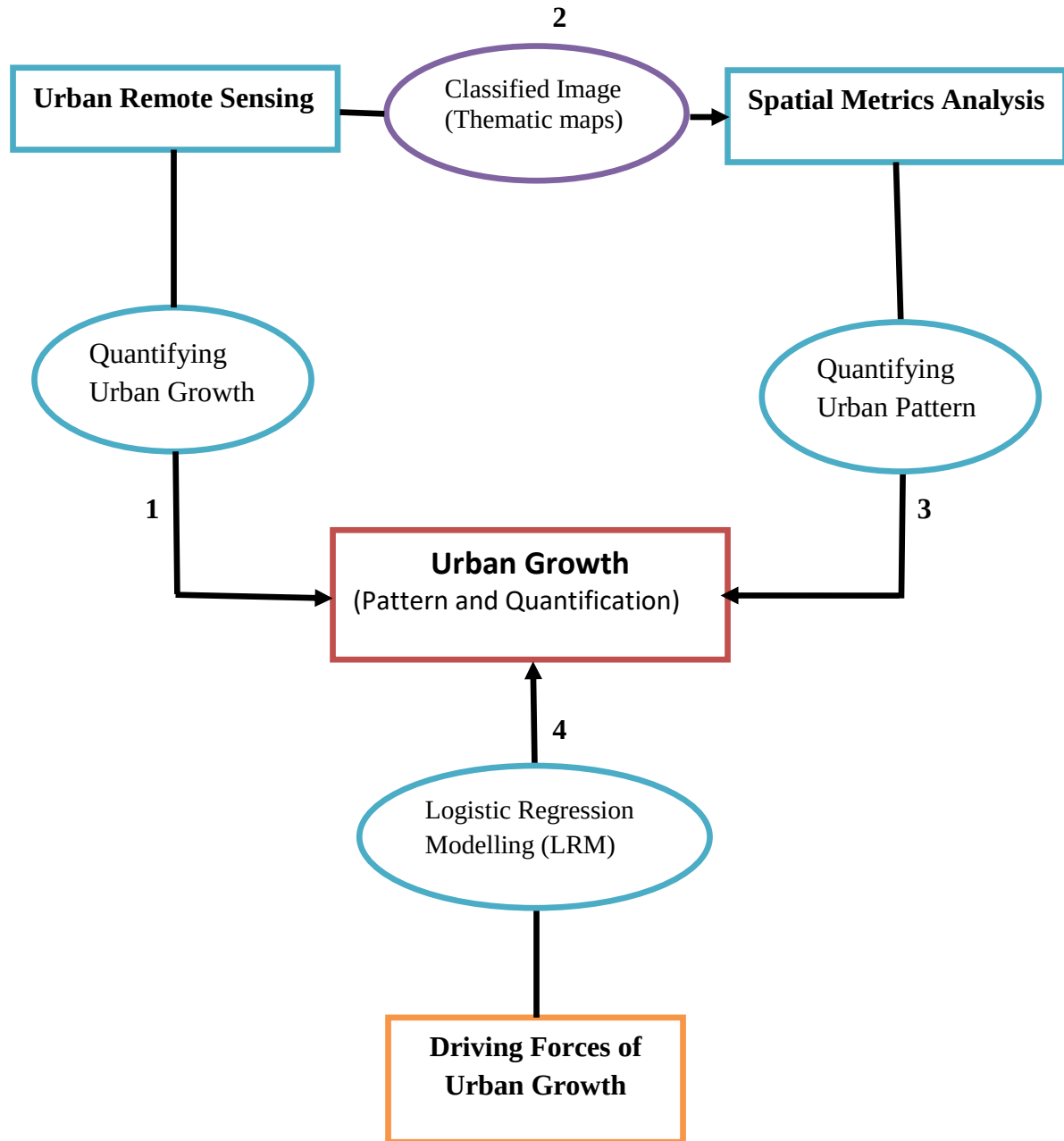


Figure 1.1 Conceptual framework for analysis of urban growth

1.8 Structure of the Thesis

The thesis is structured into five different sections in which:-The first section deals with the introduction to the research and mainly addresses the statement of problem, research objectives , research questions, the context of study area, conceptual frame work and organization of the thesis. The second section contains review of related literature s where the concept of urbanization and land cover change, urban remote sensing and spatial metrics, image classification techniques, spatio-temporal urban growth pattern, and urban landscape structures are reviewed.

In section three, the data and methodology used in this study including methods of data collection and analysis, image classification method, accuracy assessment procedures, selection and description of metrics, definition of spatial domains, methods used for identification of major physical driving forces of urban growth, including variables used in logistic regression modelling, multicollinearity analysis method and methods of model evaluation are briefly discussed.

In Section four, presents the results of data analysis and discussions including spatio-temporal urban growth analysis, presentation and interpretation of growth maps and spatial metrics, temporal patterns of land cover changes , intra urban comparison of metrics, logistic regression modelling and evaluation and interpretation of outcomes , identification of major driving forces of urban growth in the study area. In the last section, section five, conclusions are organized according to the research questions proposed in section one. Furthermore, the limitations of the research and some recommendation and future research directions are offered.

CHAPTER-2: LITERATURE REVIEW

2.1 Introduction

The literature on urban growth pattern and process were bigger than the scope of this chapter. Application of remote sensing and special metrics in the study of urban growth is extensive in terms of their variations. A general research review cannot embrace the totality. However, in this chapter efforts have been made to briefly document the important aspects that mainly focus on urban growth patterns and processes, and measurement/analysis. As a result, quantification of this phenomenon is rather complicated and sometimes confusing, especially if we use remote sensing data.

2.2 Trend and pattern of Urbanization in Ethiopia

The urban development process in Ethiopia had begun in ancient time. (Bekure 1999), classified pre-twentieth century urbanization of Ethiopia into three periods: the Aksumite period, the Zagwe period and the Gonder period. His classification was mainly based on the geographical shift of urban centers related to the seat of government and the process of urbanization following the transfer of the seat of the central government. In the pre-Aksumite period the kingdom of Damat is identified as urban society. The kingdom of Damat is believed to have existed in the northern Ethiopia between the middle of the first millennium BC and its replacement by the Aksumite kingdom sometime in the first century BC.

2.3 Land cover change

Land use and land cover change (LULCC): Also known as land change) is a general term for the human modification of Earth's terrestrial surface. Though humans have been modifying land to obtain food and other essentials for thousands of years, current rates, extents and intensities of LULCC are far greater than ever in history, driving unprecedented changes in ecosystems and environmental processes at local, regional and global scales. These changes encompass the greatest environmental concerns of human populations today, including climate change and the pollution of water, soils and air. Monitoring and mediating the negative consequences of LULCC while sustaining the production of essential resources has therefore become a major priority of researchers and policymakers around the world.

Land change studies attempt to explain (1) where change is occurring, (2) what land cover types are changing, (3) the types of transformation occurring, (4) the rates or amounts of land

change, and (5) the driving forces and proximate causes of change. The ultimate reasons for studying these change characteristics are to understand land change trends, evaluate and manage the consequences of change, and define future scenarios of change. Challenging issues are associated with measuring, gathering, and documenting the characteristics of land change. Information about urbanization, obtained from multiple multi-temporal images, can provide valuable knowledge about the patterns of urban growth and the probable factors driving the changes.

2.4 Driving Force of Urbanization in Shashemanne Town

Urban growth is derived from two sources. One from expansion to the per-urban area and the other is from urban population increase. Urban expansion to the periphery is stirred up by economic development projects. Space is needed for industry, socio-economic infrastructure, communication and road networks that require reorganization and redevelopment of space already inhabited (Cernea, 1995). Urban population increase occurred due to natural population increase and migration. Natural population growth is a major element in urban growth for all countries, but rural urban migration contributes even more in many developing countries (Gugler, 1996). He added that migration also contributes to fast growth of urban population due to economic development that attracts people to urban centers for commerce, employment and education.

A number of observers also suggest that housing price have risen unreasonably high in many cities of the developing countries and are inducing developers and investors to invest in more housing stock than would be rational in a purely market driven economy (Wu,F.2000). In short, scholars believe that there are economic and non-economic factors that are encouraging the expansion of urban to non-urban areas. The following General factors have been contribute urban expansion of this study area, the active economic activity of major satellite town like; Hawasa, Dodola, Hasasa and Bale-Robe, the presence of high government and private institutions such as U.S colleges, Paradise valley college, Rift Valley University, Hospital, high standard Hotel ...etc., other small town around the Town and rural urban migration are the major driving factors of urban growth of Shashemanne Town.

2.5 Remote Sensing and Urban Growth

Remote sensing technology is a powerful tool which is used for the comparison of different cities in terms of growth. These are the main questions such a system should help to answer: where are the geographic locations of growth, what kind of development can be observed and where are the initial seed points of growth? Especially less developed countries often neither have the infrastructure and capabilities which are necessary for modern city planning nor do they have experts for a permanent mapping and in field surveying of the urbanized regions. Many scientists, resource managers, and planners agree that, the future development and management of urban areas entail comprehensive knowledge about the on-going processes and patterns.

However, the availability of multi-temporal data is important to analyse the dynamics of land cover change over time and space. In order to detect the changes and patterns of different spatial phenomenon, it is important to make sure that the available images are acquired in the same season. This will help to avoid data inaccuracy generated due to seasonal variations. As a result the selection of temporal dimension is mostly dependent on the availability of good quality data at that particular time of interest. Particularly, this is true for developing countries like Ethiopia Shashemane Town. So that Remote sensing is a helpful tool to better understand the spatiotemporal trends of urbanization and monitor the spatial pattern of urban landscape compared to Traditional socioeconomic indicators such as population growth, employment shifts, etc. (Jun et al., 2009) Although challenged by different factors such as spatial and spectral heterogeneity of urban environments, remote sensing is an appropriate source of data for urban studies.

Different studies have been conducted on urban change using medium resolution Landsat images. For instance, Yuan et al. (2005) used multi temporal Landsat images to analyse urban growth pattern and to monitor land cover changes of two twin cities in Minnesota metropolitan area. The result shows that it has been possible to quantify the land cover change patterns in the metropolitan area and demonstrate the potential of multi temporal Landsat data to provide an accurate and economical means to map and analyse changes in land cover over time. Generally most researchers and scientists' conclusion indicate that using medium resolution Landsat images in the contemporary urban growth trend and pattern study is cost

effective, updating, simple and best option spatially in developing countries the availability of resource is very scarce. Also this study accepts their conclusions and believes the potential of remote sensing tool to study urban growth trend and pattern.

2.6 Image Classification Methods

Image classification is an important part of the remote sensing, image analysis and pattern recognition. Classification in remote sensing involves grouping/clustering the pixels of an image to a relatively small set of classes, such that pixels in the same class are having similar properties. The majority of image classification is based on the detection of the spectral response patterns of land cover classes (Brito & Quintanilha, 2012). These techniques are distinguished in two main ways as supervised and unsupervised classifications. Additionally, supervised classification has different sub classification methods which are named as parallelepiped, maximum likelihood, minimum distances and Fisher classifier methods.

These methods are named as Hard Classifier. Supervised classification is the process of assigning objects of unknown identity to one or more known features using training data. Maximum likelihood (ML) classification algorithm assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability (i.e., the maximum likelihood). Better results can be achieved in supervised classification technique by taking more features and training samples from the study area. Training data are objects selected as representative samples of known features.

2.7 Remote Sensing and Change Detection Techniques

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different time (Singh, 1989). Change detection is a complex phenomenon which includes different method and procedures such as clearly identifying the specific change detection problem, image preprocessing and variables and algorithm selection for the computations. A variety of digital change detection techniques has been developed in the past three decades.

2.7.1 Image Differencing

Image differencing is one of the most widely used to determine changes between images, and has been used in a variety of geographical environments. The difference between two images

is calculated by subtracting the imagery of one date from that of another, and generating an image based on the result, the subtraction results in large positive or negative values in areas of radiance change, and values close to zero in areas of no change. A critical challenge of this method is deciding where to place the threshold boundaries between change and no change pixels. This method is also sensitive to miss-registration and mixed pixels. To obtain good result, the two images must first be aligned so that corresponding points coincide.

2.7.2 Principal Component Analysis (PCA)

Principal component analysis is a technique used extensively in remote sensing images analysis in application well beyond that of change detection. PCA has been used for determining the intrinsic Dimensionality of multi spectral imagery, data enhancement for geological application, and land cover change detection. However, estimation of the PCA projection from data has its own limitations. Its computational complexity makes it difficult to deal directly with high dimensional data, like satellite images. Second, the number of examples available for the estimation of the PCA projection is typically much smaller than the ambient dimension of the data and this can lead to over fitting of the projection.

2.7.3 Post Classification Comparison

Post classification comparison is the most intuitive methods of change detection, is GIS overlay of two independently produced classified images. The post-classification comparison can be used to identify not only the amount and location of change, but also the nature of change. The method can produce from-to information (Lu et al., 2004). However, the accuracy of the change detection is highly dependent on the accuracy of the classification result. The method reduces the need to perform geometric and atmospheric corrections (Jensen, 2005; Liu et al., 2004). Post-classification comparison is made on classified images. Mas (1999) suggested that post classification is often considered a priori to be the superior change detection method and is, therefore, used as the standard for evaluating the results of other methods. However, every inaccuracy in the individual data classification map will also be propagated in the final change detection map. Therefore, it is imperative that the individual classification maps used in the post-classification change detection methods be as accurate as possible.

2.8 Remote Sensing and Spatial metrics

As discussed above, the main strength of remote sensing technique lays on its capability to deliver spatially consistent data set that cover a wide range of spatial extent with both high and detailed spatio-temporal resolution, including historical time series data (Herold et al., 2005). Yet, it cannot provide full description of the underlying processes that are responsible for the changing patterns of urban landscape. To bridge this gap spatial metrics are used. The thematic land cover maps obtained from the analysis of Landsat TM and ETM+ images will be used to further quantify and describe urban landscape pattern, (Gustafson, 1998). Spatial metrics are expedient tools for quantifying spatial heterogeneity and to have better insight on how spatial structures impact the system interaction in a heterogeneous landscape. Spatial metrics can provide rich numerical description of the landscape structure at patch, patch class or the whole landscape level (Herold et al., 2003). Spatial metrics can be categorized into three broad classes: patch, class, and spatial metrics (Bhatta, 2010). Patch is a relatively homogeneous area that differs from its surroundings (McGarigal & Marks., 1995). Patch metrics are computed for every patch in the landscape, class metrics are computed for every class in the landscape, and spatial metrics are computed for the entire landscape (Bhatta, 2010). However, most spatial metrics are scale dependent and they are determined by the extent of spatial domain, the spatial resolution and the thematic definition of the map categories (Šímová & Gdulová, 2012). It is up to the user to define the landscape, including its thematic content and resolution, spatial grain and extent, and the boundary of the study area, based on the phenomenon under consideration before conducting any kind of metrics computation (McGarigal et al., 2012).

2.9 Analyzing Urban Growth Pattern Using Remote Sensing & Spatial metrics

Patterns are distinguished by spatial relationships among component parts in landscape metrics. A landscape pattern can be characterized by both its composition and configuration of its component parts (McGarigal & Marks, 1995). These two characteristics of a landscape can individually or in combination affect ecological processes. A variety of metrics have been developed to quantify categorical map patterns in the past studies (McGarigal et al., 2002). Despite the availability of plenty of metrics, offered by different literature, to describe landscape structure, they are still categorized under the two major components, namely, composition and configuration of a landscape (Gustafson, 1998).

Composition metrics is easy to quantify and can be defined as features related to the presence, proportion and the variety and richness of patch types within the landscape mosaic. Nevertheless, composition metrics does not consider the spatial character, arrangement, or location of patches within the mosaic. A variety of quantitative descriptors of landscape composition are available, but the principal measure of composition includes; the proportional abundance of each class in the entire landscape, patches richness, patches evenness, and patch diversity (McGarigal et al., 2002). Shannon's diversity index (SHDI), Shannon's evenness index (SHEI), dominance (DOM) and patch richness density (PRD) are some of the examples of commonly used composition metrics. Conversely, configuration metrics is relatively more challenging to quantify. It refers to the spatial arrangement, character and position of patches within the class of patches or entire landscape (McGarigal & Marks., 1995). The principal aspects of configuration metrics includes: patch area and edge, patch shape complexity, core area, contrast, aggregation, subdivision, and isolation.

Some of the most frequently used configuration metrics includes: number of patches (NP), percentage of landscape (PLAND), edge density (ED), landscape shape index (LSI), mean patch size (MPS) and number of patches (NP), largest patch index (LPI), total edge (TE), mean shape index (MSI), area-weighted mean fractal dimension (AWMFD), total core area (TCA), mean Euclidean nearest neighbor index (MENNI), contagion (CONTAG), effective mesh size (MESH), aggregation index (AI). Urban growth and land cover change has been the major topic concerning remote sensing applications (Masser, 2001).

The spatial and temporal dimensions are major concerns of remote sensing in urban studies. To better understand the complexity of urban systems and its spatial and temporal dimensions, urban growth analysis need to be linked with land cover change model. Currently, there has been an increasing interest in applying remote sensing and spatial metrics techniques (see for example FRAGSTATS McGarigal et al., 2012) to analyze urban environment. There are several methods to analyze and quantify the dynamics of urban growth patterns and processes.

However the selection of method depends on the objectives of the problem on hand and the clear understanding of the different tools and techniques used for analyzing urban environment. Several studies reviewed in this section indicate the value of medium resolution remote sensed satellite images and spatial metrics for the analysis of urban change.

2.10 Urban growth modelling

Rapid urban growth accompanied by land cover change, has become a global phenomenon observed all over the world. Several studies have endeavored to understand the spatio-temporal pattern of land cover change and its driving forces (Lu 2003); Veldkamp & Lambin, 2001). There are two broad categories of land change models developed over the past several decades. These are dynamic simulation based models and statistical estimation models.

Moreover, most dynamic simulation models are not capable of incorporating adequate socioeconomic variables (Hu & Lo, 2007). Empirical models use statistical analysis to reveal the interaction between land cover change and explanatory variables and have much better interpretability than simulation models. Logistic regression is based on the concepts of binomial probability theory, which does not assume linearity of relationship between the independent and the dependent variables, does not require normally distributed variables, and in general has no strict requirements. In the context of urban growth modelling, logistic regression model was used to study the relationship between urban growth and biophysical driving forces.

The main purpose of urban growth modelling is to understand the dynamic processes responsible for the changing pattern of urban landscape, and therefore interpretability of models is the most important aspect the modelling process. The advantage of statistical models is their simplicity for construction and interpretation or their capacity to correlate spatial patterns of urban growth with driving forces mathematically. However, statistical models lack theoretical foundation as they do not attempt to simulate the processes that actually drive the change (Koomen & Stillwell, 2007).

CHAPTER-3: MATERIALS AND METHODS

3.1 Introduction

This chapter presents the available data, the overall methods, techniques, approaches and materials that have been used to achieve the research objectives. It mainly explains the data sources and types, methods of field data collection, reference data were used to identification of driving forces of urban growth, image classification technique employed, and change detection methods were used, accuracy assessment, selection of spatial metrics and list of software packages used in the research.

3.2 Description of the Study Area

Shashemanne was founded in 1903 E.C accordingly for the sake of south east trade movement along the town. It is the largest city of West Arsi Zone of Oromia Regional State, with area of 3852.82ha. Shashemanne has been the focus of investments both at the national and regional levels. Investment in industry, trade and hotel tourism, construction and social services constituted the largest shares.

Due to the comparative advantage the Town has potential for economic growth in these and other sectors including administration, commerce and agriculture. Geographically the town is located at 7°08'50'' to 7°18'17'' latitudes and 38°32'43'' to 38°40'58'' longitudes, with an elevation ranging from 1845 to 2053 m above msl and found at 250 km South West of Addis Ababa the capital city of Ethiopia (Figure 3.1). Eventually, the town is growing more in political leading aspect, social strength and economical developments. The population and demographic characteristics of the city showed that the population has been growing at high rate; the current population of the city estimation from the census 2007 is 190,000.

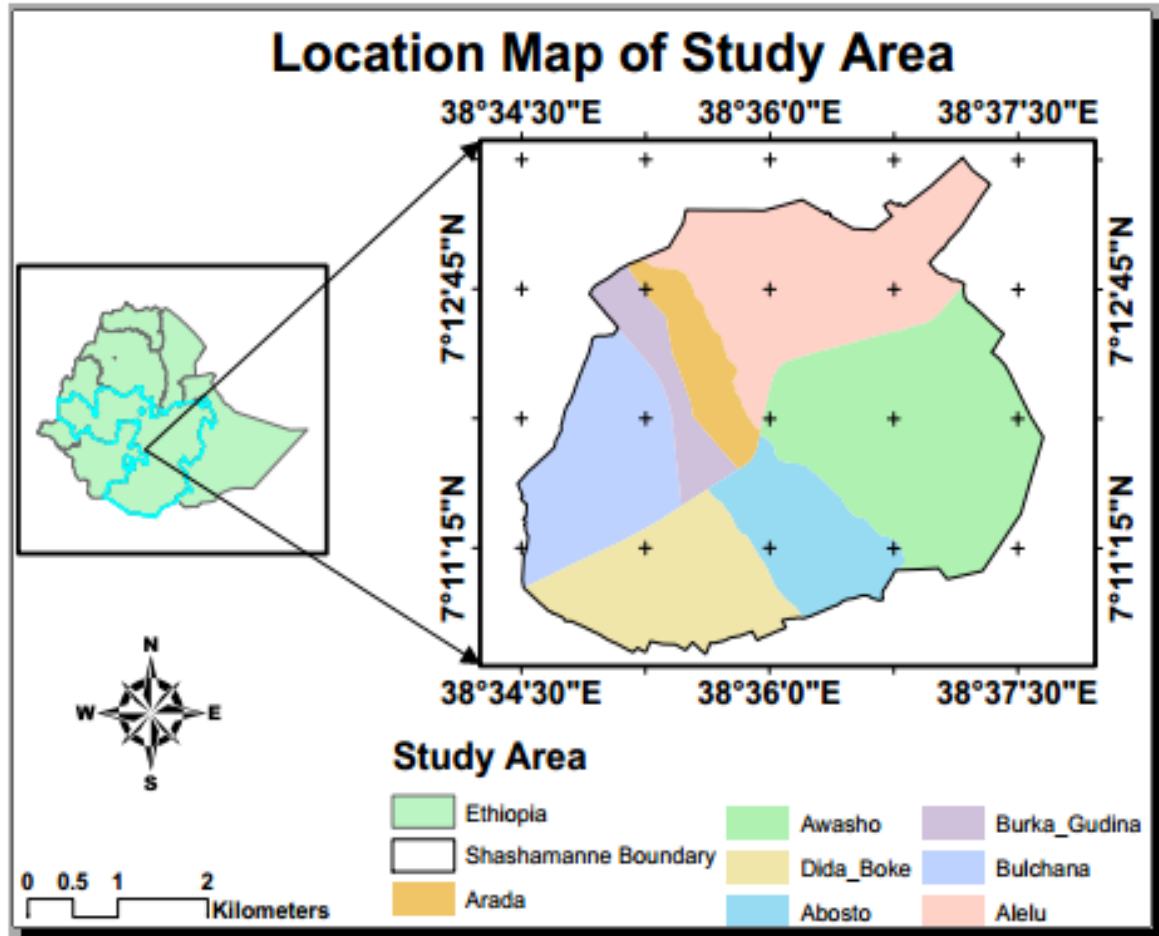


Figure 3.1 Location map of study area

3.3 Research Design

The proposed research is conducted in three phases: pre fieldwork, fieldwork and post field work phases. The first phase is a preparation phase which consists of research proposal development, including problem definition, formulation of research objectives and associated research questions, defining methods, identifying required data types, clearly defining data collection methods and preparing (field) work plans. The second phase was information and data gathering phase (field Work phase). In this phase, important data required to carrying out the research including primary and secondary data are collected during fieldwork. These includes interviewing local experts on the issues of urban growth driving forces, collecting ground truth data, visiting important places of the study area like Town Centre, new development sites, etc. In the end, the collected data were processed, analyzed and the finding were presented (post fieldwork phase) so as to meet the predefined objectives of the research.

3.4 Methodology

There are different kinds of methods, strategies and techniques to process input data in order to generate the anticipated research output in an efficient and consistent way with desired quality. However, the choice of appropriate methodology and specific technical arrangements are largely dependent on the availability of quality data, the desired inputs, the strength of logistic support including the software employed, researcher's experience and skill to manipulate and the necessary fund allocated for the task. The methodology incorporated in this study involves remote sensing image classification techniques as well as spatio-temporal analysis of spatial metrics and logistic regression methods.

First, four multi-temporal sets of Landsat images (TM 1990, ETM+ 2000, ETM+ 2010 and OIL/TIR 2019) covering the entire study area were used to produce the land cover map by using the maximum likelihood classification algorithm in ERDAS Imagine (Lillesand et al., 2008). Post-classification comparison was used to produce growth/change map, where the classified images were overlaid on top of each other in Arc GIS 10.3 using different spatial analyst tools. Consequently, the spatial extent and rate of urban growths were analyzed and quantified. Then, the classified images were used as an input data in FRAGSTATS (McGarigal et al., 2012) to further describe and quantify the changing patterns and processes of urban lands

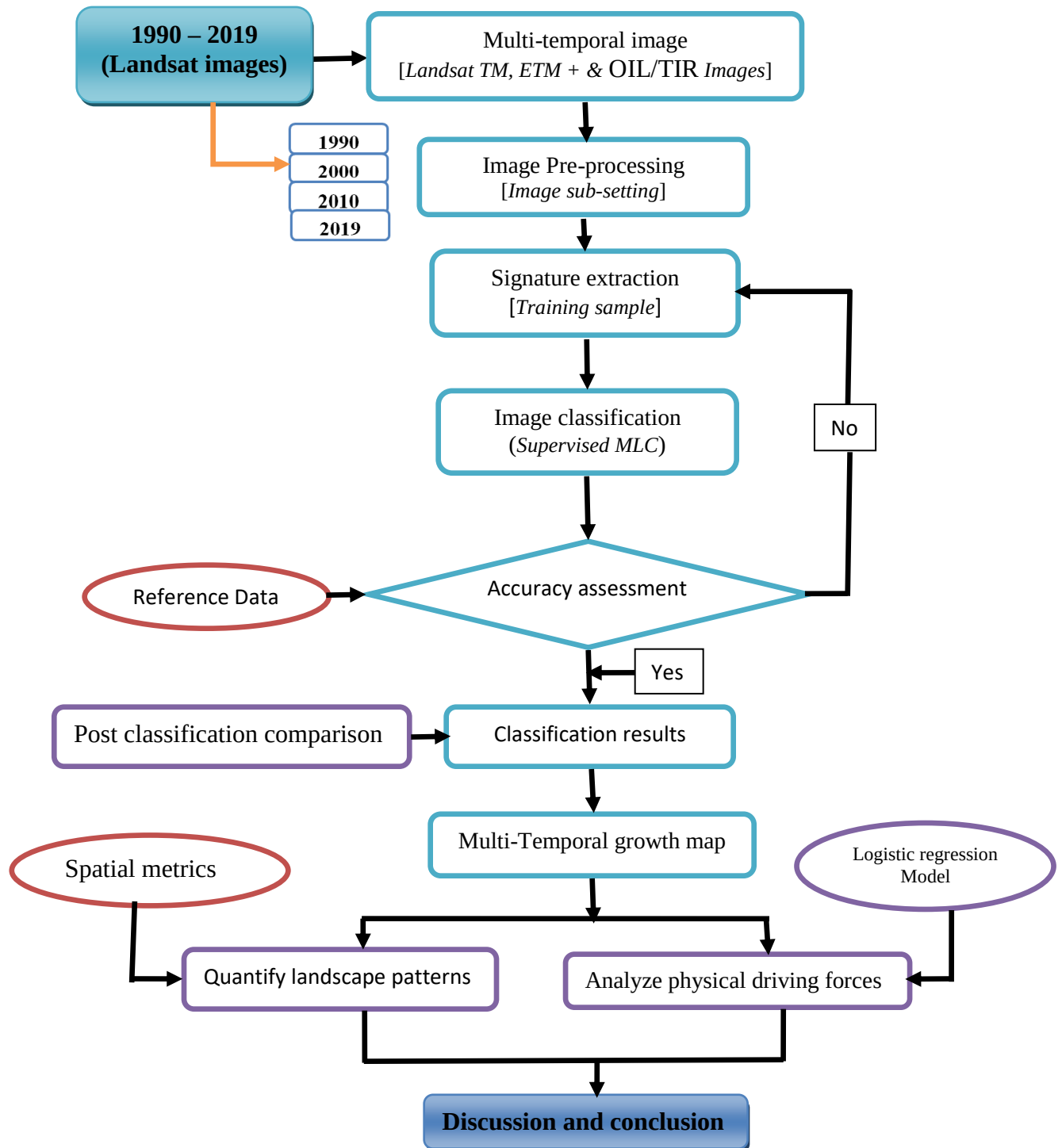


Figure 3.2 Schematic work flow of the study

3.5 Data Source and Type

Different remote sensing and GIS data from different sources are used in the proposed research. Four medium resolutions Landsat images TM 1990, ETM+ 2000, ETM+ 2010 and 2019 OLI/TIR were used to detect urban land cover change patterns of the study area). These images were obtained from the United States Geological Survey (USGS) website as standard products, i.e. geometrically and radio-metrically were corrected. In order to avoid the impact of seasonal variation, all images were selected from the same season in such a way that the cloud cover will not exceed 10%. The images were also of the same level of spatial resolution 30m which make it convenient for comparison of changes and patterns that occurred in the time under consideration. Additionally, One VHR images covering some part of Shashemanne generated from Orthophotos (2005) with 50cm resolution is used to assist field observation data in training the images during classification. The DEM used to analyze driving forces of urban growth is downloaded from SRTM-USGS centre.

Most GIS data such as location of satellite towns, Town centers, location of colleges, CBD and existing built up areas were derived from VHR Google Earth image. Other data such as administrative boundaries and five main gates of major roads were obtained from Shashemanne Town municipality. All dataset in this study will use geometrically referenced to the WGS 1984, UTM zone 37 projection systems. The detail description of the characteristics all images which will use in this study is summarized in the following Table

Table 3.1 List of satellite image (raster data) for the study area

Satellite data	Acquisition Year	Path/Row	Spatial resolution	Data source
Landsat TM	02/12/1990	168/55	30m	USGS
Landsat ETM+	05/02/2000	168/55	30m	USGS
Landsat ETM+	30/10/2010	168/55	30m	USGS
Landsat OLI/TIR	01/02/2019	168/55	30m	USGS
Orthophotos	2005	-	50cm	Sh/shmnne municipality
Topographic map	-	-	30cm	SRTM/ USGS

Table 3.2 List of spatial data (vector data) used for the study area

Spatial data	Format/ type	Source
Administrative boundaries	Shape file	Municipality of Shashemanne Town
Existing build up` area	Shape file	Derived from Google earth image
Satellite town	Shape file	Derived from Google earth image
Town center	Shape file	Derived from Google earth image
CBD	Shape file	Derived from Google earth image
Major road	Shape file	Derived from Google earth image

3.5.1 Field Data Collection

In this research used both primary and secondary data to make sure that the objectives of the study are meeting. Yet important information and data are gathered from field work. The field work for the study was carried out from 10th of February, 2020 to 10th of March, Although some secondary data are collected from literature review and open source websites, aiming at two major tasks explain below.

1. Reference data

One of the most important primary data required from field survey were ground truth data. It was used to assess the accuracy of classified land cover map. Handheld GPS was used to collect the field data. Digital camera also used to photograph the land cover material of visit sites.

2. Identifying the probable Physical driving forces of urban growth

The other most important task of the field work is to collect relevant information about driving forces of urban growth in the study area. This task was carried out in the form of interview with local experts like policy makers and city planners on the issues of urban growth driving forces. The main objectives of the interview were to identify the major physical driving forces of urban growth in the study area. From this CBD, town center, major road, satellite town like; Hawasa, Dodola and institutions in the town are major physical driving forces of urban growth in Shashemanne Town.

Table 3.3 Software's and other Instruments Used

No	Software used	Company	Purpose
1	ERDAS- 2014	ESRI	To analyze classification and accuracy assessment
2	Arc-GIS 10.3	-	Overlaying the classified images
3	Hand held GPS	ESRI	To validate the study area
4	FRAGSTATS- 4.2	-	To compute the spatial metrics
5	SPSS statistics software 23	-	For regressing of the independent variable against the remaining variables

3.6 Methods of Data Analysis

After collecting the entire relevant primary and secondary data, the next task is process and analyzing the data, as discussed earlier this research was applies remote sensing and spatial metrics techniques to quantify urban growth processes and patterns. Remote sensing image classification is a relevant method that can provide information on the extent and rate of urban growth whereas spatial metrics are computed based on the remote sensing image classification results to quantify the patterns of growth (Herold et al., 2003). Both together are believed to give better understanding of urban growth processes and patterns.

The methods are also quick ways of acquiring relevant information where availability of spatial data is scarce in Ethiopia .Apart from this binary logistic regression method is used to identify the major physical driving forces of urban growth in the study area. The accuracy of the classification results will assess using randomly sample ground truth points; obtain from fieldwork and visual interpretation of the true colour composite. The change detection method will use in this analysis is the post classification comparison technique in which GIS overlay of two independently produced classified images in Arc-GIS (Alphan 2009)

3.6.1 Remote sensing Image classification

Four multi-temporal medium resolution Landsat images are used to analyze the urban growth trends and patterns of Shashemanne for the past 29 years. Accordingly the images are classified in to different land cover classes which finally ended up generating four different year land-cover maps of the study area. In classification method, pixels with maximum

likelihood are categorized into the corresponding class. The land cover maps are composed of two major land-cover classes namely; built up and non-built up. Each land cover classes comprise different land uses classes. The built up area consist of commercial, residential, road and impervious features, continuous and discontinuous urban fabric, industrial and other associated lands, parking, dump sites, construction sites, and sport etc. while the non-built up area includes cropland (agriculture) land, forests, open spaces, grasslands and others..

3.6.2 Accuracy assessment

In remote sensing-land cover mapping study, classification accuracy is most important aspect to assess the reliability the final output maps. The main purpose of assessment is to assure classification quality and user confidence on the product (Foody, 2002). In this study , the accuracy of the classification results for the year 2000, 2010 and 2019 are assessed using 150 randomly sampled ground truth points, obtained from fieldwork. However, since it has been difficult to get reference data for accuracy assessment of image 1990, visual interpretation of the true colour composite of the Landsat TM image is used.

3.6.3 Change detection

The change detection method used in this analysis is the post classification comparison technique in which GIS overlay of two independently produced classified images in Arc-GIS 10.3 (Alphan et al., 2009). The resulting land cover maps are then visually compared and change areas are simply those areas which are not classified the same at different times . This method is the most straightforward and intuitive change detection method. The advantages and disadvantages of this method are discussed in section 2.5 of this research.

Following this method, maps are produced to show the newly built up area between each subsequent years , i.e. 1990-2000, 2000-2010 and 2010-2019 for the study area (Yang & Lo, 2002). In combination with class area spatial metrics, these make it possible to quantify the spatial extent and rate of urban growth over time in the study area. In this context, urban growth is considered as an increase in the physical extent of the built-up (urban) area. Thus, it is possible to interpret the city's growth direction by visualizing the multi-temporal

land cover maps. In this study, post classification comparison is used to detect land cover change of the study area.

3.7 Quantifying urban growth pattern using spatial metrics

The processes of urbanization usually change the landscape pattern in urban regions. Such changes are mostly accompanied by decreasing the heterogeneity of landscape compositions and increasing landscape fragmentation by generating smaller patches (Yeh & Huang, 2009). Spatial metrics are useful tools to quantify the dynamic patterns of ecological processes. Changes in urban landscape pattern can be detected by using spatial metrics that quantify and categorize complex landscapes structure into simple and identifiable patterns

3.8 Selection of Metrics and Definition of Spatial Domain

For this specific study a group of five metrics were selected based on the literature review and the potential of each metrics to best describe urban pattern. (Buyantuyev et al., 2010; Deng et al., 2009; Dietzel et al., 2005; Herold et al., 2003,2005). CA measure absolute area of each land cover classes, (NP), number of patches measure the total of patches in the landscape or it is the measure of landscape fragmentation and heterogeneity, patch density PD measure the number of patches per unit area, largest patch index (LPI), is the measure of dominance, and area weighted mean patch fractal dimension (AWMPFD), measure the complexity of urban form, these indices were computed for all (four years) land cover maps and were compare temporally, to describe and quantify the spatial pattern of the urban land cover change both at landscape and class level.

This research was adopting the region based approach for metrics calculation; to further investigate the dynamics of urban area at disaggregate spatial scale, which is the easiest way to make intra-urban comparisons. Therefore, the study area were divided in to four regions; the Northern region to the Addis Ababa road direction, Eastern region to the Bale-Robe region road direction, Western region to the Wolyta-soddo road direction, Southern region to Hawasa Road direction and the CBD region. The location of the city main center is described to be in the 'core area'. The analysis of spatial metrics was conducted at two different spatial scales. First, selected metrics were

computed at the whole landscape or city level to obtain summary descriptor of landscape heterogeneity.

Secondly, owing to the aggregating nature of spatial metrics over large spatial scale, administrative boundaries of the urban areas was used as a basis for disaggregating the study area into different regions (Herold et al., 2003). This help to quantify the detail pattern of urban land cover dynamics at regional level which was in turn facilitate the implementation of appropriate and different policy measures in the different study regions Metrics at the class level are helpful for understanding how the landscape developed over time, whereas those at the landscape level provide aggregate information on the assessment of urban growth (McGarigal & Marks., 1995).

All metrics are computed using public domain software FRAGSTAT and patch analyst software. CA: equals the sum of the areas (m) of all patches of the corresponding patch type, divided by 10,000 (to convert to hectares); that is, total class area (McGarigal & Marks., 1995), (CA) metrics simply describes the growth of urban areas in terms of area or size.NP: equals the number of patches in the landscape. Note, NP does not include any background patches within the landscape or patches in the landscape border (McGarigal et al. , 2002).

The largest patch index (LPI): is the ratio of the area covered by the largest patch in the landscape divide by the total area of the landscape (Herold et al., 2002). AWMPFD: equals the sum, across all patches, of 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m²), multiplied by the patch area (m²) divided by total landscape area.

1. Class area (CA)

Class area is one of the most intuitive and straightforward metrics used to describe the pattern of urban growth in spatial metrics computation. It is sometimes known as total area implying the total area covered by a land cover class in hectares. In the context of this study CA/TA refers to the total area covered by either built up or non-built up area.

$$CA = \sum_{j=1}^n a_{ij} \left(\frac{1}{10,000} \right) \dots \dots \dots \text{Equation 1}$$

(Class level metrics) - Units: Hectares Range: $CA > 0$, without limit.

CA approaches 0 as the patch type become increasing rare in the landscape. $CA = TA$ when the entire landscape consists of a single patch type; that is, when the entire image is consists of a single patch. Description: CA equals the sum of the areas (m) of all patches of the corresponding patch type, divided by 10,000 (to convert to hectares); that is, total class area (McGarigal & Marks., 1995, p. 86). The class area (CA) metrics simply describes the growth of urban areas in terms of area or size.

2. Number of patches (NP)

The number of urban patches is the measure of discontinuous urban areas or individual urban units in the landscape. During the period of rapid urban nuclei development number of patch is expected to increase due to the emergence of new fragmented urban patches around the nuclei. Number of patches is an indication of the diversity or richness of the landscape. This index can be calculated and interpreted very easily. However, like other richness measures, this interpretation might give misleading results because the area covered by each class is not considered here. Even if a certain class covers only the smallest possible area, it is counted. The way to count the number of patches within a given landscape is:

$$NP = N \dots \dots \dots \text{Equation 2}$$

(Class level metrics) - Units: None, Range: $NP > 1$, without limit. $NP = 1$ when the landscape contains only 1 patch.

Description: NP equals the number of patches in the landscape. Note, NP does not include any background patches within the landscape or patches in the landscape border (McGarigal et al., 2002). The number of patches (NP) measures the extent of subdivisions of urban areas. NP being high when urban expansion is proportional to an increase in subdivided urban areas or when the landscape gets more fragmented and heterogeneous.

3. Patch density (PD)

Patch density is another measure of landscape fragmentation/spatial distribution of the patches of a land cover class which indicates the density of fragmented urban units within a specified area, (for example per hectares). This index is a good indicator of landscape fragmentation. Values of this indicator are affected by the size of the pixel and also the minimum mapping unit since this is the determining factor for delineating individual patches. Smaller mapping units imply more patches and therefore higher values. PD can increase or decrease based on different circumstances. For instance, when the number of small patches in the landscape increases without substantial increase of total landscape area, the PD will increase indicating more heterogeneous and fragmented urban development. Whereas, if the total landscape area increased without significant change in the number of urban patches, the patch density will decrease implying the formation of continuous urban surface due to the merging of smaller urban patches.

However, if the number of patches and total landscape area increased together proportionally, there wouldn't be significant variation in PD for that landscape. Thus, it is important to pay attention while interpreting this measurement. 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. It is calculated as:

$$PD = \frac{N}{A} * (10,000) * (100) \dots \dots \dots \text{Equation 3}$$

(Class level metrics) - Units: Number per 100 hectares, Range: PD > 0, without limit.

Description: PD equals the number of patches in the landscape divided by total landscape area, multiplied by 10,000 and 100 (to convert to 100 hectares)|| (McGarigal & Marks., 1995, p. 88). Patch Density depends on the grain size, which is the size of the smallest mapping unit of the input data and the number of different categories. The index is a reflection of the extent to which the landscape is fragmented. This index is important for the assessment of landscape structures, enabling comparisons of units with different sizes.

4. Edge density (ED)

Edge density is another indicator of urban expansion level which measures the total length of the edge of the urban patches. It is computed by dividing the length of the urban boundary to the total landscape area. The total length of the edge of a land cover class (urban patch) increases with an increase in the land cover fragmentation. ED has direct relationship with NP. Similar to PD its value is affected by the pixel size and the minimum mapping unit since the smaller the mapping unit the delineation of the various patches will result in an increase of the edge length. Herein, the smallest mapping unit is pixel. An increment in the number of patches can certainly lead to the increase of Edge Density. An edge is the border between two different classes. Edge density (in m/ha) or ratio of Perimeter/Area equal to the length (in m) of all borders between different patch types (classes) in a reference area divided by the total area of the reference unit. The index is calculated as:

$$ED = \frac{E}{A} * (10,000) \dots \dots \dots \text{Equation 4}$$

(Class level metrics) - Units: Meters per hectare, Range: $ED \geq 0$, without limit.

Description: ED equals the sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares) (McGarigal & Marks., 1995, p. 89). If a landscape border is present, ED includes landscape boundary segments representing true edge only (i.e., contrast weight > 0). If a landscape border is absent, ED includes a user-specified proportion of the landscape boundary. Regardless of whether a landscape border is present or not, ED includes a user-specified proportion of background edge. In contrast, to patch density, edge density considers the shape and the complexity of the patches. Edge density is a measure of the complexity of the shapes of patches and similar to patch density an expression of the spatial heterogeneity of a landscape. In short edge density (ED) is a measure of the total length of urban patch edges.

5. Largest patch index (LPI)

The largest patch index (LPI) is the ratio of the area covered by the largest patch in the landscape divide by the total area of the landscape (Herold et al., 2002). This metrics

describes the total area of land covered by the largest patch in the landscape expressed in percentage. LPI is a relative measure of all patches and this can be useful to compare different area (region) with varying spatial extent. It can be considered a measure of the fragmentation of the urban landscape into smaller discrete patches versus a dominant core. The LPI increases when the urban areas become more aggregated and integrated with the urban cores.

$$\text{LPI} = \frac{\text{Max}_{j=1}^n (a_{ij})}{A} * 100 \dots \dots \dots \text{Equation 5}$$

(Class level metrics) - Units: Percent (%), Range: $0 < \text{LPI} \leq 100$

LPI approaches 0 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.

Description: LPI equals the area (m²) of the largest patch in the landscape divided by total landscape area (m²), multiplied by 100 (to convert to a percentage) (McGarigal & Marks., 1995, p. 87); in other words, LPI equals the per cent of the landscape that the largest patch comprises.

6. Area Weighted Mean Patch Fractal Dimension (AWMPFD)

(AWMPFD) The fractal dimension is a measure of patch shape complexity which describes the convolution and fragmentation of a patch as a perimeter-to-area ratio. It is estimated as the weighted mean value of the fractal dimension values of all patches of the same class. AWMPFD gives improved measure of class patch fragmentation as it averages the fractal dimensions of all patches by weighting larger land cover patches (Herold et al., 2003).

The averaging of patches will reduce the overestimation of fractal dimension given the fact that the structure of smaller patches is often determined more by the spatial resolution of the image than by the spatial characteristics of natural or man-made features found in the landscape. Generally, when a patch has a compact regular form with a relatively small perimeter relative to the area the AWMPFD will be low. Conversely, if the patches are

more irregular, complex and fragmented, the perimeter increases resulting in a higher fractal dimension (McGarigal et al., 2002). For instance, when a built up area starts to become saturated taking the shape of the urban blocks, AWMPFD will get lesser. This metrics is most likely to have less value, i.e. simple shape, for cities having compact and regular pattern of development such as grid iron pattern.

$$AWMPFD = \sum_{i=1}^m \sum_{j=1}^n \left[\left(\frac{2 \ln(2.5 P_{ij})}{\ln a_{ij}} \right) \left(\frac{a_{ij}}{A} \right) \right] \dots \dots \dots \text{Equation 6}$$

Units: None, Range: $1 \leq AWMPFD \leq 2$

A fractal dimension greater than 1 for a 2-dimensional landscape mosaic indicates a departure from a Euclidean geometry (i.e., an increase in patch shape complexity). AWMPFD approaches 1 for shapes with very simple perimeters such as circles or squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

Description: AWMPFD equals the sum, across all patches, of 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m²), multiplied by the patch area (m²) divided by total landscape area; the raster formula is adjusted to correct for the bias in perimeter. In other words, AWMPFD equals the average patch fractal dimension (FRACT) of patches in the landscape, weighted by patch area.

7. Shannon's diversity index (SHDI)

Shannon's diversity index is a quantitative measure of the variety and relative abundance of patch types represented on the landscape. The composition component of pattern is typically quantified with diversity indices. The patch richness such as the number of land use or land cover classes in the landscape are the major aspects quantified using SHDI in urban planning.

$$SHDI = - \sum_{i=1}^m (P_i \ln P_i) \dots \dots \dots \text{Equation 7}$$

(Landscape level metrics) - Units: None, Range: $SHDI \geq 0$, without limit

SHDI = 0 when the landscape contains only 1 patch (i.e., no diversity). SHDI increases as the number of different patch types (i.e., patch richness, PR) increases and/or the

proportional distribution of area among patch types becomes more equitable. Description: SHDI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion (McGarigal & Marks., 1995, p. 118).

8. Shannon's evenness index (SHEI)

Shannon's Evenness index is a quantitative measure of abundance or the area distribution of classes of different patch types. Generally, it is reported as the function of the maximum diversity possible for a given richness.

$$SHEI = \frac{-\sum_{i=1}^m (P_i \ln P_i)}{\ln m} \dots \dots \dots \text{Equation 8}$$

(Landscape level metrics) - Units: None, Range: $0 \leq SHEI \leq 1$

SHDI=0 when the landscape contains only 1 patch (i.e., no diversity) and approaches 0 as the distribution of area among the different patch types become increasingly uneven (i.e., dominated by 1 type). SHDI =1 when distribution of area among patch types is perfectly even (i.e., proportional abundances are the same).

Description: SHEI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion, divided by the logarithm of the number of patch types. In other words, the observed Shannon's Diversity Index divided by the maximum Shannon's Diversity Index for that number of patch types (McGarigal & Marks., 1995, p. 120).

9. Contagion (CONTAG)

The contagion index measures the probability of neighborhood pixels being of the same class and describes to what extent landscapes are aggregated or clumped (O'Neill et al., 1988). In other words contagion is the measure of adjacency. Landscape classes are described by a high contagion index; when the landscape consists of relatively large and contiguous patches. The presence of relatively greater number of small or highly fragmented patches in the landscape will result in low contagion index. For example, when an urbanized area becomes more amalgamated the contagion index will be high.

As an urbanized area becomes more fragmentation into a larger number of individual urban units, the contagion index will be low.

$$\text{CONTAG} = \left[1 + \frac{\sum_{i=1}^m \sum_{k=1}^m \left[\left(P_i \right) \left(\frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \right] \left[\ln \left(P_i \right) \left(\frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \right]}{2 \ln(m)} \right] (100) \dots\dots\dots \text{Equation 9}$$

(Landscape level metrics) - Units: Percent (%), Range: $0 < \text{CONTAG} < 100$. CONTAG approaches 0 when the distribution of adjacencies (at the level of individual cells) among unique patch types becomes increasingly uneven. CONTAG = 100 when all patch types are equally adjacent to all other patch types.

Description: CONTAG equals minus the sum of the proportional abundance of each patch type multiplied by number of adjacencies between cells of that patch type and all other patch types, multiplied by the logarithm of the same quantity, summed over each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage). In other words, it is the observed contagion over the maximum possible contagion for the given number of patch types (McGarigal & Marks., 1995).

3.9 Logistic Regression Modeling and Driving Forces of Urban Growth

3.9.1 Physical driving forces of urban growth

In developing countries like Ethiopia the choice of predictor variables is highly depends on the availability of well - organized and good quality data. Particularly, socio-economic data's are the Scarcest data in developing countries. Thus, to overcome the challenge, physical driving forces of urban growths were considered in this study. However, in this study, the selections of physical predictor variables were made systematically in two steps. First, the most probable driving forces urban growths were identified based on literature review (Cheng & Masser, 2003 ; Huang et al., 2009; Nong & Du, 2011; Tayyebi et al., 2010). Second discussion were made with local experts in order to make driving forces were adapted to the local context accordingly list of predictors were identified and the major Physical driving forces of urban growth in

the study area were selected from the list. Generally, in this study, the probability of a land to convert from non-built up to built up is considered as a function of the identified predictor variables. Regression analysis, which will be discussed in the next section, is carried out to identify the degree of significance of each identified variables and to examine how they enhance or hinder urban land cover change in the study area. The analysis is important to better understand the interaction between urban growth patterns and physical driving forces. It is also helpful for a variety of urban models which require selection of appropriate spatial variables for the modelling process.

3.9.2 Logistic regression modelling

In this study, the nature of the land cover change of a cell was considered as dichotomous: either the presence of non-urban to urban conversion (represented by value 1) or no change (represented by value 0). It was assumed that the probability of a non-built up cell changing to a built up cell would follow the logistic curve. The general formula of logistic regression is given as follows

$$y = a + b_1x_1 + b_2x_2 + \dots + b_nx_n$$

$$y = \log_e^{(p/1-p)} = \log \text{it} (p)$$

$$p(z = 1) = e^y / 1 + e^y$$

Where $x_1, x_2, \dots, x_n$ are explanatory variables. The utility function y is a linear combination of the explanatory variables representing a linear relationship. The parameters $b_1, b_2, \dots, b_n$ are the regression coefficients to be estimated. If z is denoted as a binary response variable (0 or 1), value 1 ($z=1$) means the occurrence of a new unit (i.e. the transition from a rural unit to an urban unit), and value 0 ($z=0$) indicates no change.

P refers to the probability of occurrence of a new unit, i.e. $z=1$. Function y is represented as $\log \text{it} (P)$, i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1. As the y value increases, probability P inevitably increases (Huang, B, & Wu, B. 2009). Arc GIS extension software Change Analyst tool is used to conduct the logistic regression modelling.

3.9.3 Preparation of input data for logistic regression model

The independent variables or the factor maps for the regression analysis are prepared for the three different periods under study. These maps are prepared in Arc-GIS 10.3 software environment. All the input data are in raster format in a cell size of 30x30 so as to match the resolution of Landsat images.

1. Dependent variables

In this model four binary land cover maps of 1990, 2000, 2010 & 2019 are used as dependent variables to carry out the logistic regression analysis. These maps are classified into two land cover classes 0 & 1. 0 represents non-built up land cover class whereas 1 represents built up land cover class. The conversion rule is based on the assumption that land cover changes from non-built up to built-up land. This is due to the fact that the possibility of land cover to change from built up to non -built up is very unusual or rare in developing countries like Ethiopia.

2. Independent variables

Nine independent variables are finally screened out based on literature review and discussion with local expertise to include in the model. However, as described in earlier section most land use/cover change models are data driven. Minor roads (as a major) was identified as important physical driving force of urban growth both in literature and on discussion made with local experts.

However, due to unavailability of data that covers the whole study area the two independent variables are removed from the model. This reduced the total number independent variables from nine to seven. These variables are: proportion of built-up land, slope, and distance from CBD, distance from higher institution (i.e. Colleges, Hospital and industry), distance from major roads, distance from town centers and distance from satellite towns. All of them are of the same resolution of 30x30m. Slope, distance from CBD, distance from higher institution and distance from satellite towns are the same for all study periods of 1990-2000, 2000-2010 & 2010-2019. The variables distance from major road and distance from Town centers are the same for the first two study periods (1990-2000 & 2000-2010); however, these variables are different for the third study period (2010-2019).

Town centers such as Abosto and Arada which are active and important economic Town centres were not active and economically import before 2010. Proportion of built up land is obviously different for all the study periods and they are calculated based on land cover map. The proportion of built up land (P_Urban) is computed using a function focal statistics in Arc-GIS. This function calculates the proportion of built-up area within a neighborhood of 7x7 window size for each pixel and assigns the central cell the mean value of all cells. The selection of the size of the neighborhood window is based on the most widely used window size in dynamic simulation models where sizes are often 3x3, 5x5, or 7x7 (Hu & Lo, 2007). Slope map is derived from the ASTER digital elevation model (DEM) of 2011 obtained from USGS website. The image was resampled to are solution of 30cm to match the resolution of land cover images.

Distance to CBD (Dist_CBD), distance to major roads (Dist_Mjrd), distance to town centers (Dist_tc) and distance to satellite towns (Dist_st) are computed in Arc GIS using Euclidean distance function. The function calculates the shortest distance from the center of the source cell to the center of each of the surrounding cells. The locations of the source cell or cells are represented by a point or line in Arc GIS. The values of all variables are standardized to 0-1 range.

3.9.4 Multi-collinearity

Multicollinearity is a situation where two or more independent variables, are strongly correlated with each other than they are with the dependent variable (Field, 2009). The existence of multicollinearity in a model may cause very high standard error and low t-statistics, unexpected changes in coefficient magnitudes or signs, or insignificant coefficients despite a high R-square value. Such problems are misleading in the interpretation of outputs and will result in incorrect conclusions about associations between independent and dependent variables. Thus, to some extent performing multicollinearity analysis is the basis or a prerequisite for conducting multiple regression (Cheng & Masser, 2003).

The presence or the absence of multicollinearity is not a problem in multiple regressions, rather the degree of presence matters. The higher the degree of multicollinearity, the greater will be the likelihood of the disturbing consequences of multicollinearity. There

are several ways of detecting the manifestation of multicollinearity in a regression model. Variance-inflation factor (VIF) perhaps the most commonly used test is one way of detecting multicollinearity in statistical analysis. The variance inflation factors measure how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related. It has been shown that the variance inflation factor for the k^{th} predictor is given by:

$$\text{VIF}_k = (1 - R_k^2)^{-1} \quad \dots \dots \dots \text{Equation 10}$$

Where, R^2 is the R^2 -value obtained by regressing the k^{th} predictor on the remaining predictors. Note that a variance inflation factor exists for each of the k predictors in a multiple regression model. In most scholarly articles and advanced statistical textbooks $\text{VIF} > 10$ is regarded as a sign of severe or serious multicollinearity (O'brien, 2007). There are a number of ways of dealing with multicollinearity problem (Field, 2009).

The first, and most obvious, solution is to eliminate some of the highly correlated variables from the model. For instance, if two variables are highly collinear, then it means that they proving the same information. Thus, we can pick one variable to keep in the model and discard the other one. When unable to decide an appropriate variable to omit from the model, we can combine the variables into a reduced set of variables.

3.9.5 Model Evaluation

The predicting capacity of the proposed models were evaluated based on Percentage Correct Prediction (PCP), which is a simple tool indicating how good the model is at predicting the outcome variable. The PCP statistic assumes that if the estimated p is greater than or equal to 0.5 then urban growth or change from 0 to 1 were expected to occur and automatically assigned 1.

However, if the estimated p is less than 0.5 then urban growths were not expected to occur and automatically assigned 0. By assigning these probabilities 0s and 1s and comparing these to the actual 0s and 1s, the correct prediction, wrong prediction and overall percent correct prediction scores were calculated (Pampel, 2000).

CHAPTER-4: RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter the outcomes of this research are presented and discussed in detail sequentially. Starting from spatio-temporal quantification of urban growth, it goes through the most important findings of growth pattern analysis using spatial metrics. The pattern analysis is conducted both at city wide level and at regional scale. Most of the discussions are supported by maps, tables and illustrative graphs. The key factors responsible for the changing patterns of urban growths are presented and discussed through results of logistic regression modelling and driving forces.

4.2 Results of image classification and accuracy assessment

According to the results of accuracy assessment the extraction of Built up has relative higher accuracy in all images. Conversely, Non-built-up class has the lower accuracy due to the mixed pixels in the classes. In addition to this, the Landsat-7 ETM+ sensor offers numerous improvements over the earlier generations of Landsat sensors such as Landsat -4 & 5 (Masek et al., 2001). The improved spectral information content of Landsat- 7 ETM+ sensor could record small bright surfaces missed by Landsat-5 TM that has been manifested on Landsat ETM+ 2000 image in this study.

The results presented based on ETM+ 2010 image in this research are subject to the images inconsistencies described above. However, the overall accuracy of all images was found to be greater than 85%, which is considered as a good result for remote sensing image based analysis (Herold et al., 2005). The following table presents the accuracy of classified images for the different time periods. The results of image classification are given in table_4.1.

Table 4.1 Results of accuracy assessment of (1990, 2000, 2010 and 2019)

sensor	Acquisition date	Classified image	Over all accuracy	Kappa statistics
Landsat TM	02/12/1990	Built up 1990	88%	0.82
Landsat TM	24/03/2000	Built up 2000	90%	0.85
Landsat ETM+	30/10/2010	Built up 2010	90%	0.85
Landsat TM	18/12/2019	Built up 2019	93%	0.90

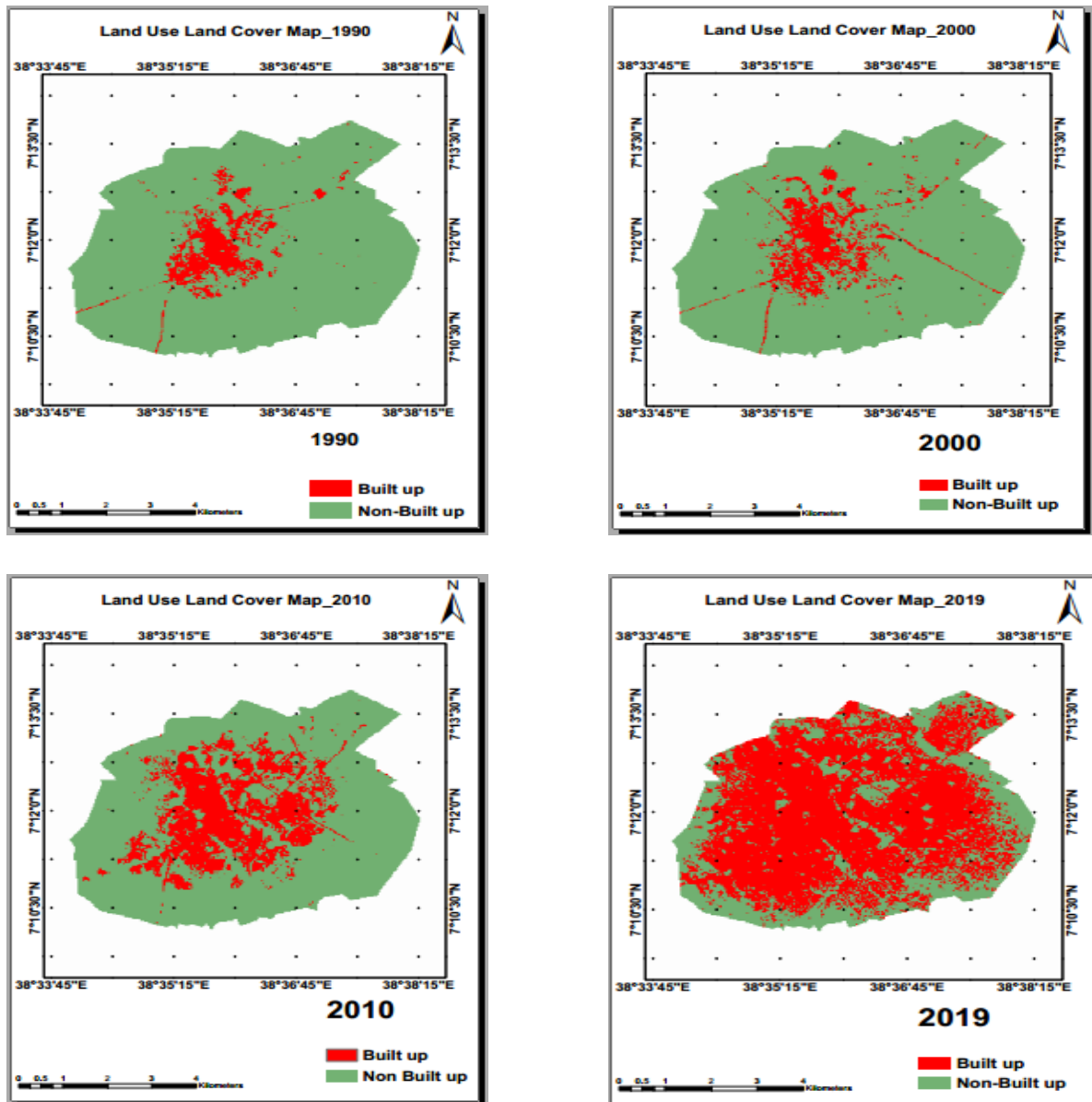


Figure 4.1 Results of image classifications of (1990, 2000, 2010 and 2019)

4.3 Spatio-temporal analysis of urban growth pattern using spatial metrics

The classification of the multi-temporal satellite images into built-up and non-built up for the four different time periods of 1990, 2000, 2010 & 2019 has resulted in a highly simplified and abstracted representation of the study area (See figure 4.1). These maps show a clear pattern of increased urban expansion prolonging both from urban center to adjoining non-built up areas along major transportation corridors. The maps show the spatio-temporal urban growth pattern in the study area. Post classification comparison of the classified images revealed the growth pattern of the city in different directions, the infilling of the open spaces between already built-up areas and the dynamics of urban expansion in the study area. However, it is important to assist the findings with statistical evidences as it is useful to describe the spatial extent and the different patterns of urban growths that have been occurring in the study area.

This will help understand how the Town is changing over time and to compare the various growth patterns taking place in different time periods quantitatively. Spatial metrics are powerful tools to quantitatively describe and compare multi-date thematic maps. Five frequently used spatial metrics are selected based on literature review (refer section 3.7) for the synoptic analysis of built-up area dynamics over space and time at landscape level. The metrics are used to describe the trends and changing patterns of the actual built-up land extracted Landsat images. Detail discussion on metrics can be found on section 3.7 of this thesis. All metrics are computed only for the built up area.

The outputs presented in table 4.2 were generated for the selected metrics in the form of numeric values for the whole study area in FRAGSTATS 4.2. The results presented in table 4.2 shows that the total built-up area has grown from 305ha in 1990 to 415 ha in 2000, to 882 ha in 2010 and to 2500 ha in 2019. The highest rate of urban growth is observed during the third period of urbanization (2010 to 2019) in which the built up area increased more than twice (64.7%) within 9 years (Table 4.2). This is followed by 26.5% and 52.9% during the first (1990 to 2000) and the second (2000 to 2010) period of urbanization respectively. This indicates a more rapid urbanization has been taking place in the study area during the period of 2010 to 2019 compared to the two other periods.

Table 4.2 Analysis of Built-up Area expansion based on Total area metrics.

Study period	change(ha)	Change (%)	Time Span	growth rate/years	Average
1990-2000	110	26.5	10	2.65%	5.04%
2000-2010	466	52.9	10	5.29%	
2010-2019	1618	64.7	9	7.19%	

Nevertheless, it should be also noted that the second period of urbanization covers the longest time span compared to the first and third periods. In terms of absolute land cover change in (ha) the third period 2010 to 2019 remains the highest witnessing the conversion of 1618ha of non-built up land to urban land. In contrast to the percentage change, the second study period (2000 to 2010) is 466ha land changed to built-up area followed by the first period of urbanization (1990 to 2000) where 110ha land is changed to built-up area.

Totally 2195ha of non-built up land has been converted to build up land over the period 1990 to 2019. As the statistics obtained from the area metrics computation confirms, the built up area has been increasing at an average annual growth rate of 2.65%, 5.29% & 7.19% during the periods 1990-2000, 2000-2010 & 2010-2019 respectively in the study area (refer figure_4.2).

Table 4.3 Results of spatial metrics calculation at the entire landscape level

Year	LUC	TA	NP	PD	LPI	FRAC_AM
1990	Built up	305	121	59.74	71.12	1.25
2000	Built up	415	242	58.35	76.79	1.26
2010	Built up	882	174	19.74	87.37	1.30
2019	Built up	2500	237	9.48	96.52	1.33

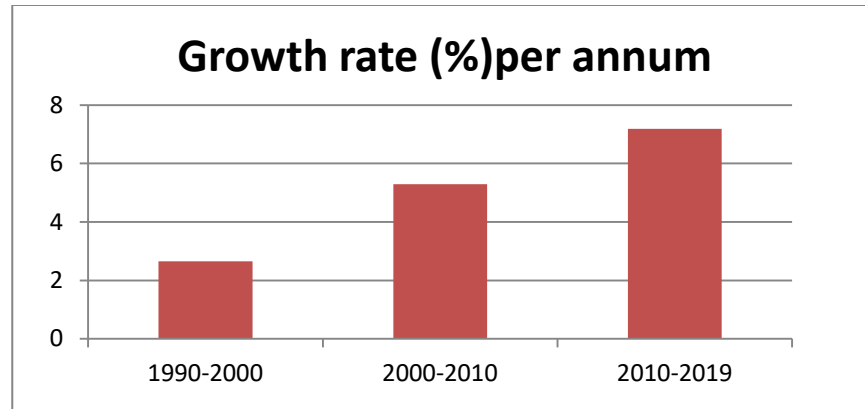


Figure 4.2 Built up area growth rate (%) per annum per study period

The rapid urban growth process in the study area has been revealed by the continuous rise of number of patches (NP) in the landscape throughout the study periods. This could be an indication of the heterogeneous and fragmented urban growth process taking place in the study area. Significant change in NP is observed during 2000 to 2010. However, the pick occurred in 2019 indicating the continuing development of scattered and fragmented urban patches in the study area. The situation can be attributed to the emergence of small and patchy built up patches around the periphery of the city and in peri-urban regions. This could happen as the Town expands outward in the form of scattered development, the gap between the peri-urban regions and the urban core will decrease by increasing the attractiveness the peri-urban area for development.

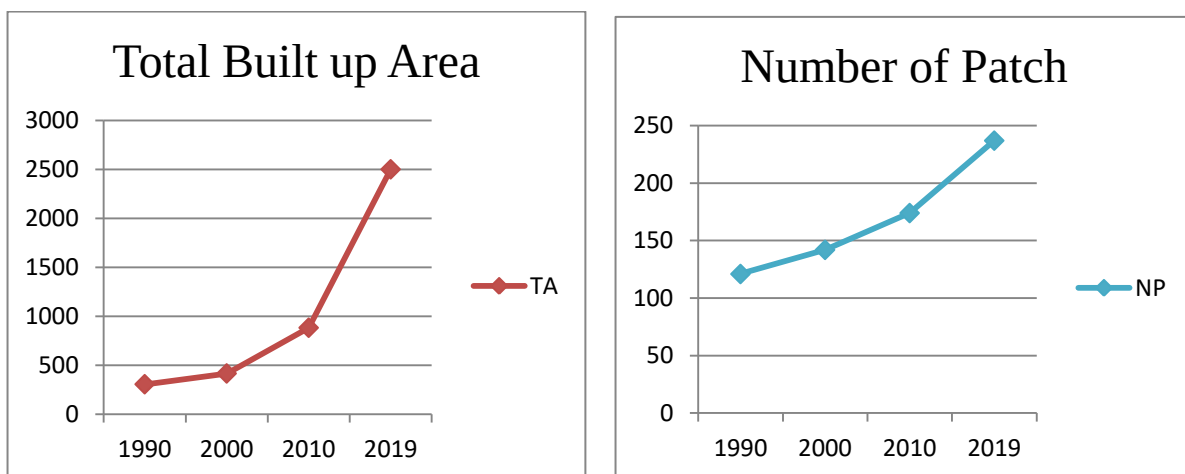
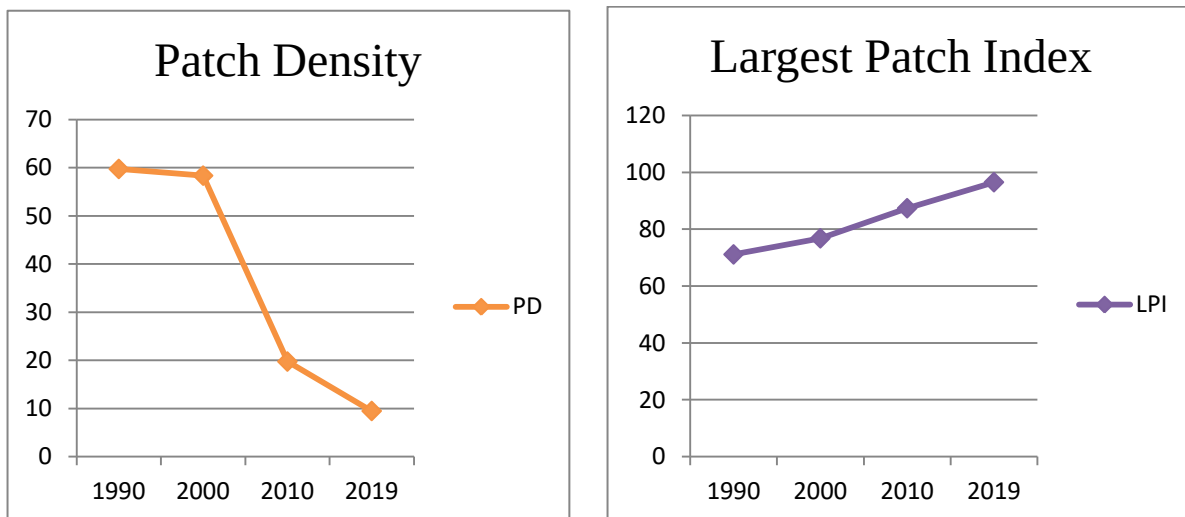


Figure 4.3 Graph showing total area (TA) & number of patches (NP) for the entire landscape area

The patch density (PD) continuously decreased from 59.74 in 1990 to 9.48 in 2019 throughout the study period. The highest reduction is observed during the second period of urbanization (2000-2010). These show that although the number of patches is continuously rising in the landscape, the built up area (TA) is increasing in much faster rate than NP. The phenomena can be observed from the slope of the two graphs (figure 4.3). Between 2000 & 2010 the slope of TA is steeper than the slope of NP in the same period on the graph. In other words, a decrease of patch density means that some patches located in close proximity to the city centre are merging with urban core to form a homogeneous urban fabric.

The effect has been manifested on the increasing largest patch index (LPI), signifying the agreement between the metrics. Inherently, the dominant or largest patch in the landscape, which is supposed to be the urban core, is growing over time (Jun et al., 2009). Visual comparison of the classified images confirms the development of urban core in the form of infill and edge expansion. The gradual expansion of the urban core might have changed the city into urban agglomeration. This could be one reason for the scattering and fragmented development of the city as urban agglomeration may push development away from the already established urban areas.



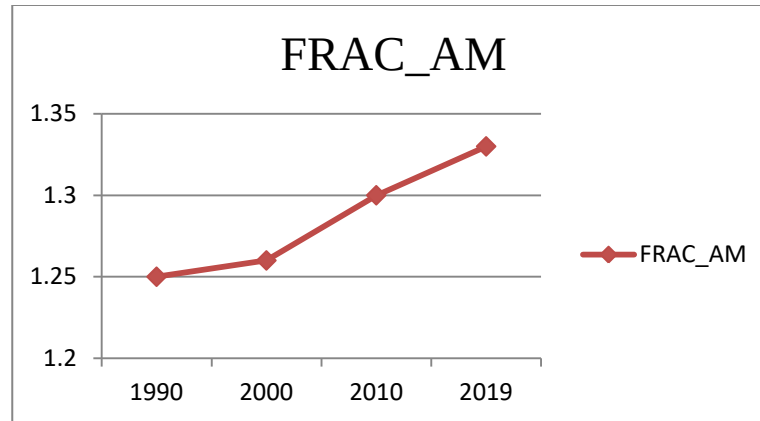


Figure 4.4 Graph showing patch density (PD) largest patch index (LPI) and FRAC_AM for the entire landscape area.

The area weighted mean patch fractal dimension (FRAC_AM/AWMPFD) is the measure of urban patch shape complexity which describes how patch perimeter increases per unit increase in patch area. In 1990, FRAC_AM was 1.25 which indicates that for a unit increase of patch area. Yet, looking at the highest value witnessed in 2019, it seems that the geometry of urban patches is getting more complex over time. This could be an indication of the prevalence fragmented low density development in the fringe areas. From the results of spatial metrics analysis of built up area it has been possible to quantify the trends and patterns of urban dynamics at the city level using the selected five metrics.

Accordingly, three metrics namely: the total built up area (TA), number of urban patches (NP) and the largest patch index (LPI) showed consistent increasing trend while patch density (PD) exhibited a decreasing trend. Nevertheless the fractal dimension (FRAC_AM) showed both increasing and decreasing trend with remarkable upturn in 2010. Despite the increasing trend of the largest patch index (urban core), the built up area remain getting more fragmented over time.

Generally, 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. Built up area has been undergoing fragmented development process in all study periods, with substantial increase of built up area during the second period of urbanization 2000-2010. In addition to urban sprawl, which can

be witnessed from the substantial increase in number of patches over time, patch density and the largest patch index also revealed that the city is experiencing infill and edge expansion around the urban core mainly during 2000-2010 (refer figure_4.4). The result of fractal dimension analysis also unveiled the increasing patch shape complexity of the study area except a slight decrease observed in 2010 which could be as a result of infill development or the merger of new patches with the existing patches during 2000-2010.

4.4 Effect of classification accuracy and post processing method on spatial metrics computation

Calculation of spatial metrics using land-cover maps extracted from remotely sensed data is becoming increasingly common (Wickham et al., 1997). To see the effects of classification accuracy and post classification technique implemented during image processing on the result of metrics calculation, this research compares two sets of classified images. The results illustrate the sensitivity of the metrics to the variation in the classification approach. The first set of images is based on the results obtained from Gezhegn aweke Abebe (2013) and the second set of image is taken from Vermeiren et al. (2012) who were conducted the research to analysis the quantification of urban growth trend and pattern of Uganda.

Apart from the slight accuracy difference the major difference between these two set of images is that the former one has applied post classification majority filter using 3x3 window sizes this study also used post classification majority filter using 3x3 window sizes but different study area and the later one has applied post processed by imposing that non built-up area was never built-up in a previous time. Both data sets and this study used maximum likelihood classification method. Using majority filter has significant influence on the statistical value of all metrics computed in Gezhegn aweke Abebe (2013) analysis. For instance, number of patches (NP), decreased by more than half almost for all images. Patch density (PD) is the ratio of number of patches (NP) to total area (TA) and it showed decreasing trend when subjected to majority filter and Total Area (TA) is inevitably influenced by filtering which can be proved by comparing the total area of built up area before and after filtering.

However, total area (TA) is primarily subject to classification accuracy (Guofan & Wenchun, 2004). The largest patch index (LPI) is also the function of total area (TA) and showed increasing trend when filtering is applied. Fractal dimension (FRAC_AM) is seemingly negatively influenced by majority filtering. Due to the aggregating nature of filtering smaller patches which were supposed to contribute to higher fractal dimension will be removed from the landscape. This also decreases the NP. Comparatively bigger patches have lower fractal dimension, i.e. Lower complexity or simple shape.

Therefore, the post-classification majority filter might have removed most of the spread out and isolated pixels and thus, reduction in fractal dimension. From the above comparison revealed that using majority filter has significant influence on the statistical value of all metrics computed in Gezhegn Aweke Abebe (2013) analysis. But it is important to note that the classification accuracy of the two sets of images is somehow comparable. Owing to the better classification results achieved in this study, the analysis is preceded with the classification results of this study.

4.5 Region Based Analysis of Growth Pattern Using Spatial Metrics

Because of the aggregating nature of metrics quantification of urban pattern at the whole landscape level may not give sufficient insight or information to relate spatial patterns to the underlying causal processes. In addition to this it is difficult to relate changes observed in the metrics to particular location in the landscape (Herold et al., 2003), at least not without visual interpretation. Therefore; it is useful to conduct detail analysis by dividing the study area into different zones or regions.

Different regions were formed using administrative boundaries at division level the town is divided into four in terms of spatial extent most of the regions Area are comparable except for the western region, which is slightly smaller than the other four regions of Shashemanne Town. Like the analysis at the whole landscape level, in the region based analysis the thematic map is composed of one class which is built up therefore; focusing only on built up area dynamics. The metrics are computed in the recent version of FRAGSTATS (4.2). The list of divisions and their corresponding region are given in table below.

Table 4.4 Administrative divisions making up regions

Region	Area (ha)	Administrative division making up regions
Northern	855	Alelu, Addis Ababa road direction
Eastern	1495	Awasho, Bale-Robe road direction
Southern	724	Dida_Boke, Hawasa road direction
Western	776	Bulchana, Burka_Gudina, Aje road direction

4.5.1 Northern Region (Addis Ababa road direction in Alelu Kebele)

Class Level Analysis

According to the results obtained from FRAGSTATS, the built up area has been considerably changed over time in the northern region (Addis Ababa road direction) of the study area. During 1990-2019 56.52 ha of built up area has been increased to 517.28 ha of built up area with an average growth rate of 5.26 % (460.76 ha) per annum in 1990 the built up land in the region has been only 56.52 ha after ten years in 2000 this figure changed to 86.85 ha.

Table 4.5 Temporal dynamic of built up area in north region based on class area (CA) metrics

Study period	Change (ha)	Change (%)	Time span	Growth rate	Average
1990-2000	26.91	32.25	10	3.23%	5.26%
2000-2010	86.85	51	10	5.1%	
2010-2019	347.04	67.1	9	7.46%	

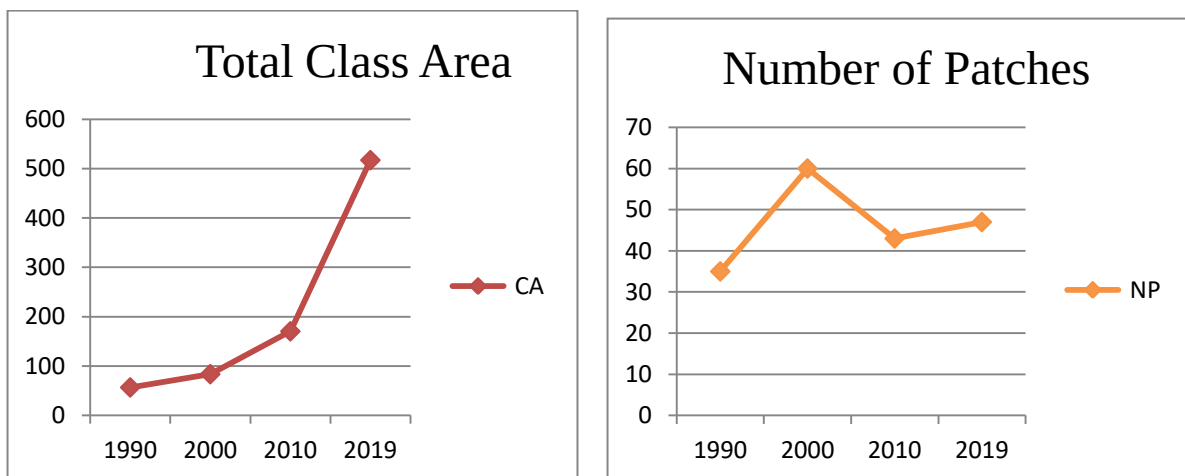
Later it increased dramatically to 517.32 ha in 2019. The region is one of the most active areas in Shashemanne Town hosting a variety of socio-economic activities. For instance, in the direction of Melka Oda Hospital where different industrial and commercial activities has found like private limited companies, hotels, markets and business are located and found in this region. For these reasons, the total built up area (CA) is continuously increasing over time.

Table 4.6 Result of spatial metric computation (north region)

Year	CA	NP	PD	LPI	FRAC_AM
1990	56.52	35	61.9	43.95	1.19
2000	83.43	60	71.9	62.46	1.20
2010	170.28	43	25.25	82.98	1.25
2019	517.32	47	9.1	74.64	1.29

During the period 1990-2000, the number of patches (NP) increased from 35 to 60 clearly indicating the emergence of new patches in the landscape as a result sprawling urban growth pattern in the region. Contrastingly, NP decreased from 60 to 43 during the period of 2000-2010. This shows the emergence of new connecting patches between fragmented urban patches along the Addis Ababa road. However, the gap is gradually filled with contiguous and fragmented built up patches in a linear pattern.

During 2010-2019, number of patches again increased from 43 to 47. The measurements of largest patch index (LPI) and area weighted mean patch fractal dimension (FRAC_AM) showed increasing trend over the entire study period (figure_4.5). LPI shows the gradual increasing size of the largest built up patch or the core area over time whereas FRAC_AM indicates the increasing complicated geometric shape of patches due to fragmentation. Generally, Addis Ababa road have played significant role in shaping the urban growth pattern in this region.



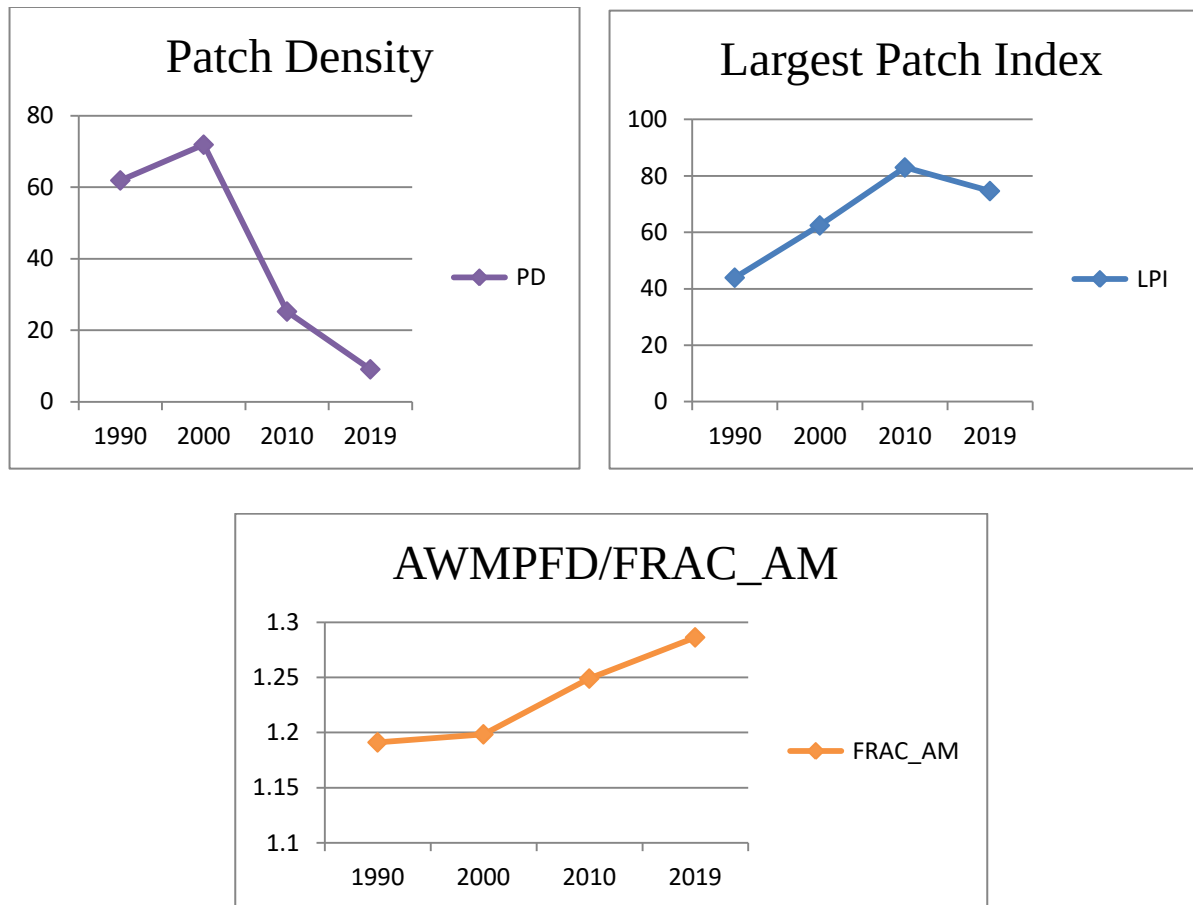


Figure 4.5 Class level metric computed for northern region

Like CA, NP and PD, the area occupied by largest patch has been increasing continuously throughout the study period in the region. The result obtained from FRAGSTATS reveals that the LPI has been 35 in 1990, 60 in 2000, 43 in 2010 and 47 in 2019 (table 4.6). This could be due to the amalgamation of small and isolated urban patches into a single patch and/or development of other urban patches around the existing built up area. The built up area is growing to the north direction as the continuation of the central region mainly following the major road and sub road. This indicates that most of the small isolated and fragmented urban sprawl and associated built ups were connected with the urban core. FRAC_AM has been 1.19 in 1990, 1.20 in 2000, 1.25 in 2010 & 1.29 in 2019 (table 4.6). The proximity of FRAC_AM value to one (1) in the earlier Course of urbanization periods indicates; the built-up area was composed of patches having comparatively simple geometric shape in earlier periods.

However, the increasing trend of FRAC_AM shows that this region is getting more fragmented and complex overtime. Thus, all the metrics at class level confirms the northern region was shows the built- up area was composed of patches having comparatively simple geometric shape and getting subsential fragmented over time. Three metrics: Contagion (CONTAG), Shannon's diversity index (SHDI), and Shannon's evenness index (SHEI) were selected to analyze the overall condition of the landscape structure. Contagion (CONTAG) is the measure of the extent to which the different land cover classes are aggregated or clumped and it is expressed in percentage . High contagion results from the aggregation of patches of the same land cover classes.

Table 4.7 Spatial metrics computed at landscape level – Northern region

Northern Region-Addis Ababa road direction			
year	CONTAG	SHDI	SHEI
1990	77.52	1.76	0.49
2000	81.17	1.77	0.43
2010	88.76	0.92	0.24
2019	90.42	0.77	0.20

Based on the result of the contagion analysis for the Northern region indicates a increasing trend confirming the fragmented urban growth. This means patches of the built up class were highly aggregate together as it is clearly seen on figure 4.5. Conversely, in 2010 the value of CONTAG increased to 90.42 (table 4.7) indicating the increasing fragmentation of the landscape as a result of emergence of built up area between the contiguous non-built up classes. Shannon's diversity index (SHDI) also confirms the landscape is getting more diversified and rich with different patches over time. As a result the distribution of area between non-built up and built up area is relatively becoming more equitable or even over time as evidenced by increasing value of Shannon's evenness index (SHEI). Thus, all the metrics at landscape level confirms the northern region is getting more fragmented over time.

4.5.2 Eastern region Bale-Robe road direction

Class level landscape pattern analysis

The result of class area metrics analysis witnessed that urbanization has been considerably influencing the landscape in the eastern part of the study area. In 2019, the region constituted 5.66% of the total built up land in the Eastern region. However, built up area covered only 2.94% (29.97 ha) of the region in 1990. After ten years in 2000 this figure increased to 6.72% (208.71 ha) indicating the urbanization process in the eastern region. The most dramatic change is observed in 2019 when built up CA reached to cover 7.31% (596.97 ha) of the region (see table 4.8). The change is not surprising as this period covers the longest time span and besides it is the period at which the highest land cover change at the city level is observed. However, it logical to say the region might have absorbed the highest percentage urban growth that occurred in 2010-2019 at the town.

Table 4.8 Temporal dynamics of built up area in east region based on class area (CA) metric

Study period	Change (ha)	Change (%)	Time span	Growth rate	Average
1990-2000	29.97	29.42	10	2.94%	5.66%
2000-2010	208.71	67.20	10	6.72%	
2010-2019	596.97	65.78	9	7.31%	

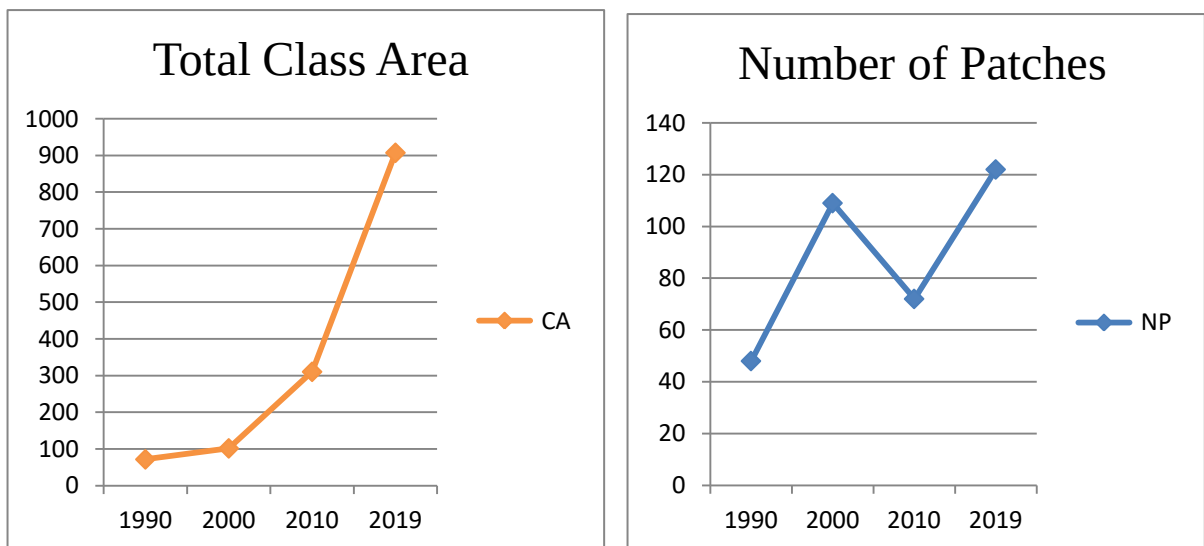
Table 4.9 Result of spatial metric computation (eastern region)

year	CA	NP	PD	LPI	FRAC_AM
1990	71.91	48	66.75	48.56	1.18
2000	101.88	109	106.99	37.81	1.18
2010	310.59	72	23.18	59.63	1.26
2019	907.56	122	13.44	94.82	1.31

Number of patches shows increasing trend in the first period and the third period of urbanization in 1990 NP is 48 this figure is increased to 109 in 2000 and then NP is changed to 72 in 2010 and to 122 in 2019. this illustrating the sprawling and fragmented growth

of the built up area were observed in this region during the first and third period of urbanization. However, in second period of urbanization (2000- 2010) NP is decreased from 109 to 72. This shows that small patch merged to form urban fabric to south-east region of the study area and observed from the analysis of the whole landscape level in second period of urbanization (2000 - 2010) NP is decreased so this may be the contribution of south-east region of the study area to whole landscape level.

The increase in NP seems somehow higher than the increase of CA. This phenomenon is reflected by the density metrics PD. The sprawling and fragmented growth can be confirmed from the lower values of patch density in the first and third period of urbanization in contrary, the largest patch index shows increase throughout the study periods. These support the idea that the number of patches is growing in higher pace than the class area. This means the existing urban patches were growing in size together with the number of patches which indicates that the sprawling urban growth is followed by infill and edge expansion in this region.



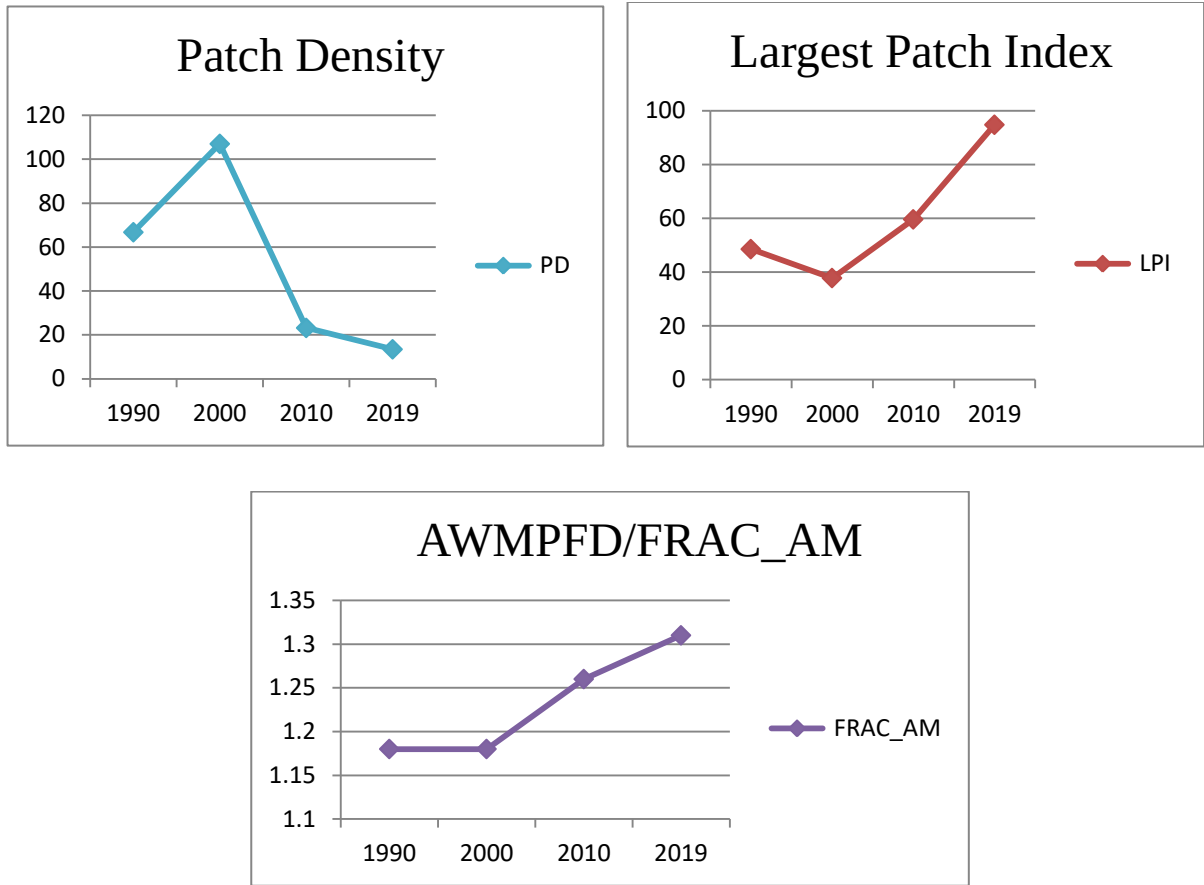


Figure 4.6 Class level metric computed for Eastern region

Table 4.10 Spatial metrics computed at landscape level – Eastern region

Eastern region - Bale-Robe road direction			
Year	CONTAG	SHDI	SHEI
1990	75.21	2.10	0.54
2000	70.85	3.04	0.65
2010	68.76	1.22	0.29
2019	66.98	0.43	0.09

Contagion (CONTAG) shows a gradual decline indicating the dispersed and low-density development pattern in the eastern region (table 4.10). As much of new built up patches develop in the region, the continuous non-built up land is interrupted resulting in fragmentation. Looking at SHDI and SHEI, it is evident that the landscape is also becoming more diversified with a variety of patch types and even distribution of class.

SHDI is low in the early stages of urban development because of the dominance of the non-built up land cover class, hence low diversity of classes, whereas SHEI scored low value as there were no equitable distribution of classes in early stages of urbanization. The results of these metrics are in line with the metrics computed at individual class level.

4.5.3 Southern Region (Hawasa road direction)

Class Level Landscape Pattern Analysis

The result of class area metrics analysis witnessed that urbanization has been considerably influencing the landscape in the southern part of the study area. In 1990, the region constituted 37.44 ha of the total built up area, this figure increased to 72.81 ha in 2000, 169.56 ha in 2010 and 595.08 ha in 2019.

Table 4.11 Temporal dynamic of built up area in south region based on class area metrics

Study period	Change (ha)	Change (%)	Time span	Growth rate	Average
1990-2000	35.37	48.58	10	4.86%	6.17%
2000-2010	96.75	57.06	10	5.71%	
2010-2019	425.52	71.51	9	7.95%	

The results shows most dramatic change observed in 2019 and relatively slower growth is noticed in 2000. The area about 35.37 ha has been increased per annum during 1990-2000 period, 96.75 per annum in 2000- 2010 and reached to 425.52 per annum in 2010- 2019. The average growth rate is 6.17% .

Table 4.12 Result of spatial metric computation (southern region)

Year	CA	NP	PD	LPI	FRAC_AM
1990	37.44	37	98.82	54.09	1.16
2000	72.81	57	78.29	55.26	1.20
2010	169.56	55	32.44	69.43	1.22
2019	595.08	37	6.22	98.26	1.24

Number of patches shows increasing trend in the first period and decreasing the third period of urbanization in 1990 NP is 37 this figure is increased to 57 in 2000 and in 2010 NP is 55 then NP is changed to 37 in 2019. This illustrating the sprawling and fragmented growth of the built up area were observed in this region during the first and third period of urbanization. However, in second period of urbanization (2000-2010) NP is decreased from 57 to 37. This shows that small patch merged to form urban fabric to southern region of the study area and observed from the analysis of the whole landscape level in second period of urbanization (2000-2010) NP is decreased so this may be the contribution of southern region of the study area to whole landscape level.

The increase in NP seems somehow higher than the increase of CA. This phenomenon is reflected by the density metrics PD. The sprawling and fragmented growth can be confirmed from the lower values of patch density in the first and third period of urbanization in contrary, the largest patch index shows increase throughout the study periods. These support the idea that the number of patches is growing in higher pace than the class area. This means the existing urban patches were growing in size together with the number of patches which indicates that the sprawling urban growth is followed by infill and edge expansion in this region. Between 1990 and 2019 the LPI grown from 54.0865 to 98.2607. The growth of this region seems highly triggered by the presence of Addis Ababa road, one of the major roads connected close proximity between the city and the neighboring satellite towns in the early stage of urban development. The built up area starts to expand from both the western and eastern part of the region. Then, it continues to spread along the high way road gradually infilling the open space between existing built up patches creating continuous urban fabric.

It is evident that fragmented urban patches are observed in the northern and southern parts of the region as the time proceeds. This is confirmed by the area weighted mean patch fractal dimension (FRAC_AM) measure of the area. FRAC_AM showed increasing trend. This showing the complex and Fragmented development process of built-up areas in the region in earlier period of urbanization

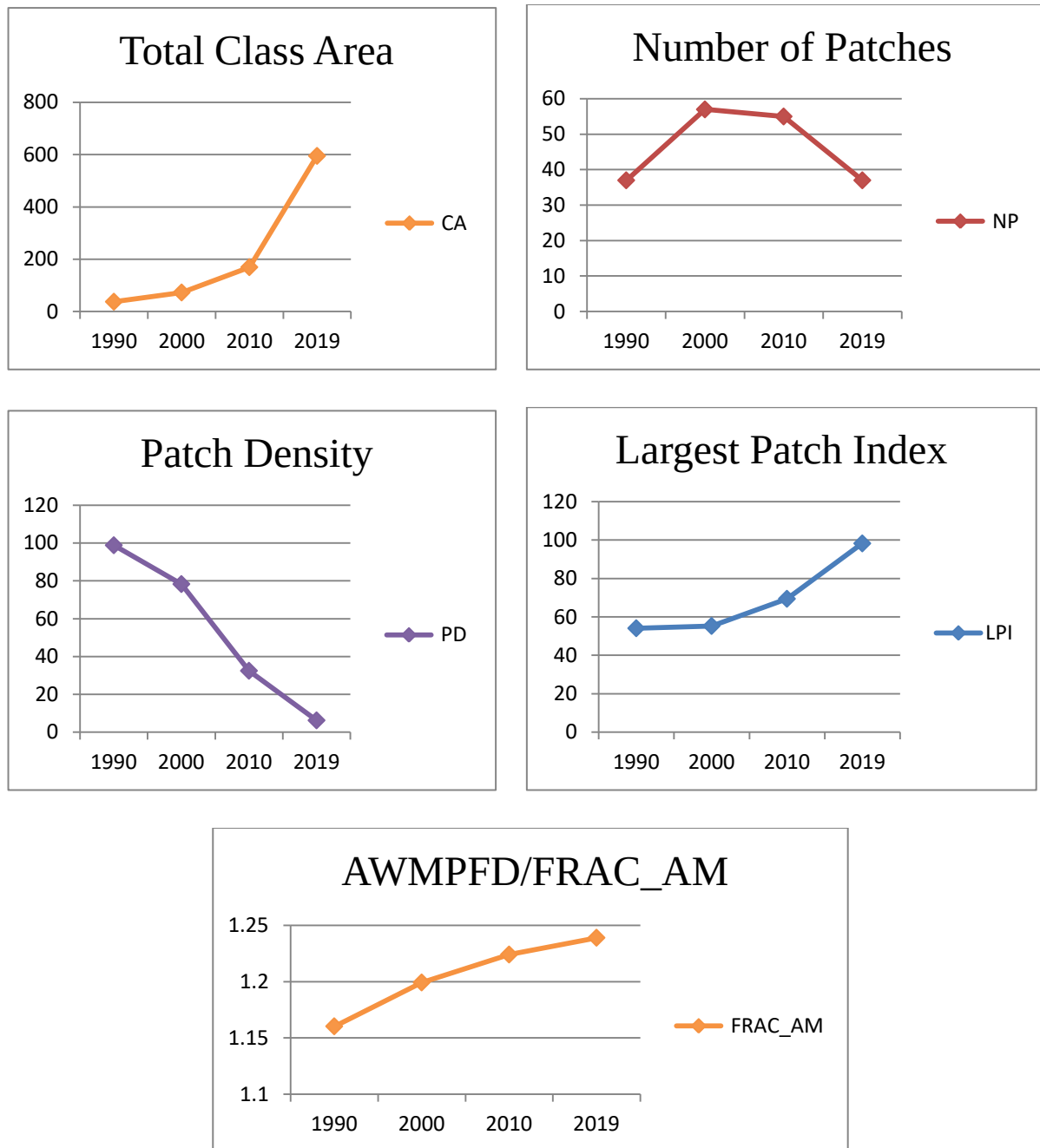


Figure 4.7 Graph showing class level metric computed for southern region

The results of metrics analysis at landscape level are consistent with the results of class level metrics (table 4.13). The probability of finding high adjacency between patches of different land cover classes is high during early stage of urbanization and decline when urban growth takes a sprawling pattern of development. Thus, higher values of CONTAG in this region is the result of the domination of the landscapes with a few large, contiguous

patches of non-built up land cover class, whereas lower values generally characterize the gradual fragmentation process due to the domination of the landscapes with many small and dispersed built up patches. This observation is in line with the decreasing trends witnessed by SHDI and SHEI indicating the diversification of patch types and even distribution of area between land cover classes.

Table 4.13 Spatial metrics computed at landscape level – Southern region

Southern Region - Hawasa road direction			
YEAR	CONTAG	SHDI	SHEI
1990	74.88	2.06	0.57
2000	80.11	1.90	0.47
2010	85.0	1.31	0.33
2019	98.37	0.14	0.04

4.5.4 Western Region (Aje road direction in Bulchana and Burka_Gudina Kebele)

Class Level Landscape Pattern Analysis

CBD and western region of Shashemanne is the highly urbanized in all study periods. This is not surprising as it is the core of the Town. Based on class area (CA) metrics, in 1990 almost 40.05 ha urbanized areas of region is increased to 347.31 ha in 2019. During the period of 1990 - 2000, the built up area increased by 2.82% (15.75 ha). However, the highest growth is observed during the period of 2010- 2019. From 1990- 2019, the area under built up was changed almost 307.26 ha. Annually 5.14%.

Table 4.14 Temporal dynamic of built up area in west region based on class area (CA) metric

Study period	Change (ha)	Change (%)	Time span	Growth rate	Average
1990-2000	15.75	28.23	10	2.82%	5.14%
2000-2010	62.37	52.78	10	5.28%	
2010-2019	229.14	65.98	9	7.33%	

The intensive urban development process in this region is also manifested by the number of patches (NP). The number of patches consistently increased from first to the second 23 in 1990 to 27 in 2000 and increased from third to fourth 21 in 2010 to 41 in 2019 that demonstrating the merging of urban patches into homogeneous urban fabric. The situation is also reflected by the gradual decline of patch density (PD) and dramatic growth of the largest patch index (LPI) in the landscape. This shows the agglomeration of urban core as a result of development pressure in and around Shashemanne. The result of area weighted mean patch fractal dimension (FRAC_AM) metrics show similar trend for this region (table 4.15). It Indicates decreasing trend between 2010 and 2019 and then increasing for the rest of study periods.

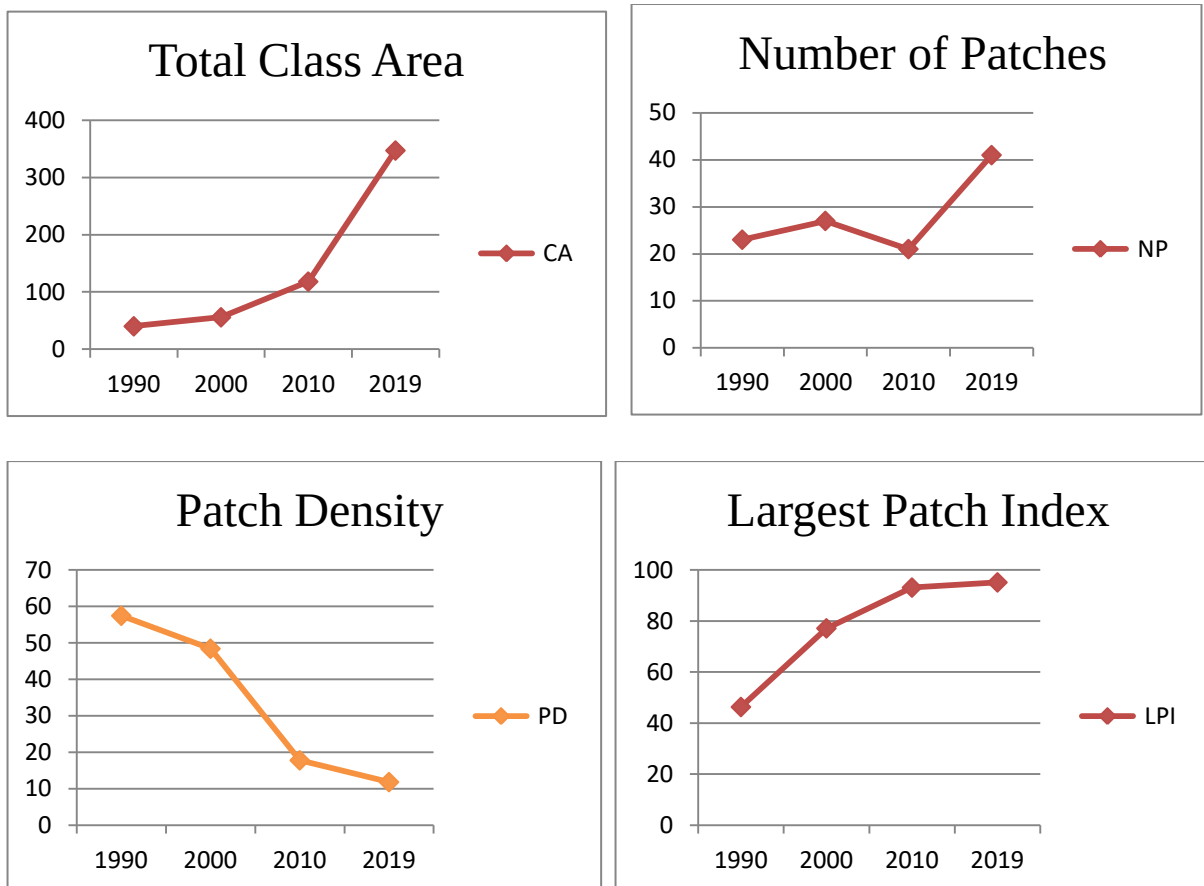
The increasing trend can be associated with the partial integration of existing individual patches and probably the formation of fewer new patches during that period. Nevertheless, in the latter years FRAC_AM start to fall down indicating the amalgamation of individual patches into a bigger patch which suddenly give rise to the LPI this kind of development can potentially eat into public open spaces and it may end up with no vacant space left over. Public open spaces and green areas have indispensable socio-economic and environmental value for the development of city and for the quality of air in urban areas.

Table 4.15 Result of spatial metric computation (Western region)

Year	CA	NP	PD	LPI	FRAC_AM
1990	40.05	23	57.43	46.29	1.17
2000	55.8	27	48.39	77.09	1.22
2010	118.17	21	17.77	93.07	1.23
2019	347.31	41	11.81	95.10	1.23

If the infilling development process continues in the future than no doubt that CBD and western region (Addis Ababa road direction) will be transformed as 100% built up area without leaving a vacant land or open spaces. Thus, at this point it is important to think about the future of open spaces and green areas in the city center. Policy

makers and planners should critically think about the issue and come up with a planning scheme that protects the existing open spaces from encroachment or restrict any more merging of patch in the future. Although compact development is the motto of modern metropolitan growth as it promotes the best use of existing services, promote increased transit use and mixed use development, improve pedestrian accessibility, it should not be any more compact that could lead to congestion and loss of open spaces.



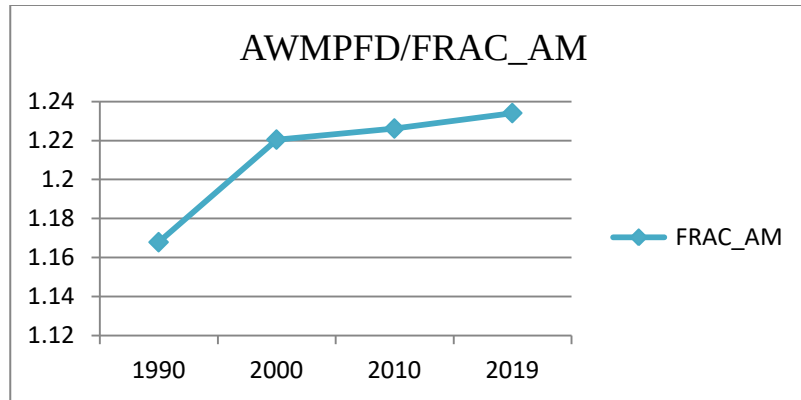


Figure 4.8 Class level metric computed for western region

. As a result the value of the CONTAG is increasing from 1990 to 2019 (table 4.16), the metrics analysis at landscape level are consistent with the results of class level metrics. The probability of finding high adjacency between patches of different land cover classes is high during early stage of urbanization and decline when urban growth takes a sprawling pattern of development.

Thus, higher values of CONTAG in this region is the result of the domination of the landscapes with a few large, contiguous patches of non-built up land cover class, whereas lower values generally characterize the gradual fragmentation process due to the domination of the landscapes with many small and dispersed built up patches. This observation is in line with the decreasing trends witnessed by SHDI and SHEI indicating the diversification of patch types and even distribution of area between land cover classes.

Table 4.16 Spatial metrics computed at landscape level – Western region

Western Region - Aje road direction			
Year	CONTAG	SHDI	SHEI
1990	72.26	1.82	0.58
2000	85.51	1.09	0.33
2010	93.96	0.41	0.13
2019	95.97	0.33	0.09

4.5.6 Intra urban growth comparison (1990-2019)

Class level metrics

Based on class area metrics, the Northern region (NR) and the Southern region (SR) are the most urbanized region in the metropolitan area in all study periods. In 2010 these two regions together constituted more than 38% of the total built up land in the study area (see figure 4.10a). The northern region (NR) and southern region (SR) are moderately urbanized, while the western region (WR) is relatively less urbanized regions in a decreasing order.

However, in terms of average growth rate (%) the NR, SR, ER and WR are the fastest growing regions in a decreasing order while the WR is growing with a relatively slower rate. all regions except the Southern region and Eastern region are growing with an average growth rate higher than the average growth rate of the study area as whole Shashemanne Town. Despite their level of urbanization, all regions show a linear resembling increasing trend for CA metrics throughout the study period indicating the rapid urbanization process taking place in Shashemanne town. In the earlier periods of urbanization, the latter four regions, i.e. SR, ER, NR & WR are almost starting from the same level of urbanization, but gradually the difference is getting larger. The two most urbanized regions NR and SR are the most fragmented regions in earlier period of urbanization, i.e., 1990. In 2019, SR and NR were the most fragmented region in the study area with highest number of patches in a decreasing order. NR and SR witnessed compact pattern of development in 2010 and 2019.

Relatively, the eastern region (ER) underwent compact pattern of development mainly following the major transportation route. The up and down trends observed on NP in WR and SR indicate the different development processes that take place in the region, i.e. fragmentation followed by infill and edge expansion. NR and SR revealed increasing and decreasing trend for PD metrics throughout the study period. This indicates the northern region is undergoing continuous fragmented development process while the Central Shashemanne is relatively undergoing compact development process. In 2019, NR, SR, WR and ER were the most fragmented regions in a decreasing order with the highest PD, whereas WR take the lowest value indicating relatively low fragmentation.

The largest patch index (LPI) exhibited similar trend with class area depicting the direct and proportional relationship between CA and LPI. Thus, those regions with high amount of built up area, i.e. SR, ER and NR are found to have large contiguous built up surface in their respective regions in a diminishing order since 2000. The Southern region is an outlier with high value for CA and LPI metrics, which is ER, is intensively urbanized region in the study area. However, WR and NR had relatively comparable value throughout the study periods. The two complexity measure metrics, edge density (ED) and area weighted mean patch fractal dimension (AWMPFD/FRAC_AM) metrics revealed that the most urbanized regions are composed of more complicated patches resulting in high value for perimeter - area ratio metrics.

The first four most urbanized regions, i.e., NR, SR, ER and WR had scored the highest value for ED metrics in a decreasing order in all study periods except in 2019 where SR, NR and WR take over ER. This could be the sign of stabilization of built up area in Eastern region. Conversely, WR scored low value in a declining order in all study periods indicating the low level of urbanization, hence low fragmentation. ER and NR appeared overlapping throughout the study periods showing the comparable level of patch complexity in the two regions, which is somehow reflected by class area (CA). The peak value observed on Northern region in 2000 (see figure 4.9e) indicates the point at which the infill and edge expansion development starts in the region.

In all study periods, NR, SR and ER scored the highest value for FRAC_AM in a decreasing order except in 1990 ER took over SR. NR and WR take the lowest value in a decreasing for FRAC_AM in the region signifying less urbanization compared with the other three regions. Generally, the town is mainly growing to the north, south, east and west direction following the main transportation routes. the western region and the peri-urban region are growing in a faster rate than they used to grow before. This indicates high potential of urban expansion in the future in these regions.

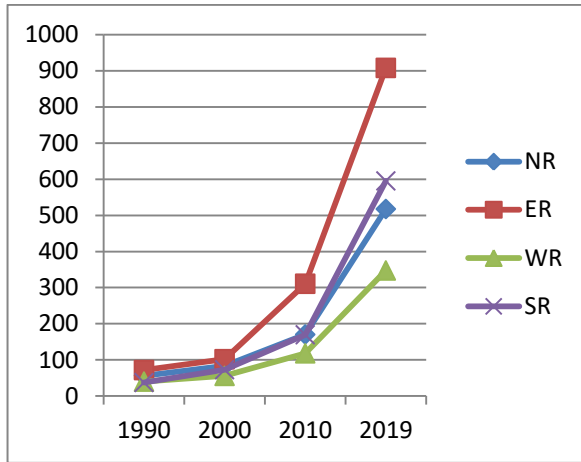
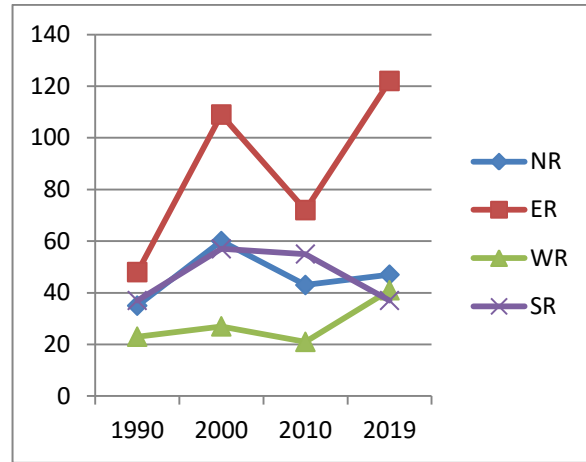
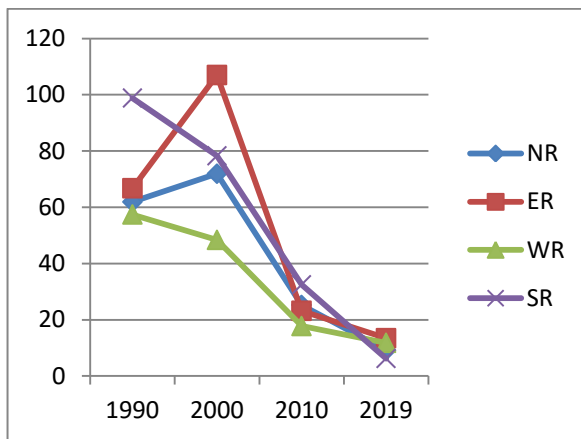
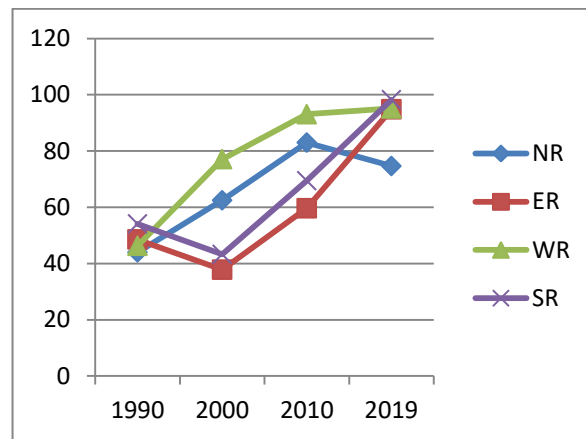
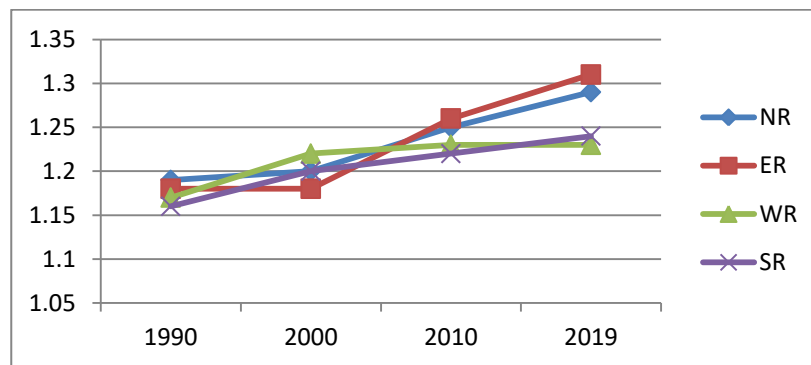
A. Class area (CA)**B. Number of patches (NP)****C. Patch density (PD)****D. Largest patch index (LPI)****E. AWMPFD/FRAC_AM**

Figure 4.9 (A, B C, D, and E) Graphs illustrating intra urban metrics comparison at class level

Shannon's diversity and evenness index showed similar pattern. This is rational since SHDI and SHEI are positively correlated. The value of a diversity index increases both when the number of classes increases and when the classes are evenly distributed in the landscape. Here in, the number of class is only two. Thus, it is convenient to easily understand and the effect of one on the other.

For instance, in 2019 SR and ER are the most diversified regions with the highest Shannon's diversity index in decreasing order. This means the abundance and distribution of patches is high in their respective lands capes. As a result, the classes are more evenly distributed giving higher Shannon's evenness index (SHEI). As the level of urbanization increases in the landscape, the diversity will increase and there will be equitable or even distribution of area among classes. All regions are exhibited increasing trend indicating the rapid urbanization process (see figure 4.10b & c).

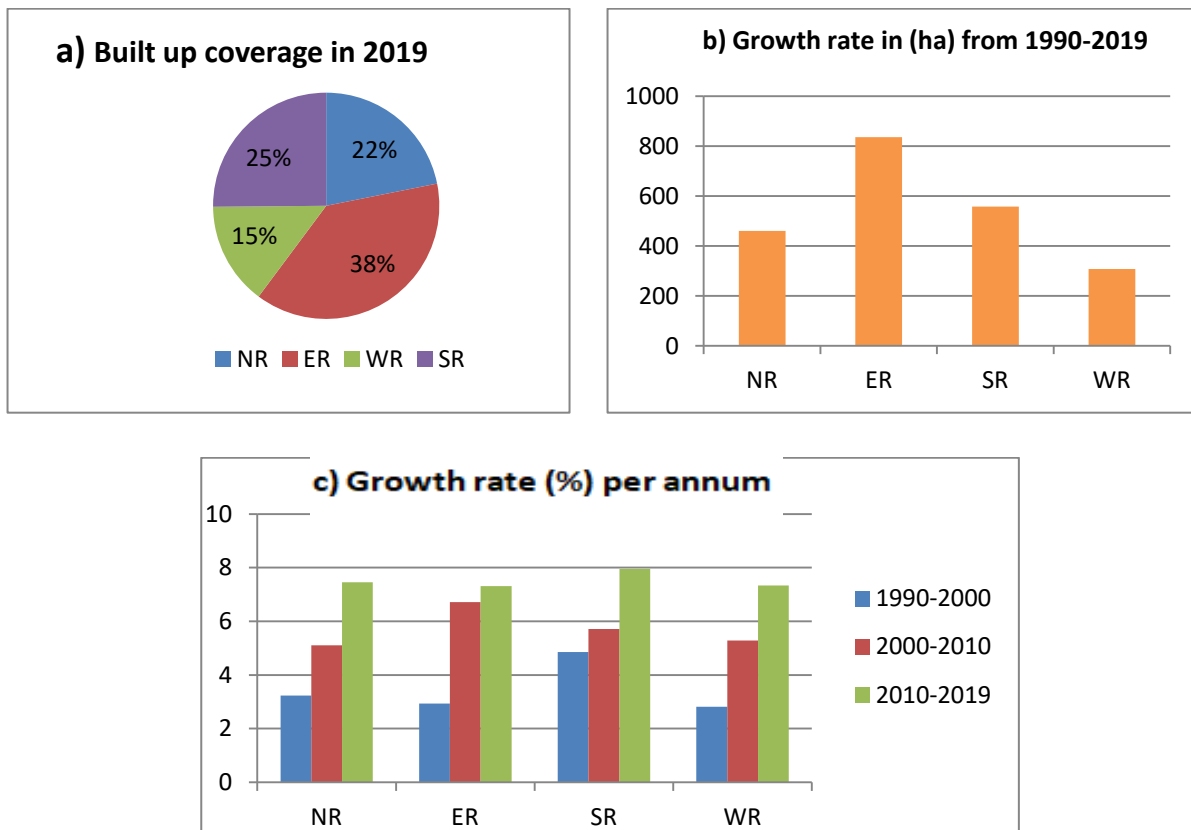
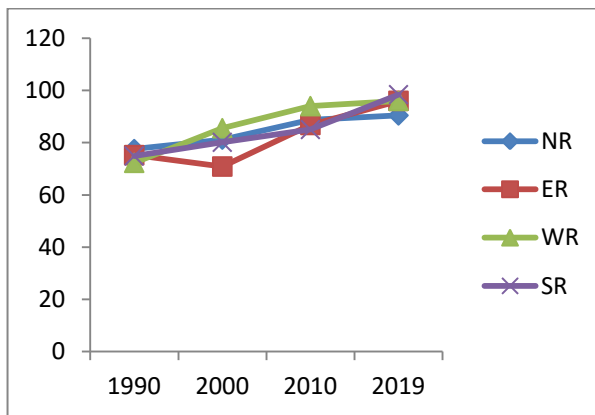


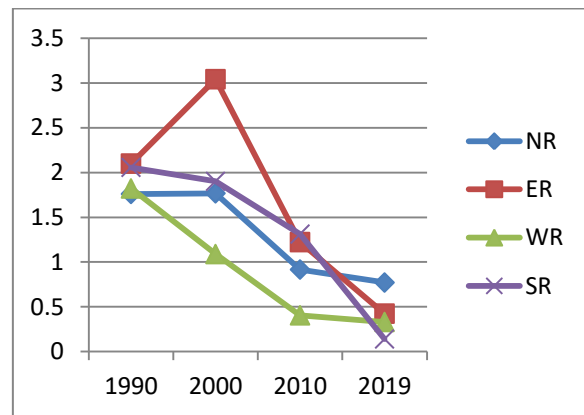
Figure 4.10 Pie chart of Each region of total built up area (a), (b) absolute urban growth rate (ha) annually (1990-2019) and (c) relative urban growth rate (%) per annual (1990-2019).

In contrast to diversity indexes, WR and NR scored high CONTAG value in a decreasing order. This could be attributed to the dominance of non-built up land in the regions. CONTAG metrics decreases when a landscape becomes more urbanized until it takes over the non-built up class and starts to fall down when the built up class becomes more dominant in the landscape. All except NR region showed decreasing trend indicating the increasing fragmented development process of the built up class. However, the decreasing trend observed on NR region during 1990-2000 (figure 4.11a) shows the fragmentation of the built up area during that period and the dominance of non -built up class, whereas, the increasing trend after 2000 shows the compact development process and the dominance of built up class.

A. Contagion (CONTAG)



B. Shannon's diversity index (SHDI)



C. Shannon's evenness index (SHEI)

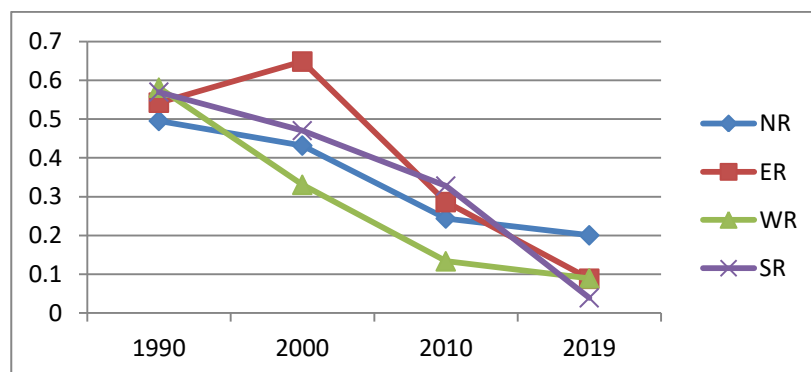


Figure 4.11 (A, B, and C) Graphs illustrating intra urban metrics comparison at landscape level (1990-2019)

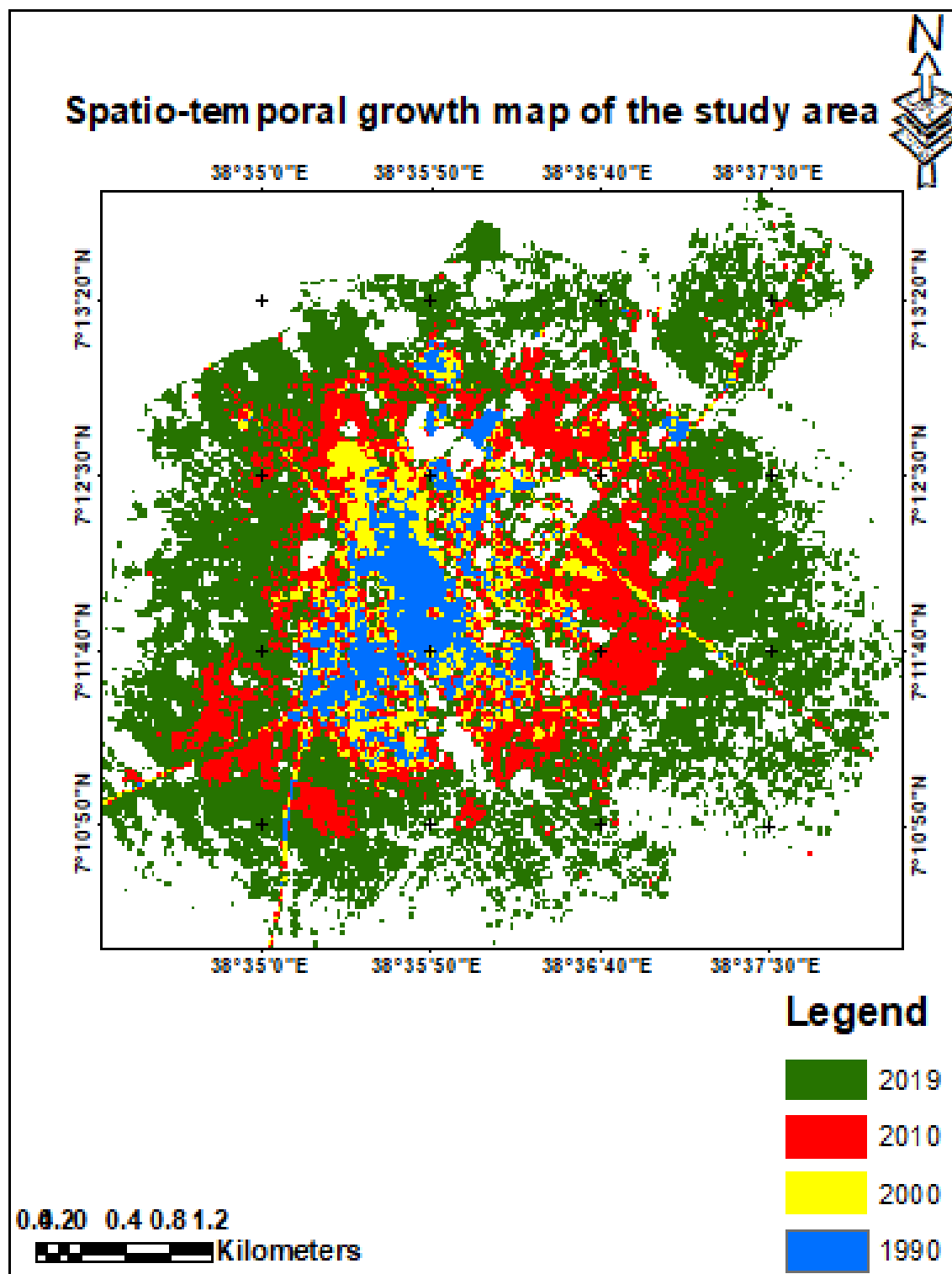


Figure 4.12 Spatio-temporal growth map of the study area (1990-2019)

4.6 Results of logistic regression modelling

4.6.1 Variables used in the model

As discussed in previous chapter (section 3.9.2) the main purpose of logistic regression, in this study, is to understand and statistically quantify the interaction between urban growth and its drivers. In this model urban growth is considered as a dichotomous dependent variable to be explained as a function of seven predictor variables listed in table 4.17 below. Each cell in the dependent variable has only two categories, either to change to built-up cell (represented by 1) or remain as it is non-built up (represented by 0). Thus, the only change allowed in the model is from 0-1.

However, the seven predictor variables included in this model are continuous in nature. The logistic regression analysis is conducted for three different time periods of 1990-2000, 2000-2010 & 2010-2019. The number of predictor variables used for all study periods are the same however, the information content is slightly different for few variable. For instance the proportion of built-up land or cell is different for all study periods. For further information refer to 3.9.3 section of this research. List of all variables included in the regression model are summarized in table 4.17.

Table 4.17 List of variables used in the logistic regression model

Variable	Meaning	Nature of data	Shape
Dependent			
Y	Land cover maps 1990, 2000, 2010 & 2019	Discrete	Polygon
Independent			
Slope	Slope	Continuous	Line
P_Urban	Proportion of built-up land with 7x7 cell size	Continuous	polygon
Dist_CBD	Distance to CBD	Continuous	Point
Dist_Mjrd	Distance to major roads	Continuous	Line
Dist_Tc	Distance to Town centers	Continuous	Point
Dist_St	Distance to satellite towns	Continuous	Point
Dist_h_Inst	distance to higher Institution	Continuous	Point

4.6.2 Multi-collinearity analysis

To exclude redundant variables from the model and maintain the stability of coefficient, multicollinearity diagnostic has been conducted for each set of variables used in different time periods. The analysis is carried out in SPSS 23 statistical software package by regressing one of the independent variable against the remaining six variables in an iterative way. In this manner each variable is diagnosed for multicollinearity. Fortunately, none of the variables have scored variance inflation factor, $VIF > 10$. The analysis revealed that almost the entire variable scored $VIF < 5$, which is a good result according to (Field, 2009). This shows that the proposed independent variables will measure different aspects of the dependent variable being modeled. The results of multicollinearity analysis for all study periods are summarized below.

Table 4.18 Results of multicollinearity analysis

Variable	Description	VIF(1990-2000)	VIF (2000-2010)	VIF (2010-2019)
P_Urban	Proportion of urban	3.475	3.466	3.221
Slope	Slope (%)	3.164	3.404	3.452
Dist_CBD	Distance to CBD	3.011	3.055	3.146
Dist_Mjrd	Distance to major roads	2.845	2.983	3.120
Dist_Tc	Distance to Town centers	2.587	2.615	3.681
Dist_St	Distance to satellite town	3.014	3.246	3.529
Dist_Inst.	distance to Institution	2.675	2.784	2.992

4.6.3 Model Results

Urban growth model 1990-2000 results

Model summary: Log Likelihood = - 44258.0124, Total sample size = 55314, Overall Model Fit: Chi Square = 78553.6656 With $df=21$ and $P\text{-Value}=0.0000$, 95% Confidence Intervals Constant = - 1.5863 Variables with * sign are significant at $\alpha = 0.05$ Variables with ** sign are significant at $\alpha = 0.1$

Table 4.19 Estimated coefficients and odds ratios for the logistic regression model of 1990-2000

Variable	Coefficient	Std_ error	Z_ value	T_ Test (P)	Odds_ Ratio
P_Urban	3.452515	0.54571	4.11798	0.0000*	110.124854
Slope	0.863645	0.451893	1.711594	0.0870*	1.452131
Dist_CBD	-1.545615	0.54571	3.11798	0.0000*	0.099914
Dist_Mjrd	-3.001512	0.366743	2.819233	0.0048*	0.002157
Dist_Tc	-4.296712	0.968923	2.76624	0.0000*	0.001002
Dist_St	-1.092045	0.451893	1.565594	0.1270*	0.065215
Dist_Inst.	5.885452	0.451893	3.221594	0.1870*	2.122453

Table 4.19 presented above summarizes the regression results of 1990-2000 urban growth model. The results are generated by a binary logistic regression model using the maximum likelihood algorithm. Accordingly, five variables: proportion of urban land (P_Urban), distance to CBD (Dist_CBD), distance to major roads (Dist_Mjrd) and distance to Town centres (Dist_Tc) are significant at $\alpha=0.05$ and the variable Slope is found to be significant at $\alpha=0.10$.

However, one variable (distance to satellite towns (Dist_St) has become insignificant in this model yielding higher p-value, which is 0.8701. Among the significant variables three of them: P_Urban and Dist_CBD are positively correlated with urban growth. The remaining three variables: Dist_CBD, Dist_Mjrd and Dist_Tc are negatively correlated with urban growth means that the higher the distance from these variables the lower is the probability of urban growth to occur or in other words urban growth tends to occur in close proximity to these variables.

The relative significance of the predictor variables can be concluded from odds ratio. Odds ratios (OR) are important parameter for the interpretation of logistic regression modelling. It is an indicator of the change in odds resulting from a unit change in the predictor. Variables with higher odds ratio (>1) are regarded as highly influential variables in the model.

Three variables: proportion of urban land (P_Urban), and Slope are possessing $OR > 1$ with z_Value significantly different from zero which indicates that the presence of these three variables has highly contributed to the growth of the city in that specific period.

Urban growth model 2000-2010 results

Model summary: Log Likelihood = -52215.1254, Total sample size=60021 with an overall Model Fit: Chi Square = 70125.3254 with $df = 21$ and P-Value = 0.0000, 95% Confidence Intervals.

Table 4.20 Estimated coefficients and odds ratios for the logistic regression model of 2000-2010

Variable	Coefficient	Std_error	Z_value	T_Test (P)	Odds_Ratio
P_Urban	4.522515	0.54571	4.11798	0.0000*	165.12693
Slope	0.863645	0.451893	1.711594	0.0065*	1.882545
Dist_CBD	1.854215	0.54571	3.11798	0.0000*	0.102693
Dist_Mjrd	-1.85221	0.366743	2.819233	0.0018*	0.001495
Dist_Tc	-2.052022	0.968923	2.76624	0.0000*	0.000992
Dist_St	-1.01245	0.451893	1.565594	0.0055*	0.654245
Dist_Inst.	5.885452	0.451893	3.221594	0.0060*	3.232545

The parameters of 2000-2010 growth models are summarized in table 4.20. The result of the regression modelling witnessed that all variables except distance to CBD (Dist_CBD) are found to be statistically significant at $\alpha=0.05$. Interestingly, in similar fashion to the 1989-1995 model; proportion of urban land (P_Urban) and Slope are observed positively correlated with urban growth. The other three variables: distance to major roads (Dist_Mjrd), distance to sub city centres (Dist_Tc) and distance from satellite towns (Dist_St) are negatively related to urban growth. However, distance from CBD which yielded p-value greater than 5%, had no significant contribution for urban growth in the study area during the period of 2000-2010. The level of significance of each variable can be determined based on their odds ratio. The variables proportion of urban land

(P_Urban), slope, had an odds ratio > 1 which indicating the presence of these variables the probability of urban growth is high.

Urban Growth Model Results of 2010-2019 periods

Model summary: Log Likelihood = -35684.2321, Total sample size=52354 with an overall Model Fit: Chi Square = 58654.4475 with df = 21 and P-Value = 0.0000, 95% Confidence Intervals.

Table 4.21 Estimated coefficients and odds ratios for the logistic regression model of 2010-2019

Variable	Coefficient	Std_error	Z_value	T_Test (P)	Odds_Ratio
P_Urban	5.856115	0.54571	4.11798	0.0000*	255.102693
Slope	0.863645	0.451893	1.711594	0.0850*	1.882545
Dist_CBD	1.995415	0.54571	3.11798	0.0000*	0.102693
Dist_Mjrd	-1.85221	0.366743	2.819233	0.0058*	0.023991
Dist_Tc	-2.001512	0.968923	2.76624	0.0000*	0.000292
Dist_St	-2.865645	0.451893	1.565594	0.3270*	1.022545
Dist_Inst.	-5.885452	0.451893	3.221594	0.1870*	3.232545

The results of the 2010-2019 regression modeling revealed that all predictors except distance to Institution are able to explain the dependent variable with different level of significance. Unlike the two other models presented earlier most of the predictor variables in this model are negatively related to urban growth. Proportion of urban land (P_Urban) and slope remains positively associated with urban growth. The odds ratio of these two variables is >1 indicating the presence of these variables yield high probability of urban growth. .

4.6.4. Model interpretation and discussion

As witnessed from the models, urban growth is more likely to occur in proximity of existing built-up areas where the proportion of urbanized cell is high. This is true for all study periods under investigation. Proportion of urban land (P_Urban) is positively correlated with urban growth with an estimated coefficient of 3.452515, 4.522515 and 5.856115 and odds

ratio of 110.124854, 165.12693 and 255.102693 for the study periods 1990-2000, 2000-2010 and 2010-2019 respectively. The odds ratios can be interpreted as; the probability of urban growth will increase with 110.124854, 165.12693 and 255.102693 with an increase of one urban cell is in the neighborhood for the periods 1990-2000, 2000-2010 and 2010-2019 respectively. The odds ratios of the independent variable P_Urban are far larger >1 in all study period indicating that proportion of urbanized cell within a 7x7 window size is the major factors driving urban growth in the study area for all study periods. Slope has been consistently significant and positively related to urban growth in all study periods.

The estimated coefficients and odds ratios are 0.863645, 0.863645 & 0.863645 and 1.452131, 1.882545 & 1.882545 for the study periods 1990-2000, 2000-2010 & 2010-2019 respectively. For all study periods slope is positively related to urban growth, indicating the higher the slope of an area the higher probability to be occupied by a new built up cell. The likelihood of a non-built up cell to change to built-up cell is 1.452131 times, 1.882545 times & 1.882545 times as large as the probability of change in an area one percent less in slope. However, the level of significance of slope during the period 1990-2000 has been at $\alpha = 0.1$ having p_value 0.0870 which makes it the only significant variable in all study period with $\alpha = 0.1$.

The rest of significant variables are important at the significance level of $\alpha = 0.05$. Distance to CBD (Dist-CBD) has been significant only for the periods 1990-2000 & 2010-2019 with significance level $\alpha = 0.05$. However, it has been totally insignificant during the period 2000-2010. The estimated coefficients and odds ratios of Dist-CBD are -1.545615 & 1.854215, and 0.099914 (1/10.00861) & 0.102693 (1/9.73776) for the periods 1990-2000 & 2010-2019 respectively. The probability of urban growth in an area is estimated as 10.00861 times and 9.73776 as large as the probability of urban development in an area one unit further away from the nearest urban area for 1990-2000 & 2010-2019 study periods respectively. For both periods distance to CBD (Dist-CBD) is negatively correlated with urban growth indicating the higher the distance from CBD, the lower is the probability of urban growth to occur.

Thus, areas within close proximity of the CBD were more favorable for urban development during 1990- 2000 and 2010-2019 study periods. Proximity to CBD can provide a better access to facilities and services and reduces transportation cost; therefore people prefer to settle close to CBD. However, through time, CBD might lose its significance in attracting urban growth when the availability of developable land is scarce. In contrast to distance to CBD is positively correlated with urban growth at significance level of $\alpha = 0.05$ for the first two study periods (1990- 2000 & 2000-2010).

The models also show that urban growth has been significantly influenced by proximity to major road in all study periods. Similar to distance to CBD, this variable (Dist_Mjrd) is also negatively associated with urban growth. The estimated odds ratios for distance to major road (Dist_Mjrd) are 0.002157(1/463.6069), 0.001495(1/668.8963) & 0.023991 (1/41.6823) for the study periods 1990- 2000, 2000-2010 and 2010-2019 respectively. The likelihood of urban growth in an area closer to major roads is estimated as 463.6069 times, 668.8963 times and 41.6823 times as large as the odds of urban development in an area a unit further away from major roads.

Road is one of the major urban elements that facilitate movement of materials and humans in urban areas and thus, influencing the spatial pattern of urban growth. The variable distance to economically active city centers (Dist_tc) has been affecting urban growth throughout the study periods with a significance level of 0.05. This variable (Dist_tc) is also negatively related with urban growth in all study periods demonstrating the closer to town centers the higher is the probability of urban growth to occur. The odds ratio for distance to town centers is 0.001002 (1/998.0040), 0.000995 (1/1,005.0251) and 0.000292 (1/3,424.6575) for the study periods 1990-2000, 2000-2010 and 2010-2019 respectively.

These indicates that the odds of a non-built up cell to convert to a built-up cell within an area close proximity to active town centers is estimated as 998.0040 times, 1,005.0251 times and 3,424.6575 times as large as that in an area one unit further away from town centers for 1990-2000, 2000-2010 and 2010-2019 study periods respectively. The results of the regression models revealed that distance from satellite towns (Dist-St) has influenced urban growth during the latter two study periods (2000-2010 and 2010-2019) at $\alpha = 0.05$.

However, it had no significance during the period of 1990-2000. The coefficient and odds ratio of distance to satellite towns (Dist-St) is -1.001245 & -2.865645 and 0.065215 (1/1.52848) & 1.022545 (1/0.97804) for the periods 2000-2010 and 2010-2019 respectively. This shows that the probability of urban development to occur in an area close proximity to satellite towns is as 1.52848 times and 0.97804 times as large as that in area one unit farther away from satellite towns for the study periods 2000-2010 and 2010-2019 respectively. This is reasonable as satellite town are located farther away from the town during earlier periods of urbanization and thus, they do not attract urban growth significantly

4.6.5 Model evaluation

Model evaluation is an important step in logistic regression modelling. Change analysis software generates an output that could be used to evaluate the predictive power of the constructed model. Percentage correct prediction (PCP), the most commonly used type of evaluation method, is used in this study. It tells the percentage of correctly predicted pixels out of the sampled pixels in the model.

The higher the PCP the higher is the predicting power of the model. This is helpful to identify which model to use for prediction when we have alternative models. Accordingly, the PCP of the three models, i.e. 1990- 2000, 2000-2010 & 2010-2019 is 98.22%, 96.61% & 94.60% respectively, which is pretty good prediction power. The outputs of model evaluation analysis are presented below.

Table 4.22 Results of regression model evaluation

1990 to 2000					2000 to 2010				
	Predicted					Predicted			
observed		0	1	Total	observed		0	1	Total
	0	2468231	6092	2474323		0	2748225	19088	2767313
	1	40020	80300	120320		1	83042	160128	243170
	Total	2508251	86392	2594643		Total	2831267	179216	3010483
Correct prediction=2548531					Correct prediction=2908353				
wrong prediction=46112					wrong prediction=102130				
Percentage of correct prediction (PCP)=98.22%					Percentage of correct prediction (PCP)=96.61%				

2010 to 2019				
	Predicted			
		0	1	Total
observed	0	2568331	22004	2590335
	1	140188	270244	410432
	Total	2708519	292248	3000767
Correct prediction=2838575				
wrong prediction=162192				
Percentage of correct prediction (PCP)=94.60%				

4.6.6 Physical driving forces of Shashemanne's urban growth

Understanding the interaction between urban growth and its drivers over space and time is helpful to predict future urban development's and construct alternative scenarios. Despite the fact that availability of data is one of the major problems to conduct research in developing countries, it is evident that logistic regression model can be built based on few, but widely available spatially explicit data such as satellite images to provide relevant information for urban planners and policy makers (Seto & Fragkias, 2007). Thus, logistic regression urban growth modelling is an ideal approach to look at significant drivers of urban growth over time, particularly for developing countries. Different literatures have reported that driving forces of urban growth might differ based on the local context in which the development is taking place and the spatio-temporal dimension at which the analysis is considered (e.g. Cheng & Masser, 2003; B. Huang et al., 2009). In this study, three spatially explicit binary logistic regression models have been developed for 1990-2000, 2000-2010 and 2010-2019 study periods.

The main purpose of the models is to figure out the major driving forces of urban growth and their level of significance in the study area. Accordingly, the models were able to reveal significant driving forces of urban growth during the three study periods for the past 29 years. Among the variables included in the 1990-2000 model, distance to major roads (Dist_mjrd) (-ve), distance to town centers (Dist_tc) (-ve), proportion of built-up cell (P_Urban) (+ve), distance to CBD (Dist_CBD) (+ve) and Slope (+ve) are found to be significant drivers of urban growth in a descending level of importance with their indicated sign of correlation with urban growth. However, distance to satellite towns

(Dist_St) is found to be insignificant factor for this study period. This might be due to the wide gap between satellite towns and the city in the earlier stage of urbanization.

According to Tobler's first law of geography "Everything is related to everything else, but near things are more related than distant things." The order of significance of the variables is also in a logical sequence as roads are major urban elements attracting urban growth in early stage of development. During 2000-2010, distance to town centers (Dist_tc) (-ve), proportion of built-up cell (P_Urban) (+ve), distance to major roads (Dist_Mjrd) (-ve), Slope (+ve) and distance to satellite towns (Dist_St) (-ve) are found to be significant driving forces of urban growth in a decreasing level of influence and with their indicated sign of correlation. Distance from CBD has been the fourth influential variable in the 1990-2000 models. However, in this model it is not any more significant. Following the rapid urban growth witnessed during 2000-2010 (refer section 4.3); the Town has expanded outward to the periphery areas in all direction. This indicates developments were occurring in close proximity to sub city centers, existing built up areas and probably more closer to major roads than CBD. Consequently, the significance of distance to CBD (Dist_CBD) will be negligible or insignificant at all.

Distance to town centres (Dist_tc) and proportion of built-up cell (P_Urban) were the second and third influential variables in the 1990-2000 model, however they become the first and second important factors in the 2000-2010 model and distance to major roads (Dist_Mjrd), the first important factor in the previous model takes the third place during the 2000-2010 period of urbanization. Proportion of built-up cell (P_Urban) (+ve), distance to satellite towns (Dist_St) (-ve), distance to major roads (Dist_Mjrd) (-ve), distance to sub town centers (Dist_tc) (-ve), distance to CBD (Dist_CBD) (-ve) and Slope (+ve) were significant drivers of urban growth in 2010-2019 study period in a decreasing sequence of importance with their designated sign of correlation with urban growth. Distance to CBD becomes important variable in this model.

This means most of the new growth tends to occur at the periphery of the town next to the already urbanized areas, i.e. Edge expansion. However, there are also some infill developments that have been taking place closer to CBD during 2010-2019 period. Despite the introduction of the northern by pass in the third model, the major road

(Dist_Mjrd) remains in the third place in this model. However, following the gradual expansion of the town, satellite towns become increasingly importance due to their proximity to the main town. Slope has been attracting development in all study periods. This is due to the fact that Shashemanne is built on hilly topography.

The variable becomes more significant factor in the period (2000-2010) than the previous period. This could be due to the fact that some land uses activities, such as high income residential land uses, may prefer relatively steeper slope for development pursuing safety and good view. As a result, the lack of such suitable land in the city may push development to steeper slopes immediately found next to the existing built up area (P_Urban). Alternatively, it could be also the reflection of the increasing severity of flooding problem in low laying areas which might have pushed development to high slopes. This has been witnessed from the increasing level of significance of slope over time and positive relationship with urban growth in all study periods. Assuming that distance to CBD might have been the most important variable above all before 1990, the pattern (order of significance) observed on the driving forces is reasonable. In early stage of urbanization roads are major urban elements structuring urban growth pattern followed by proximity to built-up area such as town centers.

Then, town centers are created at the junction or nodes of roads. These town centers eventually start to attract urban development around them. Gradually, when the availability of developable land in close proximity to CBD, major roads and Town centers become rare, the available land immediately next to existing built up area will be attractive. Some negative externalities such as congestion, overcrowdings, etc. due to the agglomeration of the town center might have pushed development away from established urban core (CDB). The results of spatial metrics analysis can be also related to the findings of these models.

The sprawling and fragmented development pattern witnessed during the early period of urbanization (1990-2000) could be driven by the major roads and economically active town centers. This means, urban development has been taking place in all direction, mostly in West, East and North direction, following the major transportation routes and dispersed around sub-Town centres. The proportion of built up cell and distance to CBD were also fair

attracting urban growth during 1990-2000 study period. During 2000-2010, the number of patches increased substantially, and therefore the town experienced rapid urban growth (refer section 4.3).

The result of logistic regression analysis confirms that those growths were mostly driven by sub-city centres and existing built up areas. This is reasonable as the probability of finding developable land close to CBD and major roads is less, the locally distributed town centres (Dist_tc) and proportion built up area (P_Urban) will attract urban growths. However, it is important to note that there is still some development going on within close proximity to major roads although it is not as important as the growth taking place around town centers and high proportion of built up areas. The variable slope confirms that following the rapid urban growth observed during 2010-2019, developments were taking place in relatively higher slope areas. The insignificance of distance to CBD during this period does not necessarily indicate the absence of development around CBD, because urban development is also taking place in close proximity to where high proportion of built up cell is found.

This could be in the form of edge expansion at the edge of urban core, which can be confirmed from the increasing largest patch index (LPI) metric (refer section 4.3). Interestingly, during 2000-2010 due to the lack developable land in close proximity to major roads and Town centres, the variable proportion of built up cell become the dominant factor attracting urban growth in the study area followed by distance to satellite towns (Dist_St). Yet, major roads remain the third important factor attracting urban growth. The position claimed by distance to satellite towns (Dist_St) is rational as the gap between the main town and satellite towns will decrease and thus, satellite towns become more attractive for development.

The variable distance to CBD, which was insignificant in the previous period, become significant factor during 2010-2019 indicating that some infill development or redevelopments has been taking place in the town center. This is reflected by the decreasing patch density (PD) and increasing largest patch index (LPI) during this period. Given, the patterns observed during these three study periods, satellite towns will be the next

significant drivers of urban growth in the foreseeable future. The top four driving forces of urban growth during the three different study periods are presented in table 4.23

Table 4.23 Major driving forces of urban growth in 1990-2000, 2000-2010 and 2010-2019

Study period	Order of Significance	Major driving forces	Correlation with urban growth
1990-2000	1 st	Distance to major roads	Negative
	2 nd	Distance to Town centers	Negative
	3 rd	Proportion of built up cell	Positive
	4 th	Distance to CBD	Negative
2000-2010	1 st	Distance to major roads	Negative
	2 nd	Distance to Town centers	Negative
	3 rd	Proportion of built up cell	Positive
	4 th	Slope	Positive
2010-2019	1 st	Distance to major roads	Negative
	2 nd	Distance to Town centers	Negative
	3 rd	Proportion of built up cell	Positive
	4 th	Distance to satellite town	Negative

Generally, three variables: distance to major roads (Dist_mjrd), distance to town centers (Dist_tc) and proportion of built up cell (P_Urban), remain among the top four driving forces of urban growth in all study periods with varying order of significance. Distance to CBD (Dist_CBD), Slope and distance to satellite town (Dist_st) were among the top four drivers of urban growth at different time periods with varying (see table 4.23).

During 1990-2000 it was not found attracting growth or it has been pushing development away and during 2000- 2010 and 2010-2019 it becomes insignificant at all. Although some attempts have been made to clarify the phenomenon, no strong logical reasoning or causal process could be found to explain how the variable distance to Institution become constraint for urban growth in this study.

CHAPTER-5: CONCLUSION AND RECOMMENDATION.

5.1 Conclusion

For the past 29 years, 1990-2019, Shashemanne has been undergoing extensive land cover change. The classification of multi-temporal satellite images of four different time periods, i.e. 1990, 2000, 2010 & 2019, in to built-up and non-built up land cover classes has resulted in a highly simplified and abstract representation of the study area. These maps show a clear pattern of increased urban expansion prolonging both from urban center to adjoining non-built up areas in all directions mainly in the east, south and north direction alongside major road corridors. The synoptic analysis of spatiotemporal land cover change revealed that urbanization has significantly transformed the urban landscape of Shashemanne. The built up area in the town has grown from 305 ha in 1990 to 3,546.82 ha in 2019 at an average growth rate of 2.65%, 5.29% and 7.19% per annum during 1990-2000, 2000-2010 and 2010-2019 study periods respectively. In total, 3,241.82 ha of non-built up land has been transferred to built up area.

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 pattern. To bridge this gap, spatial metrics are used in this study. Eight spatial metrics namely: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), area weighted mean patch fractal dimension (AWMPFD), contagion (CONTAG), Shannon's diversity index (SHDI) and Shannon's evenness index (SHEI) were used to evaluate the urban growth patterns and processes of Shashemanne town at class and landscape level.

These metrics were selected based on literature so as to measure different aspects of the landscape such as configuration, area, shape, etc. The analyses of urban pattern were conducted at two spatial scales for the four different years described above. These are at class metrics level and at landscape metrics level. Five class metrics evaluated at class level, i.e. CA, NP, PD, LPI and FRAC_AM, revealed the processes and patterns of urban growth over the entire study area indicating urbanization has substantially changed the landscape pattern of the study area, with a significant land conversion or formation of new

patches and thereby increased fragmentation. Based on the number of patches (NP), built up area has underwent fragmented development process in all study periods with substantial increase of built up area (TA) occurred during the second period of urbanization 2000 to 2010. The decreasing trend witnessed by PD shows the merger of new patches with the existing ones, particularly, at the vicinity of urban core that eventually gives rise to the largest patch. The increasing trends observed on LPI throughout the study periods could reveal that the town center or the core area has been relatively undergoing infill and edge expansion type of development process. Nevertheless the fractal dimension (FRAC_AM) showed both increasing and decreasing trend with remarkable upturn in 2010. Accordingly the study area has been divided into four spatially explicit regions namely: Northern Region (NR), Eastern Region (ER), Southern Region (SR), and Western Region (WR) based on the administrative boundary of the urban area. All the selected eight metrics are used to describe urban development patterns in each region at both class and landscape level. The synoptic analysis and comparison of class area (CA) metrics revealed ER, SR, WR and NR are the first four highly urbanized regions in the study area in a diminishing order. In 2019 the Northern region (SR) and the Eastern region (ER) together accounted for more than 63% of the total built up land in the study area. However, in terms of average annual growth rate (%) NR, ER, SR and WR are the first four rapidly urbanizing regions in the study area with a growth rate of 5.26%, 5.66%, 6.17% and 5.14% respectively. All models are subjected to multicollinearity analysis and found to yield VIF <10. The results of model evaluation indicate 98.22%, 96.61% and 94.60% for the 1990-2000, 2000-2010 and 2010-2019 models respectively indicating the high predicting capacities of the models. The result of model 1990-2000 shows that distance to major roads (-ve), distance to town centers (-ve), proportion of built up cell (+ve) and distance to CBD (-ve) were the top four driving forces of urban growth with their indicated sign of correlation with urban growth. During 2000-2010, distance to town centres (-ve), proportion of built up cell (+ve), distance to major roads (-ve) and slope (+ve) were the top four driving forces of urban growth in the study area with their indicated sign of correlation urban growth, whereas proportion of built up cell (+ve), distance to satellite towns (-ve), distance to major roads (-ve) and distance to town centres (-ve) were found to be the top four drivers of urban growth during 2010-2019

study period with their indicated sign of correlation with urban growth. The importance of proportion of built up cell, distance to town centres and distance to satellite towns increased over time while the importance of distance to CBD and distance to major roads decreased over time. This confirms to the results of spatial metrics that show outward expansion accompanied by fragmentation at the fringe areas and condensation of the core. Thus, the results of this model can help planners and policy makers better understand the drivers of urban growth in the study area and develop different alternative urban growth scenarios for the future development.

5.2 Recommendation

This study has successfully explored the potential use of satellite remote sensing and spatial metrics to quantifying the spatio-temporal urban growth patterns and processes in fast growing Ethiopian Town like Shashemanne. However, results of this study are exclusive to the specific study area. Further researches are required on different Ethiopians cities to conclude on the efficiency and effectiveness of the tools for this country. Since the quality of information extracted from spatial metrics is dependent on the quality of image classification, future studies could attempt to improve the classification accuracy.

The spatial extent of the Study area, it seems imperative to look at driving forces of urban growth at disaggregate spatial scale including more variables such as socio-economic and demographic variables and most importantly land tenure policy. This could reveal detail causal factors of urban growth pattern at local level and could give good explanation why physical factors has been constraint or insignificant factor or significant for urban growth in the study area. It could also reasonable to consider other driving force in the future models. The region based method developed in spatial metrics analysis can be adopted for this purpose. However, the results of this model can be used as a base for future studies and can help planners and policy makers develop alternative urban growth model.

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