Quantify the Spatio-Temporal Trends and Patterns of Urban Growth in Adama City using Satellite Remote Sensing and Spatial Metrics, Ethiopia.

Tarekegn Fita Eto

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 Geodesy and Geomatics Engineering

Office of Graduate Studies

Adama Science and Technology University

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Approval of Board of Examiners

We, the undersigned, members of the Board of Examiners of the final open defense by Gedamu Amare Bihonegn have read and evaluated his/her thesis entitled **Remote Sensing Based Estimation of Evapotranspiration for Irrigation Performance Assessment at Koga Irrigation Project**" 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 Geodesy and Geomatics Engineering.

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Declaration

I hereby declare that this MSc Thesis is my original work and has not been presented for a degree in any other university, and all sources of material used for this thesis have been duly acknowledged.

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This MSc Thesis has been submitted for examination with my approval as thesis advisor.

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Date of

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Table of Contents

LIST OF TABLE

LIST OF FIGURES

LIST OF ACRONNYM

ASTER	Advance Space –Born Thermal Emission Reflection Radiometer
AU	Adama University
CA	Class Area
CBD	Central Business District
EEA	European Environmental Agency
ER	Easter Region
EMA	Ethiopian Mapping Agency
ETM+	Enhanced Thematic Mapper- Plus
GCP	Ground Control Point
GIS	Geographical Information System
NASA	National Aeronautics and Space Administration
NIR	Near Infra-Red
NP	Number of Patch
NR	North Region
PCP	Percentage Correct Prediction
PD	Patch Density
RS	Remote Sensing
SPSS	Statistical Package for Social science
SWR	South West Region

TM	Thematic Mapper
UN	United Nation
UN-HABITAT	United Nation Human Settlement Program
USGS	United State Geological Survey
VHR	Very High Resolution
VIF	Variance Inflation Factor
WGS	World Geodetic System
WR	West Region

ABSTRACT

The spatio-temporal patterns and processes of urban growth of Adama city and its drivers were investigated from 1988 to 2017 by using satellite remote sensing images, spatial metrics and Logistic Regression Modeling (LRM). Four different land cover maps derived from Landsat TM image of 1988, Landsat ETM+ 2000, 2010 and Landsat OLI/TIR of 2017 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 city level are evaluated. Secondly, in order to better link the metric analysis to more specific locations, the study area is broken into three 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 1988-2000, 2000-2010 and 2010-2017 time periods. The growth was prolonging both from urban center to adjoining non-built up areas in all direction, but mainly to the west, east and north direction alongside major transportation corridors. The total built up area in the city has grown from 415.44 ha in 1988 to 5599.62 ha in 2017 at an average growth rate of 2.36%, 5.97% and 6.27 % per annum during 1988-2000, 2000-2010 and 2010-2017 study periods respectively. The study period from 2000 to 2010 was registered as the time at which the city experienced the highest urban growth. The analysis of spatial metrics at the city level revealed that the urban landscape has experienced a process of sprawling and fragmented development pattern particularly in the fringe areas while, the city center under went in fill and edge expansion development processes. The core area consolidated over time while the northern region relatively underwent compact growth and the fringe areas show scattered growth pattern. The results of binary logistic regression model revealed that distance to major roads, distance to sub city centers, proportion of built up cell, distance to CBD, distance to satellite towns and slope were the major driving forces of urban growth at different time periods with varying level of significance and correlation.

Keywords: Urban growth, Spatial metric, Remote sensing, Land cover change, Logistic regression

CHAPTER ONE

1. Introduction

. Urban places represent built environments that are physically distinguishable from the natural environment. According to Pacione (2009) four stages of urban development occurred in more developed world: urbanization, suburbanization, dis-urbanization and re-urbanization. The factors promoting urbanization vary within and between different parts of the world. According to Knox (2005), urbanization in more developed world was a result of economic growth while urbanization in less developed world has mainly resulted from demographic growth that highlights economic development.

1.1 Background

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(Ethiopia 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 per cent 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 and Kedir, 2009).Even though the background to the state of urban growth and urbanization is related to the predatory nature of the Ethiopian state (Tegenu 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.

Adama is among the fast growing urban centers in the country. The city 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). Adama, being one of the cities 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 Adama live in informal and illegal settlement either as owner-occupiers or as Renters. The Ethiopian Government's vision is to reach middle-income status with an estimated gross national income per capita of US$1,560 by 2025.2 if well managed, urbanization could be an important catalyst to promote economic growth, create jobs and connect Ethiopians to prosperity. If not managed proactively rapid urban population growth may pose a demographic challenge as cities struggle to provide jobs, infrastructure and services, and housing.

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; Vande 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

Adama is among the fast growing urban centers in the country. The city 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. Due to effects of continuous growth and expansion of the city 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 cities (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 Bedassa, 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 Sub Saharan cities like Adama where the availability of spatial data is very limited. Therefore; this study investigatinging the spatio-temporal patterns of Adama City 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).

1.3 Research Objectives

1.3.1 General Objective:

The general objective of the study is to quantifying the spatio-temporal trends and patterns of urban growth in Adama city using remote sensing and spatial metrics.

1.3.2 Specific objectives:

The specific objectives of this research:

- To analyses the extent and rate of spatio-temporal urban growth using multi-temporal satellite images.
- To quantifying the spatio-temporal pattern of urban growth and landscape fragmentation using spatial metrics.
- To determine the major physical driving factors of urban growth

1.4 Significance of the Study

This study quantifies and analyzes the changes, pattern and process of urban expansion the major physical driving factors of urban growth of Adama city. To contribute in the developments of urban land and monitoring of environmental management and monitoring plan of the areas; 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 was 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 Adama city was going to expand.

1.5 Scope of the Study

This study was an urban level study and thus focused mainly on issues within the city of Adama: The study was specifically give emphasized on spatial expansion of the city, pattern of expansion, the physical driving force for expansion and its direction of expansion.

1.6 Structure of the Thesis

The thesis consist of five different chapter In which the first chapter deals with the introduction to the research and mainly addressed the statement of problem, research objectives, The context of study area conceptual frame work and organization of the thesis the second chapter contains review of related literatures in the concept of urbanization and land use change, urban remote sensing and spatial metrics were reviewed. In chapter three, the data and methodology used in this study including methods of data collection and analysis, were briefly discussed. Chapter four presents the results of data analysis and discussions including spatiotemporal urban growth analysis, presentation and interpretation of growth maps and spatial metrics, logistic regression modeling and evaluation and interpretation of outcomes, identification of major driving forces of urban growth in the study area. In the last chapter five, conclusions were organized according to the research objective proposed in chapter one. Furthermore, some recommendation and future research directions were offered.

CHAPTER TWO

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 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. This information is important for planners, policy makers and resource managers to make informed decisions. (Veldcamp & Verburg, 2004).

2.3 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 in to three periods: the Aksumite period, the Zague 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-Akumite period the kingdom of Daamat is identified as urban society. The kingdom of Daamat 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 (Fattovich , 1994). As Bekure (1999), the Zague dynasty was overthrown in the last half of the 13th century and the seat of government continue to move southward to Shewa until the civil war with 'Gragn' in the 16th century.

The king of Shewa was mostly mobile where the king uses his camp as his capital. However, a number of towns were created among them Debre Birhan, Telq and Yelebash could be mentioned at the end of the civil war the seat of the government transferred again northwards to Begemder. He also mentioned the important towns that arose during the Gonder period. Denkez, Enfranza, Gorgora, Mekdela and Gonder. Of course, the most important of all is city of Gonder. The prominent of Gonder reduced when Gonder lost the last king Thewodros in 1968. The capital city transferred to Mekele where Yohannis IV assumed his seat. He also suggested that these towns are additional to those that already existed in the various parts of the eastern and southwestern plateau like the City of Harer. Debre Marcos, Bahir Dar, Jimma and Nekemte were the main urban centers by about the beginning or middle of the 19th century Later on, during Haile Selassie period; the merging of a number of Awrajas into province sharpened the urban hierarchy. Urban roads, rail and automobile transport network added to urbanization process. Important towns like Dire Dawa, Adama and Bishoftu had railway stations (Bekure, 1999). However, much of urban history of Ethiopia following the Axumite period was characterized by absence of fixed urban centers. Until Addis Ababa was built as the permanent seat of the government by Menilik II at the end of the 19th century According to Kebede (1994) the following factors causes lack of permanent development of urban centers in Ethiopia pre-20th century: The rugged topography which created obstacles to communication, Under development of occupation such as craftsmanship, Internal conflicts and external aggression and Absence of centralized government that could bring national cohesion.

2.4 Driving Force of Urbanization in Adama City

Urban growth is derived from two sources. One from expansion to the peri-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. According to United Nations Population Division (1999) estimation 60% of urban growth in less developed countries in 1960-1990 was from natural increase while 40% from in-migration from rural areas and the expansion of urban boundaries. Moreover, Wheeler (1998) by comparing the situation in developing and developed countries suggested that the rapid growths of urban population in less developed countries are more of rural problems than urban attraction Road-influence growth occurred along transport networks.

These locations on the travel routes provide excellent opportunities for trade which leads to serving the needs of the surrounding area. The idea is that cities emerge to provide goods and services. Carter (1995) further explained that there are variations in quantity as well as quality of goods and services offered. The primacy of Addis Ababa is getting decrease because of the emergence of new competent regional capital city like adama city the capital city of oromia region. Economically dominant and the cultural center for national identity economic function, industrial agglomeration, rural-urban migration and efficiency of modern transport agglomeration is the clustering of similar as well as dissimilar economic, social, cultural and governmental activities in a given location. Economic base is, therefore, a set of different activities like manufacturing, trade, transport etc. that serves the market of the urban center or the city Site and situation affects the location of settlement. Site refers to the exact place of the settlements while situation refers to the environment or the land surrounding the site (Robert, 2010). Bednara (2010) also described that site and situation strongly influence the growth and prosperity of an urban area. A city's relative location affects its linkages and economic domination over a large and ensures its well-being. A city's site plays a role in its origin and early survival a travel intersection points and bridging point: A settlement often grew at a point where roads or rivers can be crossed urban growth and development. For instance, in Ethiopia, Adama is the best example of such types of town.

Aspects of the economy that can affect the urban expansion include the level of economic development, difference in household incomes, exposure to globalization, the level of foreign direct investment, the degree of employment decentralization, the level of real estate finance markets, the level and effectiveness of property taxation and the presence of high inflation and acute shortage of housing (Angel et al, 2005).These are also the driving factors for urban expansion in this study.

Many believes that cities are expanding very rapidly and are growing for nonproductive reasons specifically; some scholars believe that new policies and regulations on land acquisitions and illegal land markets might have encouraged the extensive shifts of cultivated area in to built up area (Yeh et al, 2003). 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; Mojo, Assela and wolenchiti, the presence of high government and private institutions such as Adama University, Hospital, high standard Hotel ……etc., near distance to the capital city of the country and small town around the city and rural urban migration are the major driving factors of urban expansion of Adama city.

2.5 Remote Sensing and Urban Growth

Remote sensing technology is power full tool which used to 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 has 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. As a result, Understanding the urban growth patterns, dynamic processes, and their relationships and interactions is a key objective in the contemporary urban studies (Bhatta, 2009, 2010 and Deng et al., 2009). Since 1972, the Landsat satellites have provided repetitive, synoptic, global coverage of high-resolution multispectral imagery. Their long history and reliability have made them a popular source for documenting changes in land cover and use over time (Turner et al., 2003) and their evolution is further marked by the launch of Landsat 7 by the US government in 1999.Multispectral Scanner (MSS) data from the U.S. Geological Survey's (USGS) EROS Data Center (EDC) has provided a historical record of the Earth's land surface from the early 1970s to the early 1990s.

The MSS and TM sensors primarily detected reflected radiation from the Earth's surface in the visible and IR wavelengths, but the TM sensor provides (http://edc.usgs.gov/guides/landsat_mss.html#mss4). So that Remote sensing is 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).However, the availability of multi-temporal data is important to analyses 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. Nonetheless, it is difficult to find multi-date data taken at the same time of different years, particularly in tropical regions where cloud cover is prevalent

(Mas, 1999). 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 adama city. 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 (Roberts & Herold, 2004).

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 analyses 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 analyses changes in land cover over time. Yang and Lo (2002) used multi temporal/multi-resolution satellite imageries to successfully extracted land use/cover data in the Atlanta, Georgia metropolitan area for the past 25 years. The result revealed that the loss of forest and urban sprawl have the major consequences of Atlanta‘s accelerated urban development. Deka et al. (2012)showed that the integration of remote sensing (RS) and Geographical Information System (GIS) technique to effectively detect urban growth, emphasizing on the potential applicability of Landsat TM data in the urban studies at both regional as well as local level. This study also indicates the value of medium resolution Landsat images for analysis of urban growth at metropolitan scale, compared to the more resent VRH images. (M. S. Moeller Phoenix,), was made study AZ metropolitan area using mid-scale level land sat image for a period of 30 years he was demonstrate The analysis of long term remote sensing imagery enabled an in-depth monitoring of urban growth pattern.

Clarke, (2003) has applied Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Plus (ETM+), and ASTER images acquired in 1987, 2000 and 2004 respectively to map land use/cover changes in the Pic Macaya National Park in the southern region of Haiti. He concluded that the patterns obtained from remote sensing data usually represent the complex aggregate outcomes of many different individual processes, making it very difficult to disentangle the effects of the different variables and trends of interest. Cheruto et al., (2016) were studied land cover changes observed in Makueni County using multispectral satellite data obtained from Landsat 7 for the years 2000, 2005 and 2016 this study show that Urban growth in Ahvaz has been affected severely by accessing to the main roads, the city center and sub-centers. Urban growth during the period under review occurred at distances far from the river, so there is weak relation between the growth of city and factor of distance to the bridges. Generally most researcher and scientist conclusion indicate that using medium resolution land sat 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 theirs conclusions and believes the potential of remote sensing tool to study urban growth trend and pattern. So it is time to thank USGS center for its contribution to the development of remote sensing technology and to its freely available data.

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 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). At present, it is not possible to state which classifier is best for all situation as the characteristic of each image and the circumstances for each study vary so greatly. Therefore, it is essential that each analyst understand the alternative strategies for image classification so that he or she may be prepared to select the most appropriate classifier for the task in hand.

At present, there are different image classification method used for different purposes by various researchers (Butera,1983; Ernst and Hoffer, 1979; Lo and Watson, 1998; Ozesmi & Bauer, 2002; Smith, 2003; Mather, 2003; Liu et al, 2002) . 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. In supervised classification prior knowledge of the ground cover is important to select training samples. The advantage of the ML classification algorithm is that it takes the variability of the classes into account by using the covariance matrix. However, the disadvantage of maximum likelihood classification arises from the time and effort required to prepare the training samples (Al-Ahmadi & Hames, 2009). In unsupervised classification technique, an algorithm is chosen that will take a remotely sensed data set and find a pre-specified number of statistical clusters in multispectral or hyper-spectral space. Although these clusters are not always equivalent to actual classes of land cover, this method can be used without having prior knowledge of the ground cover in the study site (Hasmadi et al., 2009). Maximum Likelihood classifier is one of the most popular and widely used types of image classification technique in remote sensing Brito & Quintanilha, 2012). Several researchers have demonstrated the importance of supervised maximum likelihood classification technique for land cover change analysis. For example, Tang et al. (2008) analyzed the spatiotemporal landscape dynamics of two petroleum-based cities: Houston, Texas in the United States and Daqing, Heilongjiang province in China, They used the conventional Maximum Likelihood Classification method to classify six multi-temporal satellite images. Yuan et al. (2005) used supervised maximum classification method to map and monitor land cover change using multi temporal Landsat Thematic Mapper (TM) data in the seven-county Twin Cities Metropolitan Area of Minnesota for 1986, 1991, 1998, and 2002. (Aykut et al 2005)obtained Results from the classified images were compared and each of these images was controlled by field verification. The parallelepiped classification results were simple and have not reflected the real features on the land. For example, the urban sites on the map could not be identified; bare lands and olive trees could not be distinguished from each other. At some locations the vegetation cover has been seen as black color. Because of these anomalies, this classifier was not found proper enough for land use mapping purpose. The map derived using the minimum distances classifier seemed more reliable than the map produced by parallelepiped method. In this map, settlement sites were selectable, borders of vegetation cover, agricultural areas and olive trees were clearer than the parallelepiped classifier map. The Maximum likelihood classification result was much better than the previous two maps. In the maximum likelihood map, bare lands-olive trees discrimination could be seen clearly, boundaries of agricultural areas and forest were more apparent than both minimum distances and parallelepiped maps the map that has been produced by application of the linear discriminant classifier was more suitable than the minimum distances map and was less proper than maximum likelihood map. In October, 2009 Indian Institute of Science, Bangalore, India used maximum likelihood supervised classifiers with the aid of field collected ground truth data collected in the field and including equalized stratified random points which were visual interpreted to assess the accuracy of the classification results. The overall accuracy of the land classification for each image was 1987 (82%), 2000 (82%), 2004 (87%) respectively. This study has also used maximum likelihood classification algorithm as a parametric classifier that can train quickly with a capability to handle huge datasets. In fact, this method constitutes a historically dominant approach to RS-based automated LC derivation (Gao, 2004) and has become popular and widespread in RS because of its robustness.

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. Basically, the different algorithms can be grouped into the following categories: algebra (differencing, rationing, and regression), change vector analysis, transformation (e.g. principal component analysis, multivariate alteration detection, Chi-square transformation), classification (post-classification comparison, unsupervised change detection, expectation-maximization algorithm) and hybrid methods.

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. The complexity of image pre-processing needed before differencing varies with the type of image used.

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 priory 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. In addition to these the image classification stage of this method takes a long time because the accuracy of the classification needs to be high to get a good change detection result (Lu et al., 2004). The advantage of post-classification comparison is that it can provide from-to information which helpful to differentiate which land cove or land use class is changed to another class.

2.7.4 Change Vector Analysis (CVA)

Change vector analysis technique is an empirical method of detecting radiometric changes between multitudes of satellite images in any number of spectral bands. This method yields information about the degree and type of spectral changes by calculating a vector magnitude and direction in multispectral change space for each pixel (Black & Goksel, 2012). Like image differencing, threshold indicating change and no change area also needs to be determined in this method (Lambin & Strahler, 1994). A particular advantage of the change vector analysis method is the potential capability to process any number of spectral bands desired. This is important because not all changes are easily identified in any single band or spectral feature. Nevertheless, since no effective method has been developed to handle more than two spectral bands (Kontoes, 2008).

2.7.5 Image Rationing

Image rationing is another method for change detection in which two images from two dates are divided band by band and pixel by pixel. If the ratio of two images is equal to 1, then no change has occurred, but if the ratio is greater than or less than one that means change has occurred. A threshold needs to be decided. The common way for deciding this has been to set a threshold value and then evaluating the change detection. Image rationing produces images with a non-Gaussian distribution of pixel values and if a threshold is decided based on standard deviations from the mean, the change will not be equal on both sides.

Recently, numerous studies have indicated the use of Post-classification comparison change detection technique for land cover change analysis in urban studies. Yin et al. (2011) used post-classification comparison to detect changes of Shanghai metropolitan area, China based on Landsat MSS, TM and ETM+ images from 1979, 1990, 2000 and 2009. By overlaying the classified images over each other they were able to compare the changes in pixels of the layers pixel-by-pixel. Alphan et al. (2009) used post-classification comparison change detection method to assess the land cover changes in Kahramanmaraş (K.Maraş) and its environs from multi temporal Landsat and ASTER imagery, respectively belong to 1989, 2000 and 2004. Liu et al. (2005) also used post-classification comparison to analyses and map the magnitude and pattern of China‘s changing landscape during the 1990s from Landsat TM images covering the entire county. They classified the images in to different land cover class identified. Then the classified images were compared using some statistical measurements. Also This study were argue that the use of Post classification comparison method spatially to detect urban change pattern in metropolitan area because it enable to cheek accuracy of the classification result and helpful to differentiate which land cove or land use class is changed to another class. So that user became confidential in their result.

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 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). Attention should be paid while comparing the value of metrics computed from landscapes that have been defined and scaled differently.

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 (MNN), 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 such as FRAGSTATS (McGarigal et al., 2012) to analyses urban environment. For instance, Kuffer and Barrosb (2011) used spatial metrics in a VHR remotely sensed images to analyses the morphology of unplanned urban settlements in Dares Salaam and New Delhi. In this study, different sets of metrics were used for two case studies. After eliminating several highly correlating metrics, the authors selected a set of four metrics ,i.e. is mean area, patch density, aggregation index and Shannon‘s diversity index for Dares Salaam and a set of six metrics,i.e. effective mesh size, landscape division index, patch density, contagion, aggregation and Simpson‘s evenness index for Delhi. Both sets of metrics measure size, pattern and density. Finally, the sets of spatial metrics were combined using spatial multi-criteria evaluation to produce a composite index indicating areas of high likelihood of‗unplannedness‘ in the study area. Jain et al. (2011) applied spatial metrics and gradient analysis method for quantifying and capturing changes in urban landscape using LISS III imagery of Gurgaon, India.

The combination of landscape metrics ,i.e. percentage of landscape, mean patch size, number of patches, landscape shape index and largest patch index have been used to quantify the patterns of urban growth in different directions of the city in terms of size, shape and complexity of development. Finally, they were able to demonstrate the potential of spatial metrics and gradient analysis to quantify the impact of regional factors on the growth pattern. Pham and Yamaguchi (2011) showed the potential application of spatial metrics as secondary sources of information for supporting remotely sensed data and their use to characterize urban growth patterns of Hanoi, Vietnam. This study used the percentage of like adjacency (PLADJ) metric on the urban growth maps generated using maximum likelihood image classification technique to illustrate the changes in the urban structure in the study area. Six class-level landscape metrics,i.e. class area, number of patch, edge density, largest patch index, mean nearest neighbor distance and area weighted mean patch fractal dimension, were selected to characterize the urban the urban composition parameters of Hanoi. Seto and Fragkias (2005) effectively compared the spatio-temporal pattern of urban land use changes in four Chinese cities, using three concentric zones and a set of landscape metrics. This study used a group of six spatial pattern metrics analysis indices namely: total urban area (UA), number of urban patches (NUMP), mean urban patch size (MPS), urban patch size coefficient of variation (PSCOV), urban edge density (ED) and area-weighted mean patch fractal dimension (AWMPFD). The results of this study indicate that urban form can be flexible over relatively short periods of time.

Despite different economic development and policy background, the four cities exhibit common patterns in their shape, size, and growth rates, suggesting a convergence toward standard urban form Yu and Ng (2007) used a combination of remote sensing images, spatial metrics and gradient analysis to analyses the spatial and temporal dynamics of urban sprawl in Guangzhou, China. The results of this study shows that landscape change in Guangzhou exhibits distinctive spatial differences from the urban Centre to rural areas, with higher fragmentation at urban fringes or in new urbanizing areas. Population growth and rapid economic development were the two major driving forces of urban expansion in the study area. The authors were also able to demonstrate the importance of temporal data to reveal the complexity of landscape pattern and to capture the spatio-temporal dynamics of landscape changes Herold et al. (2005) explored the importance of spatial metrics in the study and modeling of urban land use change in Santa Barbara urban area, California, USA. Percentage of landscape (built up)(PLAND), patch size standard deviation (PSSD), contagion index(CONTAG), patch density (PD), edge density(ED), area weighted mean patch fractal dimension(AWMPFD)are the spatial metric growth signatures used in the study.

According to the research, the growth of Santa Barbara develops outward from the original downtown core. Generally this study indicate that spatial metrics can be utilized for the detailed mapping of urban land use change at different geographic scales and can help infer a number of socioeconomic characteristics from remote sensing data. Schneider et al. (2005) used remotely sensed data to map changes in land cover in the greater Chengdu area and to investigate the spatial distribution of urban development by using spatial metrics along seven urban-to-rural transects corridors of growth. Pham et al. (2011) explored and approach for combining remote sensing and spatial metrics to monitor urbanization, and investigate the relationship between urbanization and urban land use plans. The study examined four cities of Asia namely: Hanoi, Hartford, Nagoya and Shanghai, using Landsat and ASTER data. The results showed that the combined approach of remote sensing and spatial metrics provides local city planners with valuable information that can be used to better understand the impact of urban planning policies in urban areas. The spatial metrics combined with time-series of high spatial resolution remote sensing data has potential to characterize the dynamics of urban growth processes as well as it can reveal the spatial component in urban structure underlying the growth process (Herold et al., 2002). In this context, remote sensing and spatial metrics are used in a complementary way to better understand the urban growth processes and patterns.

Wu et al. (2011) analyzed the spatio-temporal patterns of urbanization in two fast growing metropolitan regions in the United States using: Phoenix and LasVegas. Based on historical land use data and landscape pattern metrics at multiple spatial resolutions they were able to characterize the temporal patterns of urbanization in the metropolitan regions. The results of this research showed that the two urban landscapes exhibited strikingly similar temporal patterns of urbanization with an increasingly faster increase in the patch density, edge density, and structural complexity of the landscape. That is, as urbanization continued to unfold, both landscapes became increasingly more diverse in land use, more fragmented in structure, and more complex in shape. Finally, the authors conclude that a small set of spatial metrics is able to capture the main spatiotemporal signatures of urbanization, and that the general patterns of urbanization do not seem to be significantly affected by changing grain sizes of land use maps when the spatial extent is fixed.

There are several methods to analyses 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. This study also trusts the potential of remote sensing and spatial metric to quantify urban change pattern and process. However; Landscape metrics quantify the pattern of the landscape within the designated landscape boundary only. Consequently, the interpretation of these metrics and their ecological significance requires an acute awareness of the landscape context and the openness of the landscape relative to the phenomenon under consideration. These concerns are particularly important for nearest-neighbor metrics. These concerns are particularly important for nearest-neighbor metrics.

2.10 Urban Growth Modeling

Rapid urban growth accompanied by land use 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 (Allen & Lu, 2003; Veldkamp & Lambin, 2001). There are two broad categories of land change models developed over the past several decades (Hu & Lo, 2007).These are dynamic simulation based models and statistical estimation models. Simulation-based models such as Cellular Automata (CA)attempts to capture the spatio-temporal pattern of urban change by incorporating spatial interaction effect in to the mode However, the poor explanatory capacity of simulation models has limited the detail understanding and interpretability of urban growth dynamics with its potential driving forces(Luo & Kanala, 2008).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. For example, regression analysis can help to identify the driving factors of urban growth and quantify the contributions of individual variables and their level of significance (Huang et al., 2009; Luo & Kanala, 2008; Nong & Du, 2011). Binomial (or binary) logistic regression is a form of regression, which is used to model the relationship between a binary variable and one or more explanatory variables yielding dichotomous outcome (Hosmer & Lemeshow, 2004).

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 modeling, logistic regression model was used to study the relationship between urban growth and biophysical driving forces (Huang et al., 2009).The conversion of non-urban to urban land use is considered as state 1, while the no conversion is indicated as state 0 in the same period of time. A set of independent variables are selected to explain the probability of non-urban land use to conversion to urban. The main purpose of urban growth modeling 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 modeling 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 THREE: MATERIALS AND METHODOLOGY

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 Study Area

Adama is a city in central Ethiopia and forms a special zone of Oromia and is surrounded by Misraque Shewa zone. It is located at 8.54°N 39.27°E at an elevation of 1712 meters, cover area of 22223ha and located 99 km southeast of Addis Ababa .The city sits between the base of an escarpment to the west, and the Great Rift Valley to the east. based on the 2007 Census conducted by the central statistical agency of Ethiopia (CSA), this city has a total population of 220,212, an increase of 72.25% over the population recorded in the 1994 census, of whom 108,872 are men and 111,340 women., Adama has a Population density of 7,374.82; all are urban inhabitants. A total of 60,174 households were counted in this city, which results in an average of 3.66 persons to a household, and 59,431 housing units. The city lies on Quaternary volcanic rocks and sediments The soil development in the Adama catchments is mostly due to the physical disintegration and decomposition of volcanic rocks, deposition of alluvial and ashes the average annual rainfall about 866.25 mm. the wind speed at Adama is high.

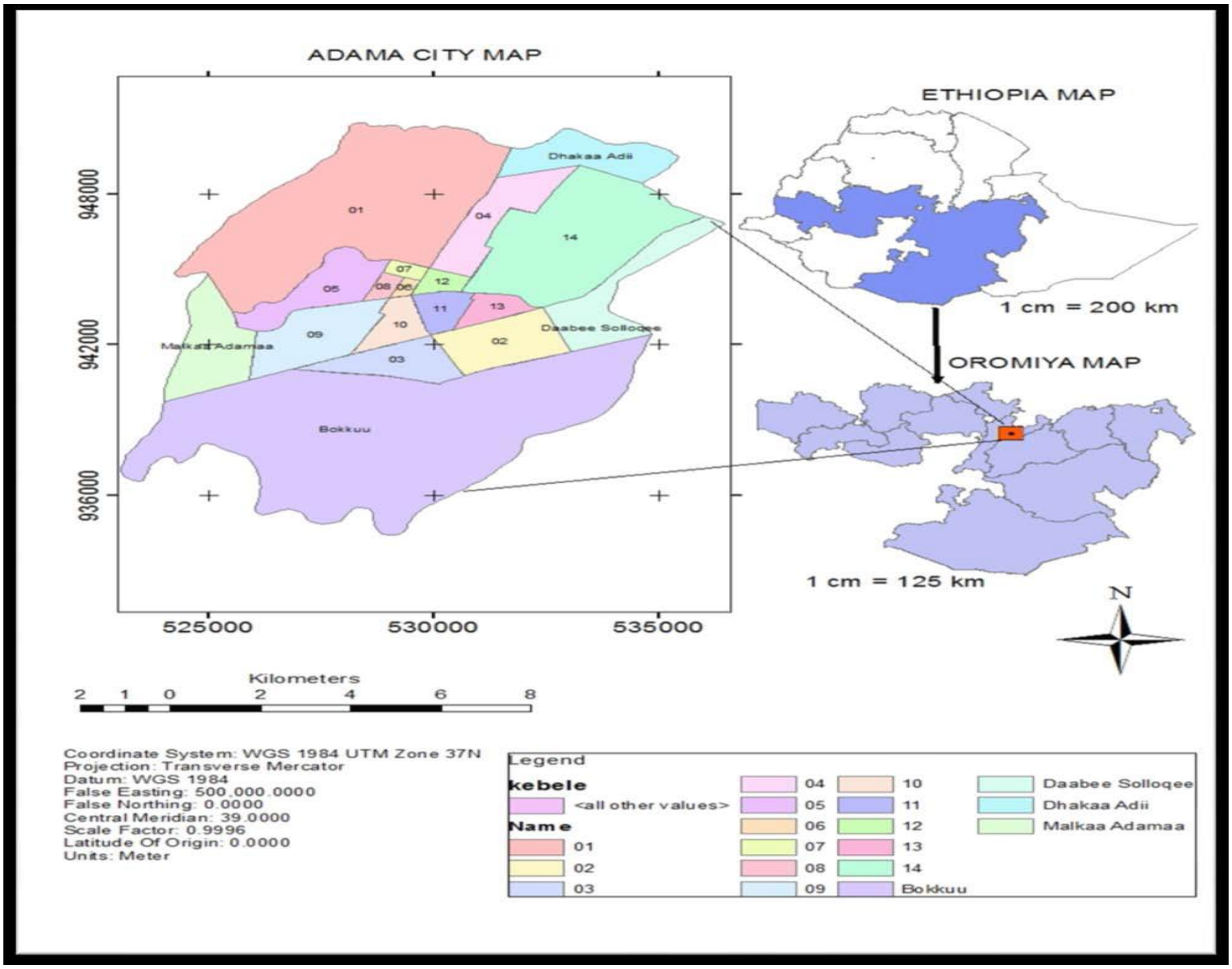

Figure 3. 1: Geographical Location of the Study Area

Topography

Adama City is located within the Main Ethiopian Rift valley made of volcanic rocks that extends from the southern Afar Rift to the Konso highland in the southern Ethiopia. The city lies on plain land that formed by geodynamic movement. These conditions have made the City susceptible for earthquake. The topography is characterized by flat land that is surrounded by ridges. The plain land is covered by lacustrine sediments and reworked volcanic while the ridges are made of volcanic rocks. The nature of topography has created three drainage sub catchments. One that drains to Awash River and the other two are closed basins. Absence of appropriate drainage network, lack of natural outlet and unplanned human intervention has made the city vulnerable to flooding (APO, 2004). The first settlers of Adama were employees of the railway station. The first structures were the railway station and a handful of houses constructed by the railway company. Later on, farmers from the surrounding region started to settle near the station in search of the station's water supply and other facilities. The first major transformation of Adama took place during the Italian occupation (1936-41). The Italians had contributed greatly to the city's development and growth. They built the city with a new plan connecting it with many of their provincial centers by telephone, telegraph and radio networks. Newly developed roads also connected it with Addis Ababa and other regional states. Even after their withdrawal the Italians have continued to contribute to the growth and stability of Adama. Thus, as a compensation for their atrocities during their occupation, they built the Awash Hydro Electric Power Plant which provided electricity to Adama as well as other parts of the region. There was no piped water supply at the time. People used to fetch water from Awash River which is about17kms to the south, traveling on foot. The Italians helped to provide piped water from this river. The municipal office of Adama was also first established by the Italians(Bedasa Regasa,2014).

Socio-economic Aspects

Adama is a city of migrants, who came following the trade route in search of jobs and livelihood. As a result, it is composed of people of different ethnic origin. According to citizens who lived in the area for more than 50 years, most of the migrants are from the agriculturally rich regions of Shoa (especially Minjar), Arsi, and Harrar. Thus, Gurages, Amharas and Oromos constitute the major ethnic groups in the city. Some of them settled and became traders. Others come periodically to trade their agricultural products. There were also Arabs and Indians who must have come following the beginning of export of agricultural products to Yemen and the Middle East countries via the railway station. In additions there were also Italians, who settled during the Italian Occupation. The Arabs used to do cereal export and retailing imported items, while most of the Indians were in textile trade. Italians involved in auto mechanics and restaurants and hotels. Even though most of these foreigners are no longer there, there are still a few two and three generations of them in the city. Economically, Adama has been serving as a major focal point for trade and small scale industries(Bedasa Regasa,2014).

The City is an important center of distribution of goods that are manufactured locally by the various industries in the City and its suburbs. It still is a relay point for goods produced and manufactured in the country and imported from abroad to the small towns and rural areas in the region. Adama also serves as the loading center for some Ethiopian export goods, particularly cereals. As a result it is characterized by lots and lots of warehouses. Even before the 1960s there were 40 to 50 warehouses in La Gare area. This number has been growing ever since. Due to its location en route to the Sodore hot water spring resort, and its strategic importance as an intersection point between economically important regions, Adama has always been full of travelers. Thus there are a lot of hotels – big and small, restaurants, bars and cafes and the majority of the population gets its livelihood from sundry commercial activities and services. There are also factory and office workers whose number is increasing lately (Bedasa Regassa, 2014).

Population

Based on CSA's 1994 Population and Housing Census and 1999 National Labor Force Survey (NLFS), indicate that there were about 187,000 people living in Adama City in 2004. Nevertheless, the 2002/3 estimates of the City Administration reveals that the City population is known to be well over 220,212. The proportion of male to female during the period was about 48.5 to 51.5 percent revealing further that the sex ratio was 94.0 percent, which implies little excess of women over the men (about 100 females for each 94 males). Furthermore, according to the CSA's 1994 census, about 33.6 percent of Adama residents were below the age of 15. Similarly, the data further reveals that populations within the working age group (15-64) and above 64 years of age were 63.5 and 2.9 percent, respectively. Form the figures it could be noted that the conventional dependency ratio for the City at the time was 57.5 percent, implying that every 100 people in the working age group supports about 58 additional people within the dependent age group in every aspect providing shelter, food etc. This was quite very low and largely differs from what the CSA has for the national (102) and regional levels (109). In general, it is rarely possible to observe such discrepancies within same character population unless there are exceptions, which explain the status quo of the area.

As a result, various studies [CSA, 1984, 1994, 1999 and Adama Project Office's (APO) socio-economic surveys, 2004] point that Adama has been one of the areas both in the region and the country that receives heavy influx of migrants each year. For instance, the 1984 Census indicates that 53.7 percent of the City populations were migrants. Similarly, after a decade, in 1994 the second census showed that the extent of migrants were 53.6 percent. The finding of the 1999

NLFS neither contradicts with the above mentioned two census outcomes. According to the results of the NLFS, hence, 52.1 percent of the populations of Adama City were contributed from migrants in 1999. The findings of many socio-economic surveys undertaken by APO in 2003-2004 too, confirm that in-migration stand out as one of the major issues in Adama City. In the Poverty and Socio-economic Problem survey undertaken in Adama, about 68.0 percent of the poor households were migrants. Similarly, in the same study it was found that about 83.0 percent and 87.0 percent of the commercial sex workers and street occupants were migrants respectively (APO, 2004). The census data further points that Adama households were estimated to have about 4.8 persons on the average. From this it could be possible to estimate that about 39.0 thousand households were residing in the city in July 2004(Bedasa Regasa,2014).

3.2.1 Research Design

The proposed research was 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 were 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 city Centre, new development sites, etc.to have the general impression of the study area. 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.

3.2.2 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 1988, ETM+ 2000, ETM+ 2010 and OIL/TIR 2017) 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 GIS10.1 using different spatial analyst tools and Envi ex 4.8. Consequently, the spatial extent and rate of urban growths were analyze and quantified. Then, the classified images was used as an input data in FRAGSTATS (McGarigal et al., 2012) to further describe and quantify the changing patterns and processes of urban landscape. Finally, binary logistic regression model was built in Edrisi saliva to identify the major physical driving forces responsible for the changing patterns of urban landscape.

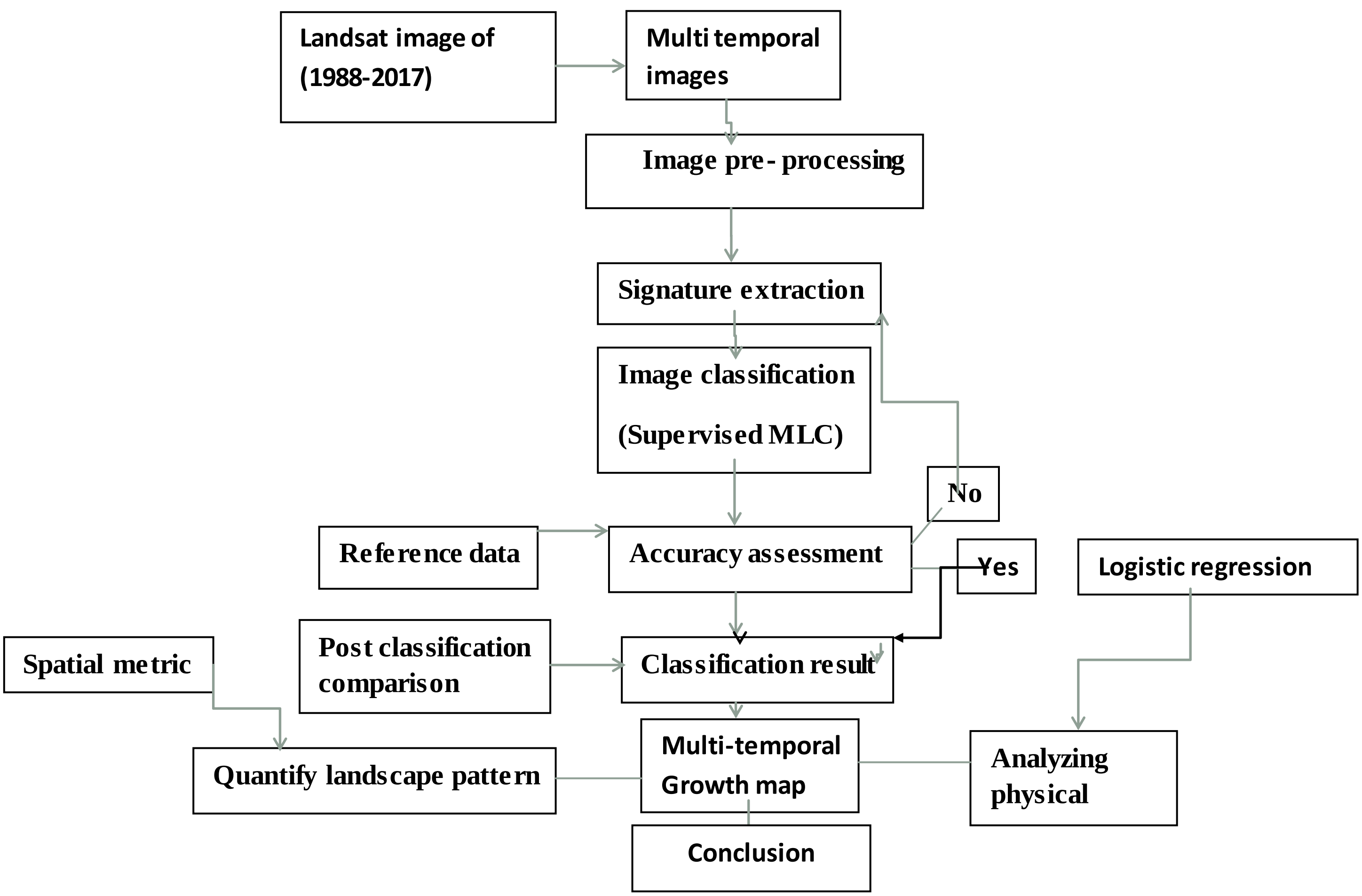

Figure 3. 2: Flow chart describing the general methodology were used in this study

3.3 Data Source and Type

Different remote sensing and GIS data from different sources were used in the proposed research. Four medium resolutions Landsat images TM 1988, ETM+ 2000, ETM+ 2010 and OIL/TIR 201 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 resolution30m which make it convenient for comparison of changes and patterns that occurred in the time under consideration. Additionally, two VHR images covering some pat of the study area and were obtained from EMA the DEM used to analyses driving forces of urban growth was downloaded from SRTM-USGS center. Most GIS data such as location of satellite towns, , sub-city centers, location of adama university, location of sodere resort, CBD and existing built up areas were derived from VRH Google Earth image. Other data such as administrative boundaries and major roads were obtained from adama city municipality .All dataset in this study used were geometrically referenced to the WGS 1984, UTM zone 37 projection systems. The detail description of the characteristics all images used in this study is summarized in Table 3. 1.

Table 3. 1: List of satellite image (raster data) collected for the study area

Satellite data	Acquisition date	Spatial resolution	Data source
Landsat TM 1988	January 1988	30m	USGS
Landsat ETM+ 2000	January 2000	30m	USGS
Landsat ETM+ 2010	January 2010	30m	USGS
Landsat OLI/TIR 2017	February 2017	30m	USGS

Orthophotos	**2010**	**50cm**	**AdamaMunicipality**
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 Adama city**
Existing build up` area	**Shape file**	**Derived from goggle earth image**
Satellite town	**Shape file**	**Derived from goggle earth image**
Adama university	**Shape file**	**Derived from goggle earth image**
Sub city center	**Shape file**	**Derived from goggle earth image**
CBD	**Shape file**	**Derived from goggle earth image**
Major road	**Shape file**	**Derived from goggle earth image**

3.3.1 Field Data Collection

In this research used both primary and secondary data to make sure that the objectives of the study were meeting. Although some secondary data were collected from literature review and open source websites, aiming at two major tasks explain below.

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. For this purpose the coordinates of 120 ground control points were collected and 100 ground truth data obtained from the privies work (BedasaRegassa).Simple stratified random sampling technique was used to determine the location of the new points. Handheld GPS was used to collect the field data. Digital camera l also used to photograph the land cover material of visit sites.

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, sub city center, major road, satellite town like; mojo, and Adama university were major physical driving forces of urban growth in adama city.

3.2 Software's and other Instruments Used

Erdas Imagine 2010, Frag Stats tool 4.1, ArcGIS 10.1, Edrisi saliva, Envi ex 4.8, Hand held GPS and patch analyst software ArcGIS plugin were the tools used in this study

3.4 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 (Hai &Yamaguchi, 2008; 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 such as in Sub-Saharan African countries like Ethiopia .Apart from this binary logistic regression method was used to identify the major physical driving forces of urban growth in the study area. The accuracy of the classification results was assessed using randomly sampled ground truth points, obtained from fieldwork and visual interpretation of the true colour composite. The change detection method was used in this analysis is the post classification comparison technique in which GIS overlay of two independently produced classified images in ARC GIS (Alphan et al., 2009)The resulting land Cover maps were then visually compared and change areas were simply those areas which were not class identified the same at different times.

3.4.1 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 etal., 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 three regions; Addis Ababa- Harar Road in the CBD-west direction, the Assela road to the East and to the north. 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 pach 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 (m^2), multiplied by the patch area (m^2) divided by total landscape area.

3.4.2 Logistic Regression Modeling and 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, only 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.

3.4.3 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 1were 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 FOUR

Result and Discussion

4.1Introduction

In this chapter the results and output of this research are presented and discussed in detail. Sequentially starting from Spatio-temporal quantification of urban growth it goes through the most important finding of urban growth pattern using spatial metrics. The pattern analysis conducting both city wide level and regional scale Most of discussions are supported by map table and illustrative graph. The key factor responsible for the changing pattern of urban growth are presented and discussed through result of logistic regression modeling and physical driving force.

4.2 Result of Image Classification and Accuracy Assessment

The result of accuracy assessment shows that the extraction of non-built-up are has relative higher accuracy in all image however; built-up class has lower accuracy duet to the mixed pixel in the classes. ETM+ 2000 might have influence the accuracy of image classification as Landsat 7 ETM+ sensor have greater radiometric sensitivity compared to Landsat TM image in addition to this landsat 7 ETM+ sensor offer numerous improvement over the earlier generation of Landsat sensor such as Landsat 4&5 (Masec et al., 2011). The improved spectral information content of landsat 7 ETM+ sensor could record small bright missed by Landsat 5 TM that has been manifested on Landsat ETM+ 2000 image in this study. Thus the result presented based on ETM+ 2000 image in this research were subject to image inconsistencies describe above. However the overall accuracy of all image was found to be greater than 85% which is considered as good result for remote sensing image based analysis (Herold et al., 2005). The following table presents the accuracy of classified image in the different time period. The result of image classification result is given (Figure 4.1).

Table 4. 1The result of accuracy assessment

Sensor	Acquisition date	Classified image	Accuracy	Kappa statics
Landsat TM	**4/25/1988**	**Built up -1988**	**85%**	**0.70**
Landsat ETM+	**4/27/2000**	**Built up -2000**	**87%**	**0.73**
Landsat ETM+	**5/17/2010**	**Built up -2010**	**86%**	**0.72**
LandsatOLI/TIR	**4/18/2017**	**Built up -2017**	**89%**	**0.79**

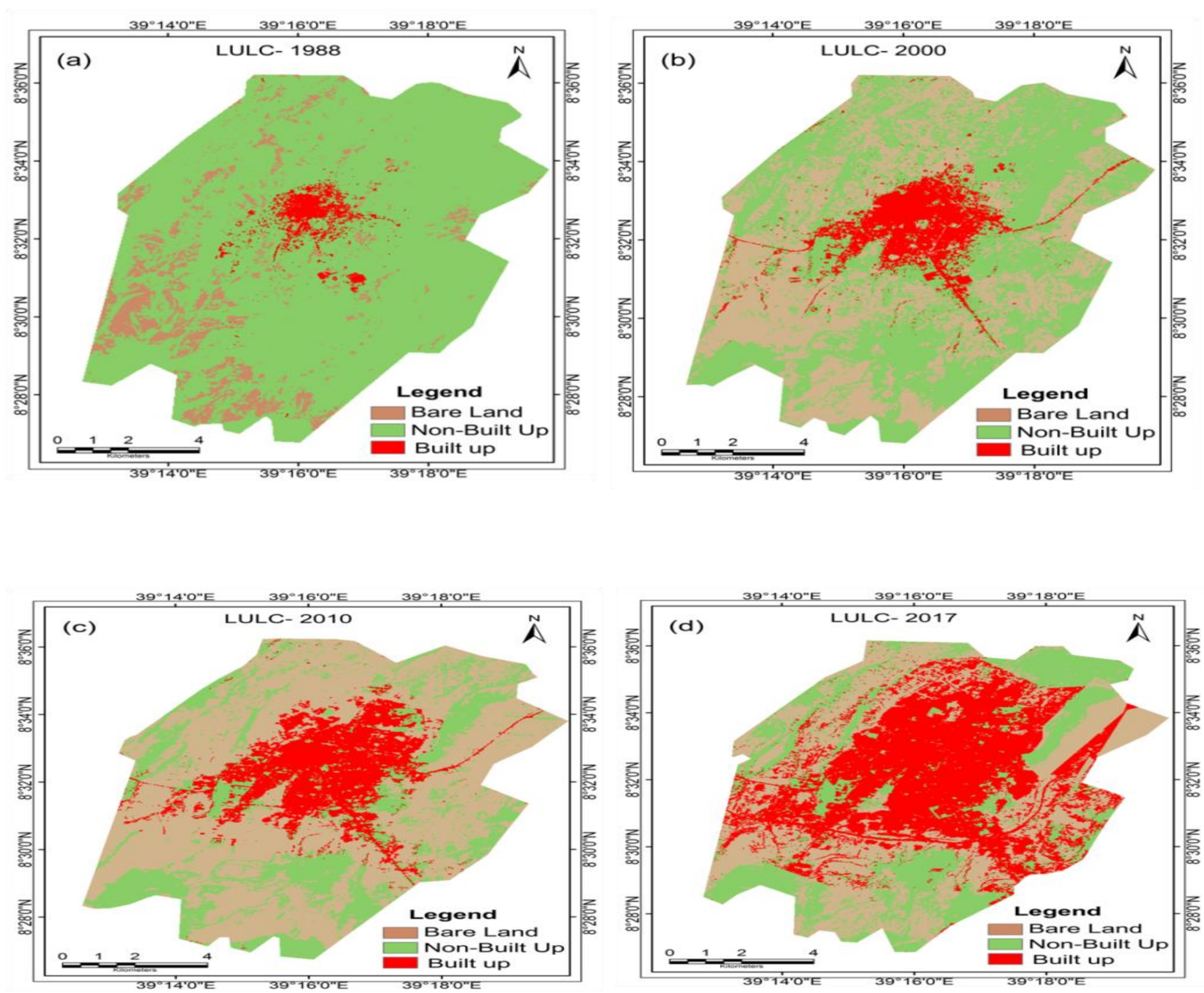

Figure 4. 1: Result of image classification

4.3 The Spatio-Temporal Analysis of Urban Growth Pattern using Spatial Metrics

The classification of multi- temporal satellite image in to built-up, non-built-up and bare land for the four different time periods of 1988, 2000, 2010 and 2017 has resulted in high simplified and abstracted representation of the study area Figure 4. 1. This map show clear pattern of increase urban expansion prolonging both from urban center to adjoining non-built up area along major transportation corridor. The map shows the spatio-temporal urban growth pattern in the study area. Post classification comparison of the classified image show the growth pattern of the study area in different direction, the infilling of open space between already built-up area and dynamic of urban expansion in the study area. But it is important to support the result with statistical evidences as it is useful to describe the spatial extent and different pattern of urban growths that have been occurring the study area. This will help to understand how the city is changing over time and to compare growth pattern taken place in different time period quantitatively. Spatial metric are power full tool to quantitatively describe and compare multi date thematic map.

Five frequently used spatial metric are selected based on literature review (refer section 3.5.1) for the analysis of built-up area dynamic over space and time at landscape level. The metrics are used to describe the trend and changing pattern of the actual built-up land extracted from Landsat image all metric computed only for built-up area the output presented in table 4.3 were generated for the selected metric in the form of numeric values for the whole study area in FRAGSTAT 4.1.

The result presented table 4.3 shows that the total built-up area (TA) has been grown from 415.44 ha in 1988 to 1463.88 ha in 2000, to 2457.27 ha in 2010 and to 5599.62 ha 2017. The higher rate of urban growth rate was during these second period of urbanization (2000 to 2010) in which built-up area increased from more than 59.57% this is followed by 28.37 % and 43.88% during the first (1988 to2000) and third (2010 to2017) period of urbanization respectively. This indicates a more rapid urbanization has been taking place in the study area during the period of 2000 to 2010 compared to the two other periods it should be also noted that the second period of urbanization covers the longest time span compared to the third periods.

Table 4. 2: Analysis of built up area expansion based on total area (TA) metrics

Study period	Change (ha)	Change (%)	Time span	Growth rate	Average
1988-2000	1048.44	28.38	12 year	2.36%,	4.86%
2000-2010	993.39	59.57	10 year	5.96%	
2010-2017	3142.25	43.88	7 year	6.27%	

As the statistics obtained from the area metrics computation confirms, the built up area has been increasing at an average annual growth rate of 2.36% 5.96% & 6.27% during the periods 1988-2000, 2000-2010 & 2010-2017 respectively in the study area. This result also approved by the result of Bedasa Regasa (2014) studied the analysis of urban expansion and modeling of land use cover change in adama city and he reveled the increased urban expansion of built up area and concluded that adama city built up area has been increased by 5% average growth rate per annual. This study also obtained almost similar result (4.86%) compare with Bedasa Regasa (2014) result conducted at the same study area.

Table 4. 3: Result of spatial metric calculation at the entire land scape level

Year/ metric	LUC	TA	NP	PD	LPI	FRAC_AM
1988	Built up	415.44	370	80	65.16	1.2211
2000	Built up	1463.88	818	55.88	80.3136	1.2817
2010	Built up	2457.27	463	19.07	88.602	1.3026
2017	Built up	5599.62	1068	18.84	87.3225	1.325

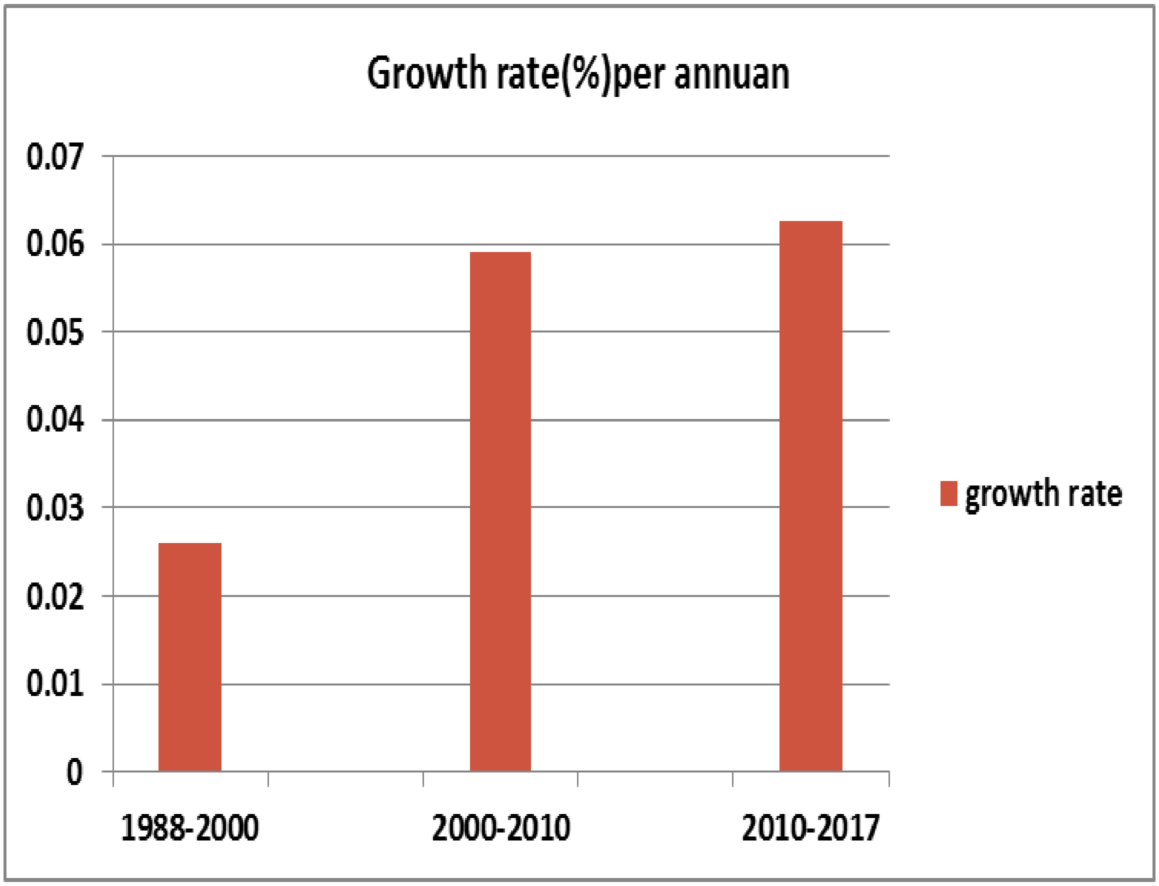

Figure 4. 2: built up area growth rate (%) per annual per study period

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 2010 to 2017 and 1988 to 2000 and, the pick occurred in 2017 indicating the continuing development of scattered and fragmented urban patches in the study area. However NP decreased in the second urbanization period. The situation can be attributed to the merging of small and patchy built up patches in CBD of the study area during 2000 to 2010.This could happen as the city 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.

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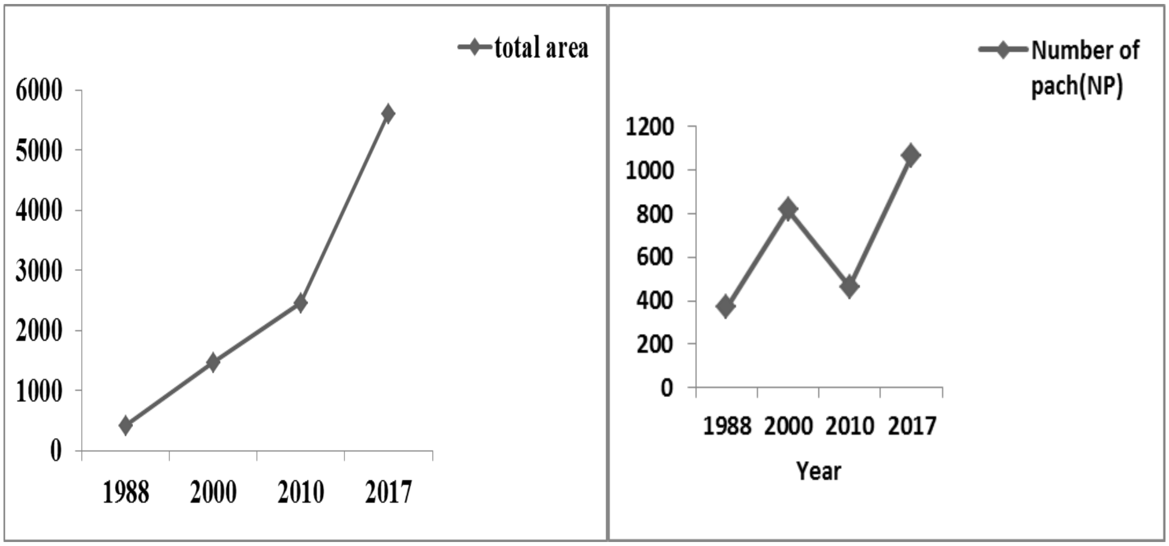


Figure 4. 3 :Total **Area (TA) & Number of Patch (NP) of entire Land scape**

The patch density (PD) continuously Decreased from 80 in 1988 to 18.84in 2017 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. In other words, a decrease of patch density means that some patches located in close proximity to the city center are merging with urban core to form a homogeneous urban fabric. The effect has been manifested on the increasing largest patch index (LPI) and this 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.

Visual comparison of the classified images confirms the development of urban core in the form of infill and edge expansion (figure 4.1). The gradual expansion of the urban core might have changed the city in to 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.

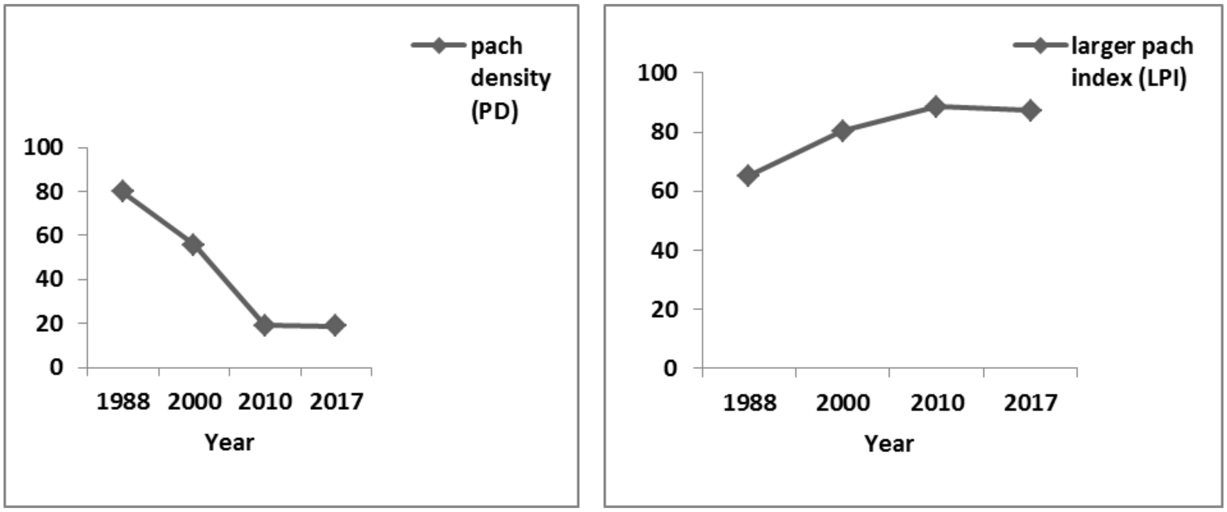


Figure 4. 4: graph showing patch density (PD) and larger patch index (LPI)

The area weighted mean patch fractal dimension (FRAC_AM/AWMPFD) is the measure of urban patch shape complexity which describes how the patch perimeter increases per unit increase in patch area. In 1988, FRAC_AM was 1.2211which indicates that unit increase of patch area, the perimeter is increasing by 32% and by 40% in 2017. Yet, looking at the highest value witnessed in 2017, 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 (figure 4.1). It is also important to note that topography might have played inevitable role for the fragmented development of the city particularly the rift valley area of Adama city is not suitable areas for urban development, those it breaks the continuity and isolate or fragment the built up patches.

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, FRAC_AM (NP) and the largest patch index (LPI) showed consistent increasing trend while patch density (PD) exhibited a decreasing trend. 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 that the urbanization has substantially changed the land cover of the study area with a significant PD and LPI conversion. Built up area has been undergoing fragmented development process in all study periods except the second period of urbanization which shows infill development with substantial increase of built up area during the second period of urbanization (2000-2010). In addition to this, the manifestation of urban sprawl is witnessed from the substantial increase in number of patches over the time period. 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 (figure 4.3). The result of fractal dimension analysis also shows that the increasing patch shape complexity of the study area in the first and third period of urbanization.

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 rend 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 reveled 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 in to different zones or regions. Different regions were formed using administrative boundaries at division level the city is divided in to three In terms of spatial extent most of the regions Area are comparable except for the northern region, which is slightly smaller than the other three regions of Adama city. 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 (4.1). The list of divisions and their corresponding region are given in table below.

Table 4. 4: Administrative region make up region

Region	Administrative division
North	College, kebele 04 , mebrat haile , harer road direction, bole… etc.
East	Asela road direction, kebele 11, Posta bet,..etc.
CBD to west	Adis abeba road direction, franco, menaharya..etc.

4.5.1 Northern Region (Adama university and Harer road direction)

Class Level Analysis

According to the results obtained from FRAGSTATS, the built up area has been considerably changed over time in the northern region (Adama university and Harer road direction) of the study area. During 1988-2017 61.85 ha of built up are has been increased to 1510.17ha of built-up area with an average growth rate of 1.92 (52.07ha) per annum. In 1988 the built up land in the region has been only 61.85ha after twelve years in 2000 this figure changed to 267 ha.

Table 4. 5: Result of spatial metric computation (north region)

Year	CA	NP	PD	LPI	FRAC_AM
1988	61.85	23	2.6	1.2	1.0582
2000	267.57	25	2.9	1.26	1.0683
2010	694.8	29	3.4	1.32	1.0869
2017	1510.17	32	4.5	1.89	1.0948

Later it increased dramatically to 1510.17 ha in 2017.The region is one of the most active areas in Adama city hosting a variety of socio-economic activities. For instance, in the direction of Adama university 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: **Temporal dynamic of built up area in north region based on class area (CA) metric**

Study period	Change (ha)	Change (%)	Time span	Growth rate	average
1988-2000	205.72	23.11	12	1.92%	4.11%
2000-2010	427.23	38.51	10	3.85%	
2010-2017	815.37	46	7	6.57%	

In 1988, the number of patches (NP) in the region was 23 and gradually increased to 25 in 2000, 29 in 2010 and finally reached to 32 in 2017.This indicates that during the urban growth process there has been a development and emergence of a number of small fragmented built up areas. According to the observation during fieldwork, this could be mainly attributed to the development of discontinuous urban patches and other impervious surface features due to uneven topography and valley barrier. In addition to this it is also possible that there might be a gradual development of new urban centers in the region. Similarly an increasing trend is observed for patch density (PD) is over time. In 1988 PD was 2.6 which touches 2.9 in 2000, reached at 3.4 in 2010 and finished at 4.5 in 2017. The total area of the landscape is much higher than the number of patches in the landscape; as a result the value of patch density is observed low. This is the manifestation of the non-built up area as a dominant land cover class in the landscape. Nevertheless, patch density appears to increase over time indicating the fragmented development process of the built up area were observed same part of the region.

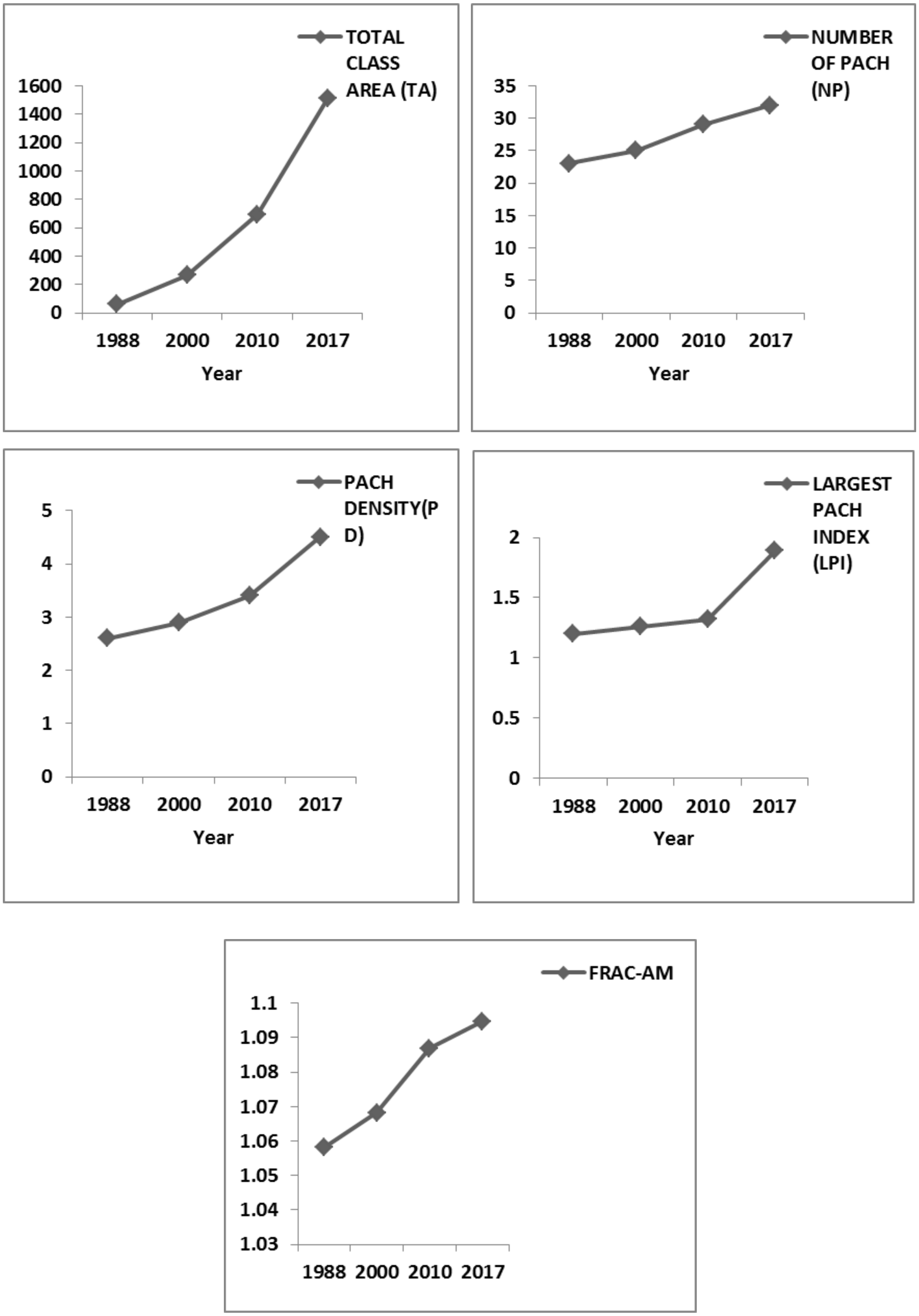


Figure 4. 5: Class level metric computed for north region

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 1.2 in 1988, 1.26 in 2000, 1.32 in 2010 and 1.89 in 2017 (table 4.7). 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 1.0582 in 1988, 1.0683 in 2000, 1.0869 in 2010 &1.0948 in 2017 (table 4.7). 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.

4.5.2 South Eastern Region (Asela 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 south-eastern part of the study area. In 1988, the region constituted 84.15ha of the total built up area, this figure increased to 408.33ha in 2000, 1149.65ha in 2010 and 2079.05ha in 2017.

Table 4. 7: Temporal dynamic of built up area in south- east region based on class area (CA) metric

Study period	Change (ha)	Change (%)	Time span	Growth rate	Average
1988-2000	324.18	20.61	12	1.72%	4.38%
2000-2010	741.32	35.52	10	3.55%	
2010-2017	929.4	55.30	7	7.90%	

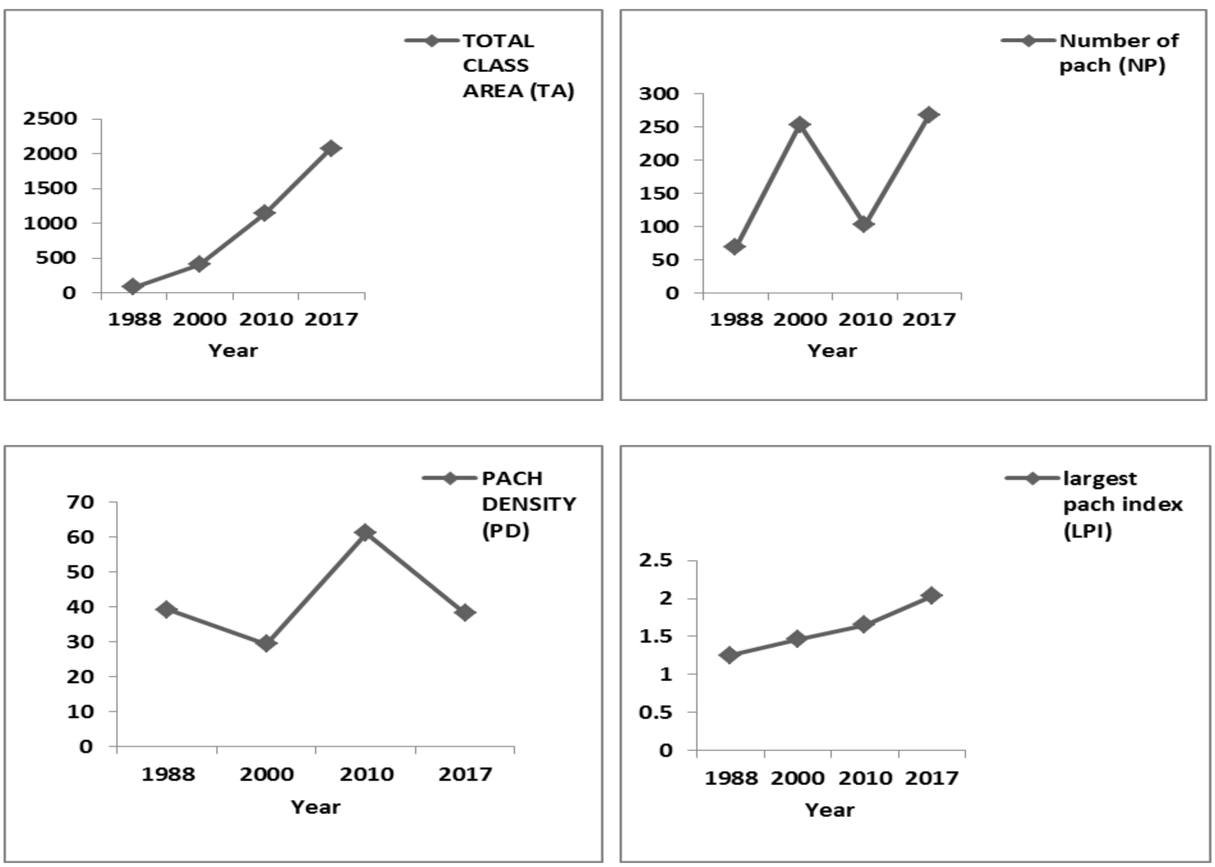
The results shows most dramatic change observed in 2017 and relatively slower growth is noticed in 2000. The area about 27.015 ha has been increased per annum during 1988-2000 period, 74.132 per annum in 2000-2010 and reached to132.7714 per annum in 2010-2017.. The average growth rate is 4.38% which is much higher than the growth rate of the northern region and comparatively much lower than the average growth rate of the city.

Table 4. 8: Result of spatial metric computation (south-east)

Year	CA	NP	PD	LPI	FRAC_AM
1988	**84.15**	**69**	**39.2**	**1.25**	**1.1061**
2000	**408.33**	**254**	**29.45**	**1.46**	**1.17**
2010	**1149.65**	**103**	**61.2**	**1.65**	**1.12**
2017	**2079.05**	**268**	**38.2**	**2.03**	**1.2979**

Number of patches shows increasing trend in the first period and the third period of urbanization in 1988 NP is 69 this figure is increased to 254 in2000 and in 2010 NP is 103 then NP is changed to268 in 2017.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 254 to 103. 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 land scape 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 land scape 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

1988 and 2017 the LPI grown from 1.25 to 2.03. The growth of this region seems highly triggered by the presence of Asela 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 except for the period 2000-2010. This showing the complex and Fragmented development process of built-up areas in the region in earlier period of urbanization.



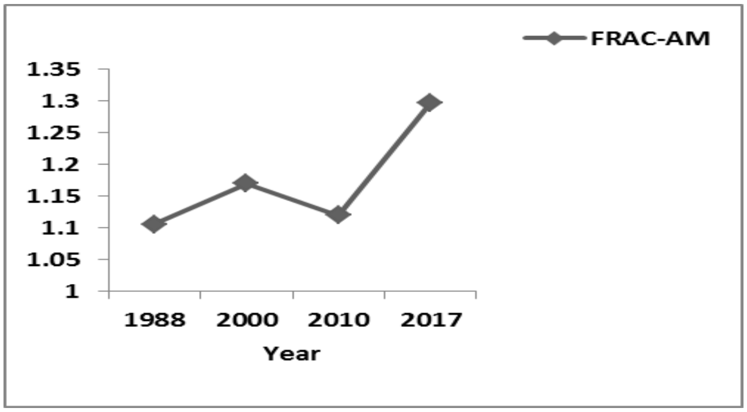


Figure 4. 6: Graph showing class level metric computed for south east region

4.5.3 CBD and Western Region

Class Level Landscape Pattern Analysis

CBD and western region of Adama is the highly urbanized in all study periods. This is not surprising as it is the core of the city. Based on class area (CA) metrics, in 1988 almost 269.37 ha urbanized areas of region is increased to 1510.45 ha in 2017. During the period of 1988-2000, the built up area increased by 37.17% (518.85 ha). However, the highest growth is observed during the period of 2010-2017. From 1988-2017,the area under built up was changed almost 1241.08 ha. Annually 17.83% built up area have been increased in this region which is much higher than the growth rate of the northern, South-Eastern and the growth rate of the whole landscape which has found most growth rate region in the metropolitan area.

Table 4. 9: Temporal dynamic of built up area in west region based on class area (CA) metric

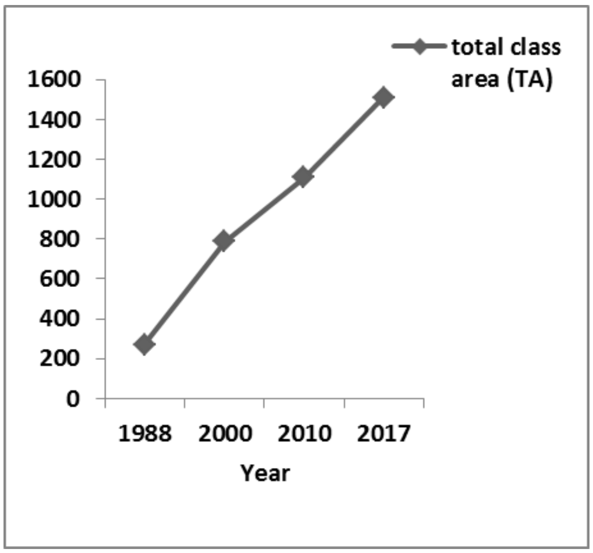
Study period	Change (ha)	Change (%)	Time span	Growth rate	average
1988-2000	518.85	34.17	12	2.85%	
2000-2010	319.6	71.15	10	7.11%	6.81%
2010-2017	402.63	73.34	7	10.48%	

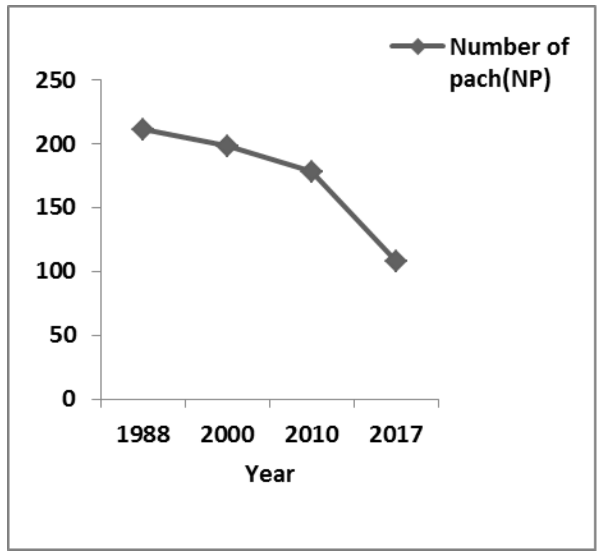
The intensive urban development process in this region is also manifested by the number of patches (NP). The number of patches consistently decreased from 211 in 1988 to 111 in 2017 that demonstrating the merging of urban patches into homogeneous urban fabric. The situation is also reflected by the gradual decline of patch density (DP) 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 Adama. The result of area weighted mean patch fractal dimension (FRAC_AM) metrics show similar trend for this region (table 4.14). It Indicates decreasing trend between 2010 and 2017 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.

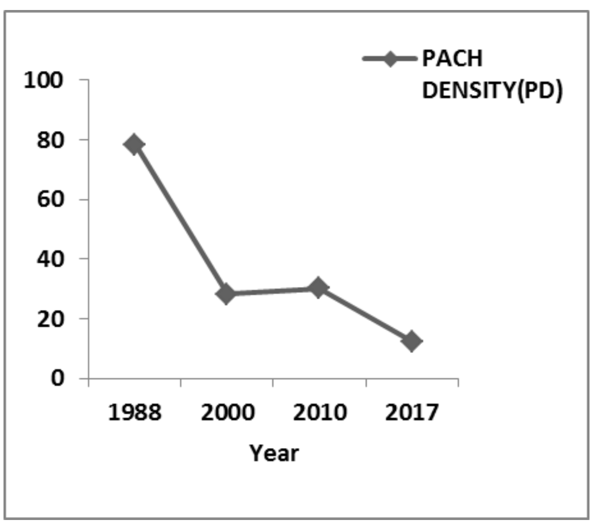
Table 4. 10: Result of spatial metric computation (CBD and West)

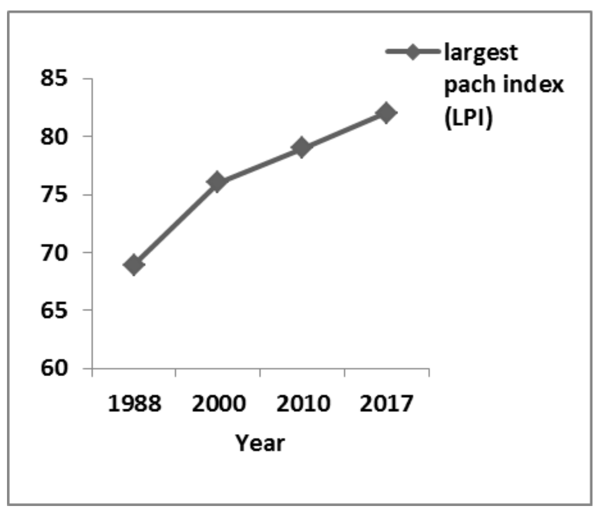
year	CA	NP	PD	LPI	FRAC_AM
1988	269.37	211	78.3309	68.8941	1.1928
2000	788.22	198	28.2916	76	1.2338
2010	1107.82	178	30.0734	79	1.2755
2017	1510.45	108	12.3967	82	1.2212

If the infilling development process continues in the future than no doubt that CBD and western region (Adis Abeba 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.









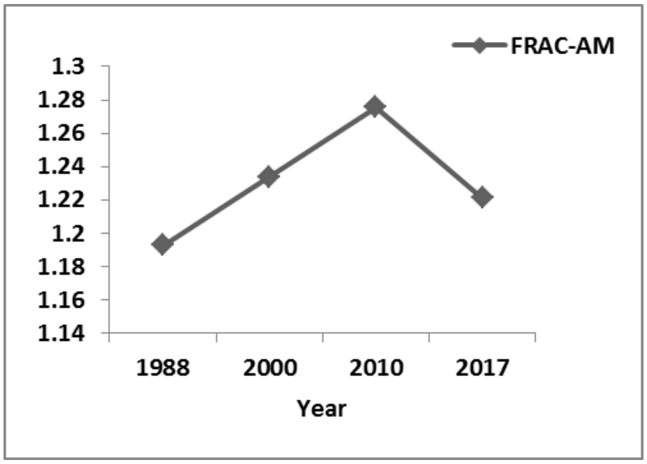
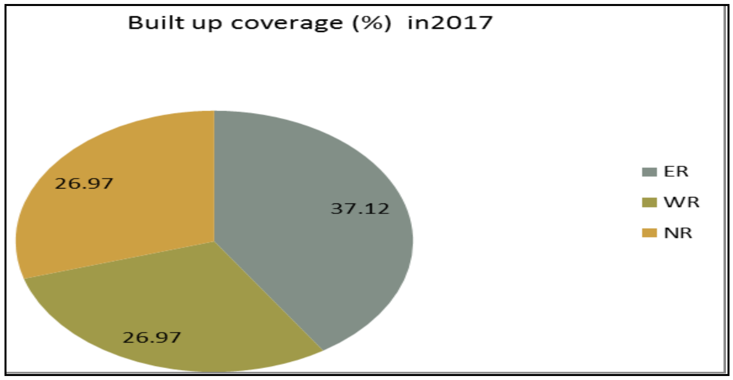


Figure 4. 7: Class level metric computed for CBD &West region

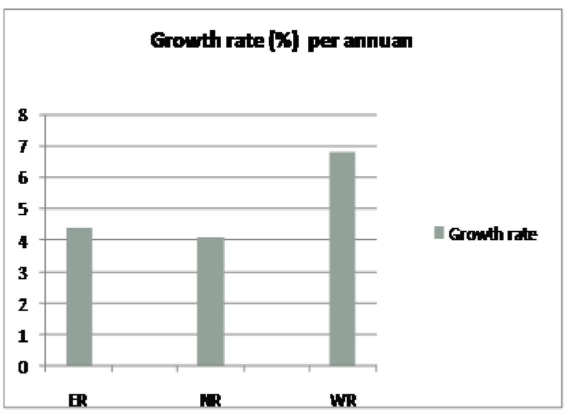
4.5.4 Intra Urban Comparison (1988-2017)

Based on class area metrics, south- east region (Asela road direction) is the most urbanize region in the metropolitan area in all study periods. In 2017, this region constituted more than 37.1284% of the total built-up land in the study area (figure 4.6). In terms of absolute growth rate (ha) the north region is growing with 49.94 ha per year, CBD - Western region is growing with 42.79ha each year and South- Eastern region growing with 68.79 per year. This is reasonable since central adama is the heart of the city (CBD) and the city as whole, where different socio-economic, commercial and administrative activities are accommodated. The South-East region is also noticed as the most dynamic urban expansion and Northern region is relatively less urbanized regions. However, in terms of average growth rate (%) the south - East region north region and central and west region were the fastest growing regions in a decreasing order. As it can be observed from the bar chart of the CBD, western region is growing with an average growth rate which is higher than the average growth rate of the study area as whole. The number of patches (NP) appeared highest for the northern region and Eastern region and lowest for CBD - western region the in all periods of urbanization. It is indicating that the Northern region and South-Eastern region have been dispersed and highly fragmented development pattern, whereas CBD - western region was continuous urban fabric is found.

(A)



(B) (C)



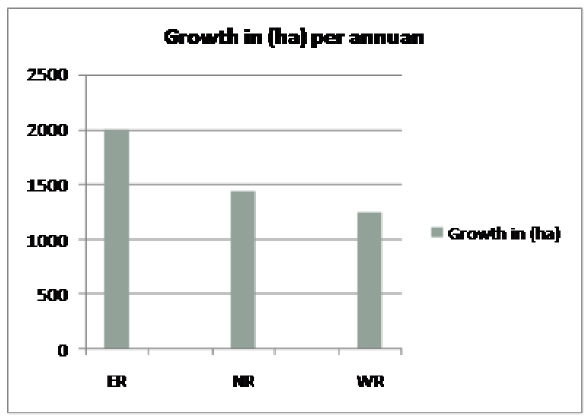


Figure 4. 8: Each region of total built up area (a), (b) absolute urban growth rate (%) annually (1988_2017) and (c) relative urban growth rate (%) per annual (1988-2017).

Note: ER-East Region, WR-West Region & NR- North Region

4.6 Results of Logistic Regression Modeling

4.6.1 Variables used in the Model

The main purpose of logistic regression model in this study was to understand and statistically quantify the relation between urban growth and its drivers. In this model urban growth was considered as a dichotomous dependent variable to be explained as a function of seven predictor variables listed in table (4.11) 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 was from 0--->1.However; the seven predictor variables included in this model were continuous in nature.

The logistic regression analysis was conducted for three different time periods of 1988-2000, 2000-2010 & 2010-2017. The number of predictor variables used for all study periods were the same however; the information content was slightly different for few variable. For instance the proportion of built up land or cell was different for all study periods, whereas since the location of adama university was never changed from the very beginning. For further information refer to (3.6.3) section of this research. List of all variables included in the regression model are summarized in table (4.11) below.

Table 4. 11: List of variable used in logistic regression model

variable	meaning	Nature of data	shape
dependent			
Y	**Land cover map of 1988,2000,2010 & 2017**	**Discrete**	**polygon**
Independent			
Dist-CBD	**Distance to CBD**	**Continues**	**point**
Slope	**Slope**	**Continues**	**line**
Dist-Mjrd	**Distance to major road**	**Continues**	**line**
Dist-Scc	**Distance to sub city center**	**Continues**	**point**
Dist-St	**Distance to satellite town**	**Continues**	**point**
P-urban	**Proportion of urban land with 7x7 cell size**	**Continues**	**polygon**

Dist-Au	**Distance to Adama university**	**Continues**	**point**

4.6.2 Multicollinearity Analysis

To exclude redundant variables from the model and maintain the stability of coefficients, multicollinearity diagnostic has been conducted for each set of variables used in different time periods. The analysis was carried out in SPSS 21 statistical software package by regressing one of the independent variable against the remaining six variables in an iterative way. In this Manner each variable was 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 were measure different aspects of the dependent variable being modeled. The results of multicollinearity analysis for all study periods are summarized below

Table 4.12

Table 4. 12: Result of Multicollinearity Analysis

variable	**description**	**VIF (1988-2000)**	**VIF (2000-2010)**	**VIF (2010-2017)**
Dist-CBD	**Distance to CBD**	**3.031**	**3.076**	**3.171**
Slope	**Slope %**	**4.072**	**4.180**	**4.228**
Dist-Mjrd	**Distance to major road**	**2.920**	**3.008**	**3.322**
Dist-Scc	**Distance to sub city center**	**2.700**	**2.750**	**2.815**
Dist-St	**Distance to satellite town**	**3.270**	**3.540**	**3.611**

P-urban	**Proportion of urban land**	**4.621**	**4.631**	**4.383**
Dist-Au	**Distance to adama university**	**2.785**	**2.850**	**2.996**

4.6.3 Model Results

Urban Growth Model Results of 1988-2000 periods

Model summary: Log Likelihood = -41752.4136, PCP =98.42%, Total sample size = 55465, Overall Model Fit: Chi Square = 76422.7016 With DF=21 and P-Value=0.0000, 95% Confidence Intervals Estimated coefficients and odds ratios for the logistic regression model of 1989-1995 Constant = -2.6091 Variables with * sign are significant at α=0.05Variables with **sign are significant at α=0.1

Table 4. 13: Estimated coefficient and odd ratio for the logistic regression model of (1988-2000)

Variable	Coefficient	Std_ error	Z_ value	T_ Test (P)	Odds_ Ratio
Dist_CBD	-2.271015	0.44471	-5.11798	0.0000*	0.102693
Slope	0.643645	0.381893	1.711594	0.0870**	1.882545,
Dist_Mjrd	-9.296712	0.951923	-9.76624	0.0000*	0.000092
Dist_Scc	-5.264417	0.604664	-8.706345	0..0000*	0.005172
Dist_St	-0.080518	0.492371	-0.16353	0.8701	0.922639
P_urban	4.208638	.23345	22.097435	0.0000*	172.547465
Dist_Au	1.04521	0.370743	2.819233	0.0048*	1.0854

Table 4.13 presented above summarizes the regression results of 1988-2000 urban growth models. The results were 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 Adama university (Dist_Au) distance to major roads (Dist_Mjrd) and distance to sub city centers (Dist_Scc) are significant at α=0.05 and the variable Slope was found to be significant at α=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, slope and Dist_AU were positively correlated with urban growth. The remaining three variables: Dist_CBD, Dist_Mjrd and Dist_Scc were negatively correlated with urban growth. That means higher the distance from these variables the lower 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 modeling 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), Slope and distance to Adama university (Dist_AU) 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 Results of 2000-2010 periods

Model summary: Log Likelihood = -41125.1154, PCP=96.27%, Total sample size=62531 with an overall Model Fit: Chi Square = 69815.7459 With DF = 21and P-Value = 0.0000, 95% Confidence Intervals.

Table 4. 14: Estimated coefficient and odd ratio for the logistic regression model of (2000-2010)

Variable	Coefficient	Std_ error	Z_ value	T_ Test (P)	Odds_ Ratio
Dist_CBD	**0.217434**	**0.271437**	**0.801048**	**0.0000***	**1.242883**
Slope	**3.45352**	**0.239342**	**12.674363**	**0.0000***	**19.750020**

Dist_Mjrd	**-5.751076**	**0.580022**	**-9.915275**	**0.0000***	**0.003179**
Dist_Scc	**-8.295676**	**0.376278**	**-22.046667**	**0.0000***	**0.00025**
Dist_St	**-2.162361**	**0.346399**	**-6.242397**	**0.4231**	**0.115053**
P_urban	**5.747832**	**0.193304**	**35.166554**	**0.0000***	**901.914252**
Dist_Au	**2.452809**	**0.233547**	**10.502402**	**0.0000***	**2.983978**

Estimated coefficients and odds ratios for the logistic regression model of 2000-2010 Constant = -3.2510 Variables with * sign are significant at α=0.05.The result of the regression modeling witnessed that all variables except distance to satellite towns (Dist_St) are found to be statistically Significant at α=0.05. Interestingly, in similar fashion to the 1988-2000 models; proportion of urban land (P_Urban), Slope and distance to adama university (Dist_AU) are observed positively correlated with urban growth. The other three variables: distance to major roads (Dist_Mjrd), distance to sub city centers (Dist_Scc) and distance to (CBD) are negatively related to urban growth. However, distance from satellite towns (Dist_St) 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, distance to adama university (Dist_AU) and distance from CBD had an odds ratio > 1 which indicating the presence of these variables the probability of urban growth is high.

Urban Growth Model Results of 2010-2017 periods

Model summary: Log Likelihood = -3.425, PCP=94.98%, Total sampling size= 66785, Overall Model Fit: Chi Square = 61892.8157 With DF = 21 and P-Value = 0.0000, 95% Confidence Intervals.

Table 4. 15: Estimated coefficient and odd ratio for the logistic regression model of (2010-2017)

variable	Coefficient	Std_ error	Z_ value	T_ Test (P)	Odds_ Ratio
Dist_CBD	**-1.939788**	**0.232614**	**-8.339098**	**0.3345**	**0.143734**
Slope	**0.817092**	**0.216624**	**4.233571**	**0.0000***	**2.654004**
Dist_Mjrd	**-2.891817**	**0.435104**	**-6.646264**	**0.0000***	**0.055475**
Dist_Scc	**-2.676289**	**.282257**	**-9.481762**	**0.0000***	**0.068818**
Dist_St	**-3.4041**	**0.309865**	**-10.985753**	**0.0000***	**0.033237**
P_urban	**5.245207**	**0.139777**	**39.67181**	**0.0000***	**249.116644**
Dist_Au	**-0.178101**	**0.184528**	**-0.965171**	**0.0000***	**10.980989**

The results of the 2010-2017 regression modeling revealed that all predictors except distance to Dist_CBD 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 form 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 4.208638, 5.747832 and 5.245207 and odds ratio of 172.547465, 901.914252 and 249.116644 for the study periods 1988-2000, 2000-2010 and 2010-2017respectively.The odds ratios can be Interpreted as the probability of urban growth will increase 172.547465, 901.914252 and 249.116644 with an increase of one urban cell is in the neighborhood for the periods 1988-2000, 2000-2010 and 2010-2017respectively 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 were 0.643645, 3.45352 & 0.817092 and 1.882545, 19.750020 & 2.654004 for the study periods1988- 2000, 2000-2010 and 2010-2017

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 1.882545 times, 19.750020 times & 2.654004 times as large as the probability of change in an area one percent less in slope. This could be attributed to the rift valley topographic nature of Adama, where settlement is on lower slope or close to wetlands is un favorable due to the presence flood hazards and epidemic diseases like mosquito. Thus, steeper slopes were more preferred for settlement than low laying Areas. However; the level of significance of slope during the period 1988-2000 has been at $\alpha=0.1$ having p-value 0.087 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 1988-2000 & 2000-2010 with significance level $\alpha=0.05$. However; it has been totally insignificant during the period 2010-2017 The estimated coefficients and odds ratios of Dist_CBD are -2.276015 & -1.939788, and 0.102693 (1/9.737762) & 0.143734 (1/6.957296) for the periods 1988-2000 & 2000-2010 respectively. The probability of urban growth in an area is estimated as 9.737762 times and 6.957296 as large as the probability of urban development in an area one unit further away from the nearest urban area for 1988-2000 & 2000-2010 study periods respectively. For both periods distance to CB (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 2010 study periods. Proximity to CBD can provide 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. Adama University is one of the variables that have been significantly correlated with urban growth in the study area particularly during 2000-2010 & 2010-2017 study periods. However, it had no more significant contribution for urban growth during the first period urbanization (1988-2000). In contrast to distance to CBD distance to Adama university (Dist_AU) is positively correlated with urban growth at significance level of α=0.05 for the two study periods (2000-2010 & 2010-2017). The estimated odds ratios are 2.983978 and 10.980989 for the two periods respectively which means that the odds of urban growth in area one unit farther away from Adama University is estimated as 2.983978 times and 10.980989 times as large as that in area closer to the university the closer a cell is to Adama University the less likely it is to be urbanized. This could be attributed to unbalanced urban growth distribution revealed by spatial metrics analysis. In other words, since most of the growths were taking place closer to major roads, sub-city centers and where high proportion of built up cell is found, more developments were happening around the urban core compared to Adama University.

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 0.000092 (1/10869.5652), 0.003179 (1/314.5643) & 0.055475 (1/18.026138) for the study periods 1988-2000, 2000-2010 and 2010-2017 respectively. The likelihood of urban growth in an area closer to major roads is estimated as 547.5654 times, 320.5645 times and 120.026147 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 goods and people in urban areas and thus, influencing the spatial pattern of urban growth. The variable distance to economically active sub city centers (Dist_Scc) has been affecting urban growth throughout the study periods with a significance level of 0.05. This variable (Dist_Scc) is also negatively related with urban growth in all study periods demonstrating the closer to sub-city centers the higher is the probability of urban growth to occur. The odds ratio for distance to sub city centers is 0.005172 (1/193.3488), 0.00025 (1/4000) and 0.068818 (1/14.531081) for the study periods 1988-2000, 2000-2010 and 2010-2017 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 sub city centers is estimated as 193.3488 times, 4000 times and 14.531081 times as large as that in an area one unit further away from sub city centers for 1988-

2000,2000-2010 and 2010-2017 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 2010-2017)at α=0.05. However, it had no significance during the period of 1988-2000.The coefficient and odds ratio of distance to satellite towns (Dist_St) is-2.162361 & -3.4041 and 0.115053 (1/8.691646) & 0.033237 (1/30.086951) for the periods 1995-2003 and 200-2010 respectively. This shows that the probability of urban development to occur in an area close proximity to satellite towns is as 8.691646 times and 30.086951times as large as that in area one unit farther away from satellite towns for the study periods 2000-2010 and 2010-2017 respectively.

4.6.5 Model Evaluation

Model evaluation was an important step in logistic regression modeling. 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 was 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. 1988-2000, 2000-2010 & 2010-2017 was 98.45%, 96.51% & 95.27% respectively, which was very good prediction power. The outputs of model evaluation analysis were presented below.

Table 4. 16: **Result of regression model evaluation (1988-2017)**

1988-2000

	Predicted			
		0	**1**	**Total**
Observed	**0**	**2789110**	**5986**	**2795096**
	1	**39080**	**79321**	**118401**
	Total	**2828190**	**85307**	**2913497**

Correct prediction: 2868431

Wrong prediction: 45066

Percentage of correct prediction (PCP): 98.45%

2000-2010

	predicted			
		0	**1**	**Total**
Observed	**0**	**2659318**	**18799**	**2678117**
	1	**82766**	**152614**	**235380**
	Total	**2742084**	**171413**	**2913497**

Correct prediction: 2811932

Wrong prediction: 101565

Percentage of correct prediction (PCP): 96.51%

2010-2017

	Predicted			
		0	**1**	**Total**
Observed	**0**	**2507443**	**21132**	**2528575**
	1	**116768**	**268154**	**384922**
	Total	**2624211**	**289286**	**2913497**

Correct prediction: 2775597

Wrong prediction: 137900

Percentage of correct prediction (PCP): 95.27%

4.6.6 Physical Driving Forces of Adama City Urban Growth

Understanding the complex 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 (Fragkias & Seto, 2007).Thus logistic regression urban growth modeling is an ideal approach to look at significant drivers of urban growth over time, particularly for developing countries like Ethiopia . Different literatures has 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; Huang et al., 2009). In this study three spatially explicit binary logistic regression models has been developed for 1988-2000, 2000-2010 and 2010-2017 study periods.

The main purpose of the models is to identify 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 or the past 29 years. Among the variables included in the 1988-2000 model, distance to major roads (Dist_mjrd) (-ve), distance to sub city centers(Dist_Scc) (-ve),proportion of built up cell (P_Urban) (+ve), distance to CBD (Dist_CBD) is positive, distance to Adama university (Dist_AU) (+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

Variable 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 sub city centers (Dist_Scc) (-ve), proportion of built up cell (P_Urban) (+ve), distance to major roads (Dist_mjrd) (-ve), Slope (+ve), distance to Adama university (Dist_AU) (+ve) and Distance from CBD (Dist_CBD) (+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 1988-2000 models. However, in this model it is not any more significant. Following the rapid urban growth witnessed during 2000-2010 the city 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 sub-city centers (Dist_Scc) and proportion of built up cell (P_Urban) were the second and third influential variables in the 1988-2000 model. However these 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 from CBD (Dist_CBD) (+ve), distance to major roads (Dist_mjrd) (-ve), distance to sub city centers (Dist_Scc) (-ve), distance to CBD (Dist_CBD) (-ve) and Slope (+ve) were significant drivers of urban growth in 2000-2010 study period in a decreasing sequence of importance with their designated sign of correlation with urban growth. Distance from satellite town appeared insignificant in this model. However, distance to CBD becomes important variable in this model. This means most of the new growth tends to occur at the periphery of the city 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 2000-2010 periods. Despite the introduction of the northern bypass in the third model, the major road (Dist_Mjrd) remains in the third place in this model. However, following the gradual expansion of the city, satellite towns become increasingly importance due to their proximity to the main city. Slope has been attracting development in all study periods. This is due to the fact that adama were built on rift valley 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 and uses may prefer relatively steeper slope for development pursuing safety and good view. However, it should be noted that slope may not necessarily attract development. For instance, given the rift valley topography of adama it can be assumed that relatively flat lands or foot slopes according to Vermeiren et al (2012), which are suitable for development are already accompanied during the earlier period of urbanization. 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).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 1988. 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 sub-city centers. Then sub-city centers are created at the junction or nodes of roads. These sub-city centers eventually start to attract urban development around them. Gradually, when the availability of developable land in close proximity to CBD, major roads and sub-city 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 city 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 (1988-2000) could be driven by the major roads and economically active sub-city 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-city centers.

The proportion of built up cell and distance to CBD were also fair that attracts urban growth during 1988-2000. During 2000-2010, the number of patches increased substantially and therefore the city experienced rapid urban growth.The result of logistic regression analysis confirms that those growths were mostly driven by sub-city centers and existing built up areas. This is reasonable as the probability of finding developable land close to CBD and major roads are less. The locally distributed sub-city centers (Dist_Scc) 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 sub-city centers and high proportion built up areas.

The variable slope confirms that following the rapid urban growth observed during 2000-2010 developments were taking place in relatively higher slope areas. The insignificance of distance to CBD during (2010-2017) 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. Interestingly, during 2010-2017 due to the lack developable land in close proximity to major roads and sub-city centers. 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 city 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 2010-2017 indicating that some infill development or redevelopments has been taking place in the city centre. 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 (table 4.17).

Table 4. 17: Major driving force of urban growth in 1988-2000, 2000-2010 & 2010-2017 study period

Study period	Order of significance	Major driving force	Correlation with urban growth
		Distance to major road	Negative
1988-2000	1^{st}	Distance to sub city center	Negative
	2^{nd}		
	3^{rd}	Proportion of built up cell	Positive
	4^{th}	Distance to CBD	Negative
Study period	Order of significance	Major driving force	Correlation with urban growth
2000-2010	1st	Distance to sub city center	Negative
	2nd	Proportion of built up cell	Positive
	3^{rd}	Distance to major road	Negative
	4th	Slope	Positive
2010-2017	1st	Proportion of built up cell	Positive
		Distance to satellite town	
	2nd	Distance to major road	Negative
	3rd	Distance to sub city center	Negative
	4th		Negative

Centers (Dist_Scc) and proportion of built up cell (P_Urban) remains among the top four driving forces of urban growth in all study periods with varying order of significance. Generally, three variables: distance to major roads (Dist_Mjrd), distance to sub city _CBD, Slope and distance to satellite town (Dist_St) were among the top four drivers of urban growth throughout the period.Unfortunately, distance to Adama university (Dist_AU), which was included in the models based on the suggestion of local experts, was not among the top four driving forces of urban growth in during 1988-2000 and 2000-2010 it was not found attracting growth or it has been pushing development away and during 2000-2010 and 2010-2017 it becomes significant.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Adama city has been undergoing extensive land cover change. The classification of multi-temporal satellite images of four different time periods, 1988, 2000, 2010 & 2017 in to built-up, non-built up and bare 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 no-built up areas in all directions mainly in the west, east and north direction alongside major transportation corridors. The analysis of spatio-temporal land cover change revealed that urbanization has significantly transformed the urban landscape of Adama city. The built up area in the city has grown from 415.44 ha in 1988 to 5599.62 ha in 2017 at an average growth rate of 2.36%, 5.96% 6.27% annually during 1988-2000, 2000-2010 and 2010-2017 study periods respectively. Totally 5184.18 ha of land have been transformed to urban area.

Analyzing the spatial extent and rate of urban growth and identifying the growth direction alone does not give sufficient insight into the patterns of urban development processes, which are important to better understand urban pattern. To bridge this gap, spatial metrics are used in this study. Five spatial metrics namely: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), area weighted mean patch fractal dimension (AWMPFD)were used to evaluate the urban growth patterns and processes of Adama city at class and landscape level. These metrics were selected based on literature so as to measure different aspects of the landscapes such as configuration, area, shape, etc.

The selected five metrics are used to describe urban development patterns in each region at both class and landscape level. The analysis and comparison of class area (CA) metrics revealed WR, ER and highly urbanized regions in the study area in a diminishing order. In 2017, East and the CBD-western region together accounted for more than 64.10 % of the total built up land in the study area in the same year. However; in terms of average annual growth rate (%) north, East, and CBD-West were the first three rapidly urbanizing regions in the study area with a growth rate of 4.09%, 4.04%, and 17.83% respectively. All models are subjected to multicollinearity analysis and found to yield VIF <10. The results of model evaluation about PCP shows 98.45%, 96.51% and 95.27% accuracy for the period 1988-2000, 2000-2010 & 2010-2017 respectively that indicates the high predicting capacities of the models. The result of model 1988-2000 shows that distance to major roads (-ve), distance to sub city 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 sub city centers (-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 is distance to sub city centers (-ve) were found to be the top four drivers of urban growth during 2010-2017 study period with their indicated sign of correlation with urban growth. The importance of proportion of built up cell, distance to sub-city centers 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. If not policy measures are taken these factors will continue to play vital role in expanding the city in a disorganized way. 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.

The city has experienced fragmented urban growth process particularly at the fringe areas with substantial built-up increase while the city center underwent relatively compact growth by infilling open spaces and through edge expansion over time. Based on number of patches, the region based analysis revealed different parts of the city have experienced different pattern of development. Therefore if the expansion would increase with the same growth rate so there will be no open spaces in the city for other purposes and in future this rapid urbanization may bring problems for the community. This kind of continuous monitoring of urban growth are very important to quantify the changes in land cover and concern bodies must implement such polices to restrict it and make the cities smarter with proper planning.

5.2 Recommendation

Finally 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 city like Adama. 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 effectives 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 images used in this study, particularly, the accuracy of Landsat ETM+ 2000 image or perhaps use images from the same sensor, for instance all images from Landsat-M.Ths. could help solving the problem of image consistency. Owing to the spatial extent of the metropolitan 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 (system). 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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