Multi-Temporal Morphological Analysis of Urban Area: A case of Adama Town

By

Demelash Ayalew

A Thesis Submitted to

The department of Geomatics Engineering

School of civil Engineering and Architecture

Presented in Partial fulfillment for the Degree of Master's in Geo-Informatics

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

November, 2020

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CANDIDATE'S DECLARATION

I, Demelash Ayalew W/Tsadik 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 properly acknowledged.

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This MSc Thesis has been submitted for examination with our approval as thesis advisor/co-advisor.

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Date of submission: ____________

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ADVISOR’S APPROVAL SHEET

To: Geomatics Engineering Department

Subject: Thesis submission

This is to certify that the thesis entitled ”Multi-Temporal Morphological Analysis of Urban Area: A case of Adama Town” Submitted in partial fulfillment of the requirements for the degree of master’s in Geo-informatics, the graduate program of the department of Geomatics Engineering, and has been carried out by Demelash Ayalew W/Tsadik ID.NO PGR/18148/11,under our supervision. Therefore, we recommend that the student has fulfilled the requirements and hence here by he can submit the thesis to the department.

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Name of Major Advisor	Signature	Date
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BOARD OF EXAMINERS APPROVAL SHEET

We, the undersigned, members of the Board of Examiners of the final open defense Demelash Ayalew W/Tsadik have read and evaluated his thesis entitled: Multi-temporal Morphological Analysis of urban area: a case of Adama Town and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Master of Science in Geoinformatics.

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Demelash Ayalew

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LIST OF ACRONYMS

ASTU	Adama Science and Technology University
CAD	Computer-Aided Design
EMA	Ethiopia Map Agency
GPS	Global Positioning System
TM	Thematic Mapper
ETM+	Enhanced Thematic Mapper plus
OLI	Operational Land Imager
GCP	Ground Control Point
GIS	Geography Information System
TIFF	Tagged Image File Format
LULC	Land Use Land Cover
RS	Remote Sensing
UN	United Nation
MLC	Maximum Likelihood Classification
CBD	Central Business District
AHP	Analytical Hierarchy Process
CSA	Central Statistical Agency

ABSTRACT

The spatial configuration and dynamics of urban growth are important topics of analysis in the contemporary urban studies. Adama Town is undergoing rapid changes and need to be study the urban morphological analysis of the town. This research focuses on analyzing the spatial pattern, driving forces of built-up expansion and identifies different urban growth types in Adama Town during 2000-2019. To analyze the spatial patterns of built-up expansion area and the selected explanatory factors, remote sensing and GIS tools are utilized. Built-up and non-built up land cover classes as of 2000, 2010, and 2019 are extracted from Landsat images. The extent of expansion during the study period is quantified; the growth pattern is analyzed using selected factors and identified the growth types. The Spatial regression model was used to identify the major factors that significantly contributed to the resulted growth pattern over the last 19 years. The findings revealed that the average annual built-up expansion in the first temporal periods (2000-2010) is 243ha and 107ha in the second temporal period (2010-2019). Moreover, the results of spatial regression model revealed that distance to road, Slope, distance to Institutions, distance to CBD, and distance to Industry area were the major driving forces of urban growth at different temporal periods with varying level of strength. Identifying the three urban growth types confirmed that edge-expansion was the dominant growth type followed by outlaying and infill growth type on both temporal periods. Overall, this study shows a better understanding of urban growth and its major driving forces responsible for resulted morphology of the town, and helps to provide an effective way for urban planning.

Keywords: Morphological Analysis, urban growth, spatial regression model, Adama, GIS, Remote sensing

CHAPTER I. INTRODUCTION

1.1 Background of the Study

Urbanization is among the most significant process that has shaped land use activities and has to drown a great deal of attention throughout the world. It is estimated that urban population will rise from 3.57 billion in 2010 to 6.34 billion in 2050 where almost 70% of the world's population is expected to live in the cities (United Nation, 2014).This immense figure is mainly due to migration from rural to urban in search of a better quality of life generated by urban activities and services. However, an increase of urban population has forced cities to expand vertically or horizontally encroaching into agricultural land and natural boundaries and changing land use/cover without us realizing it (Su.et al.2011). Rapid urbanization, especially in developing countries is continuing to be one of the crucial issues affecting the physical dimension of cities. Urban expansion in the developing world often takes places in an unplanned manner and administration are unable to keep track of growth related process (Griffiths.et al.2009).That has entailed several problems derived from the generated urban patterns. The spatial configuration and dynamics of urban growth are important topics of analysis in the contemporary urban studies (Bhatta B.2012).Fast population growth coupled with economic development resulted in rapid urban physical growth. Consequently, unless managed well it can often lead to a series of negative environmental and socioeconomic issue. In the future, understanding the process and driving factors is critical to put forward appropriate policies and monitoring mechanism on urban growth.

Like any other cities in the developing world, Adama Town has been gradually expanding both physically and in terms of its population. It has been the locus of economic activity and transportation nodes in Ethiopia. Urban areas are dominated by built-up lands with impervious surfaces (Xu et al., 2000). Since the expansion of urbanized areas results in the encroachment of surrounding valuable natural lands, the conversion of natural lands in to impervious built-up area may have significant impacts on the ecosystem, hydrologic system and biodiversity in the area (Xu, 2007). The study of urban spatial expansion always needs accurate, quick and timely information on urban/built-up areas in the form of size, shape, and spatial context for urban land use planners and decision makers. The information on pattern and extent of built-up area expansion in the past few decades even becomes more important for the various decision making process in terms of resource and utility allocation and distribution to attain urban land use sustainability. Time-series satellite remote sensing data with different spatial and spectral resolutions have been found very promising to meet these requirements and have been used in several built-up area mapping and urban studies (Batty and Howes, 2001)

The influx of people into urban influences the form, structure and morphology of cities. Urban form is the physical layout and design of the city taking into consideration density, street layout, transportation and employment area and other urban design issues while urban structure describes the arrangement of land use their access and connectivity in urban areas. Urban morphology however is an approach to studying and designing urban form which considers both the physical and spatial components of the urban structure of plots, blocks, streets, buildings and open spaces. All of which are regarded as part of the history of the evolutionary process of the development of the particular part of the city under consideration (Bentley, I & Butina, G.1990). urban morphology is Primarily a spatial construct inseparably related to development pattern and human activity (Nedovic-Budic et al., 2016).It can affect the quality of urban life and pleasantness to live, if it is not guided by well-planned (Lai et al., 2018).Besides the patterns of urban areas, identifying and examining the process of its development and its subsequent alterations have become a focus of urban studies (McCartney & Krishnamurthy 2018). The dynamism of the existing trend of in urban forms, every city is unique and factors contributing to its pattern are specific to local conditions such as social, political, economic, and physical characteristics. To understand how a city grows and develops one also need to understand what some of the possible causes of the unstructured growth practices seen in developing countries. This study will examine some of the main factors that cause growth and development in the town of Adama. There are several factors that cause urban growth such as socioeconomic factors, biophysical constraints and potentials, neighborhood characteristics, and institutional factors in the form of spatial polices (Verburg et al.2004).

Therefore, to understand the spatial and temporal dynamics of these processes, the factors that are the triggering cause of urban growth must be identified and analyzed (Aguayo et al. 2007). Spatial regression is an empirical estimation model in which statistical techniques are used to model the relationship between land use/land cover changes and the drivers based on historical data (Zeng et al. 2008). Spatial regression is also widely used to develop the probability maps of land use change in urban areas considering only the effects of individual factors; such as roads or slope (Schot et al.2004). One of the main advantages of this model is to determine weights for driving factors based on empirical data rather than using expert knowledge (Hoymann.2010).

1.2 Statement of the Problem

In the 21^{st} century, rapid urbanization and urban growth have been one of the crucial issues of global change that affect the physical dimension of cities. Due to rapid urbanization cities underwent a process of urban growth that has continued until nowadays (Berling-wolff et al.2004). This process has generated several problems derived from the generated urban patterns (chin, N., 2002). Such as agriculture land loss, fragmentation of natural resources, environmental pollution, residential crowding and traffic congestion. Urban growth is complex processes that can be influenced by various factors and suggest the importance of identification of the factors associated with the existing form of the city.

The factors influencing growth and the characteristics of each city may vary depending on the geographical location of the city and its socioeconomic context, it remains that common features, growth process and regularities are persistently found. A renewed understanding of the nature of cities is key in advancing appropriate tools and methods of analysis that take into consideration the multiplicity of the physical and social aspects of a city as well as the elements and actors that play a role in their transformation. Such tools are needed to ensure that contemporary cities are equipped with the ability to understand the possible impacts of rapid or simultaneous changes and developments (Macartnay s., Krishnamurthy s., 2018).

Ethiopia has been experiencing a rapid urbanization process since the implementation of economic development and privatization policy (Kassahun, s. & Tiwari, A., 2014) to stimulate national economic growth. However, as it is observed in numerous developing countries, the intensified constraints following the fast urbanization process in the country are unplanned and uncontrolled that resulting in scattered urban growth, loss of farm land and environmental degradation. Besides, the urban physical growth rate has been faster than the rise in infrastructures and service delivery in Ethiopia cities (MUDHCo, 2014).

Adama is one of the fast growing town in Ethiopia, and entering a new stage of transformation with a large industrialization and rapid urbanization. But many developments have occurred outside of proposed growth area and a majority of uncontrolled urban development or open space encroachments have occurred at the western and eastern part of the town following the main road from Addis Ababa –Djibouti. In addition, findings revealed that the growth rate of built-up lands exceeds significantly that of a population which demonstrates a massive urban land growth and an inefficient use of land resources in Adama Town (Bulti & Sori, 2017). Excessive alteration of land use has been occurring in the town (Sinha et al.2016).The physical expansion of the town with the fast growing population does not appear to match infrastructural development in the town (Yhdego,S.,2007). All these studies only investigated the dynamics of urban areas without give due consideration of growth framework that limits the urban growth direction but the current study fills this gap by considering the urban growth morphological aspect by identify major influential factors related to the existing form of the town and identify the urban growth types occurred during the study period. Because a better understanding of those factors that are influence the town growth and growth types is needed for a sustainable future development in Adama town and achieving a desired information for local and regional land use planners and policy makers in order to establish the necessary decision and polices. Therefore, to analyze the built-up expansion change in urban structure/morphology and its main driver using spatial regression analysis model will be applied in the GIS environment.

1.3 Objectives

The general objective of this study is; to evaluate the morphology of urban spatial growth of Adama Town from different urban spatial growth models point of views.

The specific objectives of this study are to conduct:

1. Urban land use land cover change analysis of Adama Town from 2000 to 2019.
2. Spatial regression analysis for the determination of influential growth factors on urban morphology.
3. Correlation analysis between the actual urban growth and the spatial urban growth models.

1.4 Research Questions

This study will answer the following research question corresponding to the problem of statement.

1. What are the spatial and temporal patterns of built-up land expansion in Adama Town from 2000 to 2019?
2. Which factors highly influence the growth morphology of Adama Town?

3. Which urban spatial growth model fits the actual spatial growth of Adama Town?

1.5 Significance of the Study

The result of this study will benefit three different groups:

- Individual researchers, urban planners, and decision makers considering the significant factors that are governing the city morphology for further analysis on different urban modeling and also use the result as reference for teaching learning process.
- Government: the result of this study also helps the city administrator and urban planning institute for decision making in order to protect disorder development of the city and maintain sustainable development.
- Society: society will be benefit from this study result if the government takes appropriate action to maintain the quality of urban life and pleasantness to live.

1.6 Scope of the Study

The geographic scope of this study is Adama Town. It stretches between $8^0$26'15"to $8^0$37'00" North latitude and $39^0$11'57" to $39^0$21'15" East longitude and covers an area of 313.042km^2. The conceptual scope of the study is focused on two issues. These are analysis of urban growth morphology controlling factors and identification of spatial urban growth model for Adama town.

1.7 Organization of the Thesis

The thesis consists of five chapters in which the first chapter deals with the introduction to the research and mainly address the problem statement, research objective, research question significance of the study and scope of the study. The second chapter contains a review of related literatures in the concept of urbanization and land cover change, urban growth type, spatial regression analysis, empirical literature and conceptual framework is review. In chapter three the data and methodology used in this study including description of the study area, methods of data collection and data source, software used, and methods of data analysis is briefly discussed. Chapter four presents the results of data analysis, interpretation and discussion. In the last, chapter five focuses on conclusion and recommendation.

CHAPTER II. LITERATURE REVIEW

2.1 Introduction

Urban growth is complex processes that can be influenced by various factors and suggest the importance of identification of the factors associated with the existing form of the city. The word 'form' has different meanings, such as shape, configuration, structure, pattern, organization, and system of relations. In terms of the study of cities, form will represent the spatial growth pattern of elements composing the city in terms of its networks, buildings, spaces, defined through its geometry mainly, but not exclusively, in two rather than three dimension .Yet form can never merely be conceived in terms of these local properties but has a broader significance, a more global significance in the way cities grow and change (Batty and Longley, 1994).

2.2 Theoretical Literature Review

The rapid urban growth in major cities poses enormous opportunities and challenges for the future sustainable development of a country .For instance, large cities are expected to be centers of innovation and wealth creation and need more resilient infrastructures and services resources as compared to smaller towns (Zhang et al., 2013).This development, however also draws energy and materials from distance and nearby ecosystems. Currently, more than 54 percent of the world's inhabitants are living in urban regions. This implies that, by 2050, 68 percent of the world's inhabitants are expected to be urban, with nearly 90 percent of this growth will occur in Asia and Africa (United Nations, 2014).This fast population growth coupled with economic development resulted in rapid urban physical growth (Artmann et al.,2019).consequently, unless managed well it can often lead to a serious negative environmental and socioeconomic issues such as urban heat islands, air pollution, traffic congestion, decreases of green spaces, habitat losses, inadequate infrastructure and services, and inefficient resource utilization (Arsiso et al.,2018),especially in the countries where most urban dwellers growth is expected (United Nations, 2018).

There are numerous studies on the expansion of urban land in single metropolitan regions (Magidi, J. & Ahemed, F., 2018). Changes and differences in the patterns of urban growth have been observed over time among some megacities (Zhang et al., 2013) and scattered pattern of urban has been confirmed in small and mid-sized cities (Anees. et al., 2018).However, particularly in Africa, urban growth patterns and population dynamics of cities, varying in size are not well documented. Africa is the least urbanized continent with 43 percent of its inhabitants living in the urban region (United Nations, 2014).Nevertheless, most African cities are challenged by problems related to unplanned and uncontrolled rapid urban growth as informal settlements (Magidi, J. & Ahemed, F., 2018), become a part of the urban ecosystems. Therefore, understanding and comparing the evolution of urbanization, in large and mid-sized cities could provide a reference for urban and ecological planning, and for sustainable development.

2.3 Urbanization and Urban Expansion

Urbanization is simply defined as "the movement of people from rural to urban areas with population growth equating to urban migration" (United Nation, 2005). Urbanization is also a social process which involves the changes of behavior and social relationships as a result of people living in urban area (Bhatta, 2010).Essentially, it involves the complex change of life styles which result from the Impact of cities on society (Bhatta et al., 2010). Nowadays however, urbanization is commonly used in more broad sense and it refers to much more than simple urban population growth; it involves the physical growth of urban areas as well as the changes in the socioeconomic and political structure of a region as a result of population immigration to an urban area (Cohen, 2004; Deng et al., 2009).

Urbanization has been a dynamic complex phenomenon taking place all around the world. This process, without a sign of slowing down has led to the significant changes in land cover and land scape pattern (Braimoh & Onishi, 2007; Deng et al., 2009). Dramatic urbanization, especially in the developing countries will continue to be one of the important issues of global change influencing the human dimensions (Deng et al., 2009). Associated with the process of rapid urbanization, the spatial expansion of built- up areas has been accelerating. Though urbanization promotes socioeconomic development and improves the quality of life, urban growth inevitably results in significant land cover changes in urban area, such as the conversion from the forest and wetlands into agricultural or built-up lands since more land is used for the production of goods and services and more residential land is required for the people living in the urban. While urban areas currently cover only 3% of the earth's land surface (Dewan & Yamaguchi, 2009). The conversions resulted from the urban growth are among the most significant types of anthropogenic land cover dynamics, and the ecological and environmental impacts of urban growth go for beyond the urban boundaries (Wu et al., 2011; Liu & Lathrop, 2002). This is particular the case in the fast developing regions where land cover changes caused by rapid urban growth resulted in serious issues threatening urban sustainable development, for example.

Local and regional climate change (Kaufmann et al., 2007), forest loss and fragmentation (Miller, 2012) and etc.

The process of urban growth can be described as either a change in the area of urban (a measure of extent) or the pace at which non- urban land is converted to urban uses (a measure of rate) (Seto & Fragkias, 2005). However, the extent and rate of urban growth cannot provide detailed information about spatial patterns of urbanization or the underlying processes. Therefore, the urban spatial pattern has been the other subject of interest for geographers and economists to study the changes in urban areas.

2.3.1 Urban Growth Types

Urban, as used in this study, is synonymous with developed land, and includes residential as well as commercial and industries land uses that result in a developed or built landscape. When modeling urban growth, therefore, we are looking at the pattern of development on the landscape, rather than referring to relative differences in the density of development or population (i.e. “urban” as distinguished from “rural”). The model identifies three categories of urban growth. Infill, edge-expansion and outlaying with outlaying urban growth further separated into isolated, linear branch, and cluster branch growth.

Figure 2.1a shows an infill growth is characterized by a non-developed pixel being converted to urban use and surrounded by at least 50% existing developed pixels. It can be defined as the development of a small tract of land mostly surrounded by urban land cover. Ellman (1997) defines infill polices as the encouragement to develop vacant land in already built-up areas. Infill development usually occurs where public facilities such as sewer, water, and roads already exist. As shown in figure 2.1b an edge-expansion growth is characterized by a non- developed pixel being converted to developed and surrounded by no more than 50% existing developed pixels. This conversion represents an expansion of the existing urban patch. Edge- expansion type development has been called metropolitan fringe development or urban fringe development (Heimlich & Anderson, 2001; Wasserman, 2000).

Figure 2.1c shows Outlaying growth is characterized by a change from non-developed to developed land cover occurring beyond existing developed areas. This type of growth has been called development beyond the urban fringe (Heimlich & Anderson, 2001). The outlaying growth designation is broken down into the following three classes: isolated, linear branch, and clustered branch.

Isolated growth is characterized by one or several non-developed pixels some distance from an existing developed area being developed. This class of growth is characteristic of a new house or similar construction surrounded by little or no developed land. Linear branch defines an urban growth such as a new road, corridor, or a new linear development that is generally by non-developed land and is some distance from existing developed land. A linear branch is different from isolated growth in that the pixels that changed to urban are connected in linear fashion.

Cluster branch defines a new urban growth that is neither linear nor isolated, but instead, a cluster or a group. It is typical or a large, compact and dense development. Harvey and Clark (1965) define a similar type of growth called leap-frog development as the "settlement of discontinuous, although possibly compact, patch of urban uses".

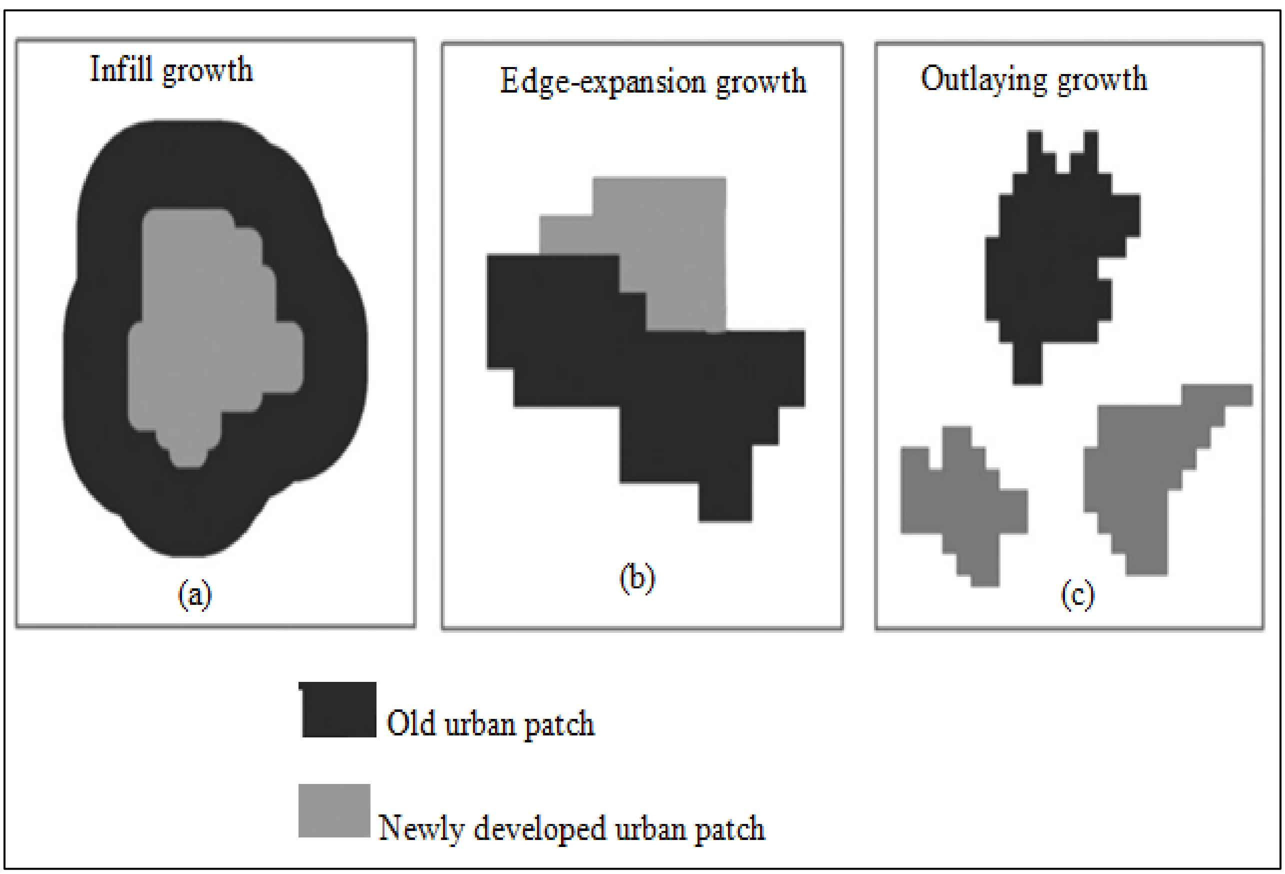


Figure 2. 1 Three types of urban growth.

2.3.2 Urban Growth Challenges

In developing countries, urban growth is subjected to uncontrolled challenges due to rapid population growth, rapid technological change, increasing motorization rates, and urban expansion(Zegras & Gakenheimer, 2000), as well as massive traffic congestion, loss of farmland, urban disinvestment, and high costs of public infrastructure (Nelson, Pendall, Dawkins, & Knaap, 2002) . The rapid growth of the cities in developing countries faced the challenge to provide land and infrastructure to satisfy the massive demand of private households.

2.3.3 Urban Form, Function and Structure

The term “urban form” is used to describe a city’s physical characteristics. It refers to the size, shape and configuration of an urban area or its parts. Study of urban form is performed in order to understand the spatial structure and character of a metropolitan area, city, town or village by examining the patterns of its component parts and the ownership or control and occupation. Urban form is closely related to scale and can be described as the “morphological attributes of an urban area at all scales” (Williams et al.2000).This scale at which urban form can be considered includes the individual building, street, urban block, neighborhood, and city. These levels of spatial disaggregation influence how an urban form is understood, measured, analyzed and shaped (Dempsey et al.2010).

- **On the metropolitan scale,** urban form refers to the spatial extension of the city.it refers to land use (rural or urban land), human activities (industries, offices, housing), and the way they are organized and distributed on the territory.
- **At the broad city scale,** urban form has been defined as the spatial configuration of fixed elements (Anderson et al.1996).Feature of urban form at this scale includes urban settlement type, such as a market town, central business district, or suburbs(Dempsey et al .2010).
- **On the district scale,** urban form refers to how streets and transportation networks are organized as well as how urban amenities such as parks, hospitals or schools are distributed within the city.
- **On the neighborhood scale,** urban form relates to the form and the size of urban blocks and the way they are divided into plot subdivisions. It also relates to the physical texture of the urban fabric and its bioclimatic potential. (Urban morphology-complex system institute 2018).

Urban Function can be conceptualized as function of city in relation to the society, hinterland, or other settlements as activities taking place inside of cities or as a relation between urban (social) needs and urban (spatial) forms. Urban functions are generator that shape morphological characteristic of urban space .The location; size and shape of urban space are in direct relation to functional needs of inhabitants or society. Urban functions are complex concepts that depend on the scale at which functionality is studied. It is possible to distinguish the functions internal to the city, the functions of the city in relation to the territory (countryside, agriculture, villages and hamlets, smaller towns. subordinated with in a networks), and lastly, the functions of the city. Each city in the social whole (the technical and social division of labor between cities, various networks of relations, administrative and political hierarchies).Levels of functions stand in relation to urban structure and can be related to the structure of the city (of each city, morphologically, socially, topologically and topically), then the urban structure of society, and finally the social structure of town –country relations (Lefebvre 1996).

Urban Structure is the arrangement of land use in urban areas. Sociologists, economists and geographers have developed several models explaining where different types of people and businesses tend to exists within the urban setting. Urban structure can also refers to the urban spatial structure, which concerns the arrangements of public and private space in cities and the degree of connectivity and accessibility. The existing of spatial structure take an important roles as appoint of initiation of new growth center of urban growth, In this case when we know how the structure shaped the city ,we will know how should we initiate for planned activities, we do known the flows. Second is as the area of industrial support, education, trade and service. After we know the flows of human and goods mobility, we can choose which area can be used for support the existing of settlement surrounding such as education, trade etc. Another role is as director of network infrastructure definitely spatial structure made us understand about the space activity and mobility so it can help us to direct the construction of infrastructure because we know which location need it. A review of the city's internal spatial structure can be done with a variety of approaches among others, such as:

1. Ecological approach

   Reviewing the city as an object of study in which there is a complex society ,has undergone a process of interrelations between humans and their environment .its product is urban land use pattern regularity.

2. Economic approach

   Economic approach to the spatial structure of the city is based on the understanding that the value of the land rent and cost have a close connection with land use patterns pathways and transport node has a big role to the development of the city.

3. Urban morphological approach

   Urban morphology focus on physical forms an urban area that is reflected from the type of land use, road network system and blocks of buildings, “town scape”, urban sprawl, and the pattern of the road network as an indicator of the morphology of the city. Based on this approach, an outline is the spatial expression of the town, which can be seen from the physical pattern or arrangement of the physical elements of the city such as buildings and the environment, so the city can be distinguished from the shape of the city is compact and non-compact urban form (Hoyt H.1939).

2.4 Land Cover Change

Mapping and monitoring land cover have been widely recognized as an important step to better understand and provide solutions for social, economic and environmental problems (Adb El-Kawy et al., 2011; Foody, 2002). Therefore the continual historical and precise information of land cover and land cover change is becoming increasingly important for urban planning towards sustainable development (Barnsley & Barr, 1996; Remankutty & Foley. 1999). Although most of the developed countries are well equipped with detailed land cover information (Dewen & Yamaguchi, 2009). Longley and Mesev (2000) argued that our current understanding of the land cover change and its effects are largely limited by the lack of accurate and timely land cover data in the developing countries. Land cover data are inadequate or unavailable of in consistent quality and out of data; while generating it is time consuming and expensive (Haack & English, 1996).

Since the launch of the first earth resource satellite Landsat-1 in 1972, satellite remote sensing has become an increasingly powerful and effective tool for monitoring and management of land cover (Zhang & Zhu, 2011). Compared with more traditional mapping methods such as field survey and basic aerial photointerpretation, land cover mapping has the advantage of low cost, large area coverage, repetitive data, digital format, and accurate georeferancing procedures (Jensen, 1996; Yuan et al., 2005). Consequently, land use information products from satellite images have become as essential database for land cover management and urban planning.

Several recent developments to sensor technology have the potential to improve the capability of mapping urban area significantly. The increasing availability of satellite imagery with significantly improve spectral and spatial resolution has played an important role in more detailed land cover mapping, meanwhile, the rapid development of image process technology has provided more powerful tools for satellite processing and analysis. It is now possible to monitor and analyze urban growth in a timely and cost effective way (Deng et al,. 2009).

An important task of satellite image process is to develop image data analysis approaches suitable to a particular application. The classification of land cover types from satellite images is probably the most important objective of digital image analysis. It is a process of categorizing pixels in an image to one of land cover classes. The fundamental basis of remote sensing image classification is the spectral characteristics of earth surface features. While it is relatively easy to generate a land cover map from remote sensing image, it is difficult to make it accurate (Zhang & Zhu, 2011).

In the past few decades, a variety of classification algorithms have been proposed to conduct the remote sensing image classification. Traditional multispectral classification methods make use of spectral information of different surface objects. Supervised and unsupervised multispectral classifications are the two main spectral recognition methods. Supervised classification aims to allocate pixel based on their similarity to a set of predefined classes that have been characterized spectrally (Foody, 2002). Therefore, it requires a prior knowledge of the study area to ensure the selection of the training sites.

The maximum likelihood classifier (MLC) is the most commonly used supervised classification method, which creates decision surfaces based on the mean and covariance of each class (Srivastava et al., 2012). These classification methods have been widely used for remote sensing application and have generated fairly good results for a wide variety of images. However, there are some challenges in obtaining accurate land cover information in urban areas. A major difficulty in urban remote sensing processing is attributed to the high heterogeneity and complexity of the urban environment in terms of its spatial and spectral characteristics (Deng et al., 2009; Lu et al., 2011; Setiawan et al., 2006).

Change detection is the process of identifying differences in the state of a feature or phenomenon by observing it at different times (Singh, 1989). The goal of remote sensing change detection is to (Im & Jensen, 2005).

1) Detect the geographic location of change;
2) Identify the type of change;
3) Quantify the amount of change.

Change detection is useful in many applications related to land use and land cover changes, such as shifting cultivation, land scape changes, land degradation, desertification, urban land scape pattern change, and deforestation. Timely and accurate change detection of land cover provides a better understanding of relationships and interactions between human and natural phenomenon. Change detection involves the analysis of multi-temporal datasets to quantitatively assess the temporal effects of the phenomenon.

There are various ways of approaching the use of satellite imagery for determining land cover change in urban environments. Martin (1989) divided the methods for change detection into two classes: pixel-to-pixel comparison and post-classification comparison the first method conducts the pixel-to-pixel comparison of multi-temporal images without classifying the data. This method applies algorithms, including image differencing and image rationing, to single or multiple spectral bands, vegetation indices or principal components directly to multiple temporal images to generate change maps. Prior classification is not necessary for the comparison and errors from classification can therefore be avoided. However, the results of these methods could not provide information about the land cover conversion matrix.

The post classification comparison method is used to compare two or more separately classified images of different dates to produce land cover change maps, in which not only the amount and location of change but also the nature of change can be, identified (Howarth & Wickware, 1981). In addition, this method can be minimized the problems associated with multi-temporal images recorded under different atmospheric and environmental conditions (Lu et al., 2004). A major pitfall, however, the accuracy of change maps is strongly dependent on the accuracy of individual classification results (Yuan et al., 2005).

2.5 Factor Affecting Spatial Urban Growth

It is important to understand several factors directly or indirectly contributing to urban growth. There has been an increasing interest in identifying and understanding the effects of the driving factors on urban land cover change because this knowledge is crucial not only for the development of spatial models (Arsanjani et al., 2013; Zheng et al., 2012). "What drivers/ causes urban growth?" has always been one of the most common research questions? Urban growth can be described by the complex interaction of behaviors and structural factors associated with the demand. Technological, capacity, social relations, and the nature of the environment (Lambin et al., 2001; Verburg et al., 2004). However, there are no standard driving factors that are responsible for urban growth.

The selection of the factors that are involved in the specific analysis often relies on prior understanding of the underlying processes of urban growth. According to the literature review, these factors considered in studies of urban land cover change can be grouped into four classes. (1) natural factors, (2) socioeconomic factors, (3) spatial policies, and (4) neighborhood factors.

In urban environment, natural factors are correlated with the suitability and costs of a location for development. Topography often determines the location of new urban area because flat areas are suitable for urban development (Li et al., 2013). Each location has a specific soil characteristic that determines the production of agricultural vegetation. The good quality agricultural land is not suitable for urban development in order to sustain future food supply (Li & Yeh, 2000).

Socioeconomic factors are the most important factors of urban growth. A wide range of urban growth studies are based on socioeconomic theory. Urban economists identify three underlying driving factors that contribute to the urban growth; population growth rising household incomes, and accessibility improvement (Mieszkowski & Mills, 1993). Urban area must extent to a large area to accommodate more people. In order to promote life quality, households need more living space as they become richer. In addition, they focus on the site characteristics of live space, including house prices, level of services, quality of landscapes (Geoghegan et al., 1997; Mertens et al., 2000). Other than census based socioeconomic variables, accessibility also strongly affects urban growth (Hu & Lo, 2007; Linard et al., 2013). The improvement accessibility indicates faster and more convenient travel and lower commuting costs. Verburg et al., (2004) pointed out that "the influence of the socio economic conditions in the region can be best characterized by the access that a location has to these facilities."

Spatial policies at national or regional level have significant impacts on land cover change (Dieleman & Wegener, 2004). They define the legal regulations for future land uses (Barredo et al., 2003). In particular, spatial polices can affect the urban development in two aspects. One is to serve as an accelerating factor to promote more new development in areas planner or proposed for development (Cheng & Masser, 2003), and the other is as a constraint to limit the development with in a specific region, for example, the conservational or protected areas (Long et al., 2012; Verburg et al., 2004).

"Everything is related to everything else, but near things are more related than distance things." The neighborhood factor is related with the Tobler's (1970) first law of geography. Land cannot be developed independently at each individual location; land cover patterns nearly always show spatial autocorrelation causes by a number of attractions and repulsion forces (Overmars et al., 2003). It is especially important to consider the neighborhood effect due to the fact that urban development can be regarded as a self-organizing system (Verburg et al., 2004). A large number of studies demonstrated that locations are more likely to be converted to urban area if they are surrounded by more urban land. Neighborhood factors are introduced to consider the possible effects of spatial interaction and neighborhood characteristics by different approaches. For instant, the proportion of urban land and some other land cover types in the neighborhood of a cell (Braimoh & Ohishi, 2007; Long et al., 2012); distance to existing urban areas (Poelmans & Van Rompaey, 2009).

2.6 Geographic Information System and Spatial Analysis

Geographic information system (GIS) is systems designed to store, manage, and display spatial data and aid in the analysis and interpretation of spatial data (Maguire et al.1991). Spatial analysis is techniques applied to geographic data to measure; interpret, and explore characteristics and association (Fortheingham et al.2013). Geographic data can include defining the locations of a point in space (Known as point pattern data), quantifying values of a characteristic at a given location (geostatistical data), or describing an entire geographical region (area-level data). With the rise and increasing accessibility of computing power and relevant software, GIS and spatial analysis are finding wider audiences and novel applications. Spatial analysis or spatial statistics includes any of the formal techniques which study entities using their topological, geometric, or geographic properties. Complex issues arise in spatial analysis, many of which are neither clearly defined nor completely resolved. The most fundamental of these is the problem of defining the spatial location of the entities being studied. Classification of the techniques of spatial analysis is difficult because of the large number of different fields of research involved, the different fundamental approaches which can be chosen, and the many forms the data can take.

2.7 Methods of Analyzing Driving Forces of Urban Expansion

Various research methods are applied to inspect the driving forces of urban expansion such as structural equation modeling, analytic hierarchy process, and spatial regression analysis.

2.7.1 Analytical Hierarchy Process

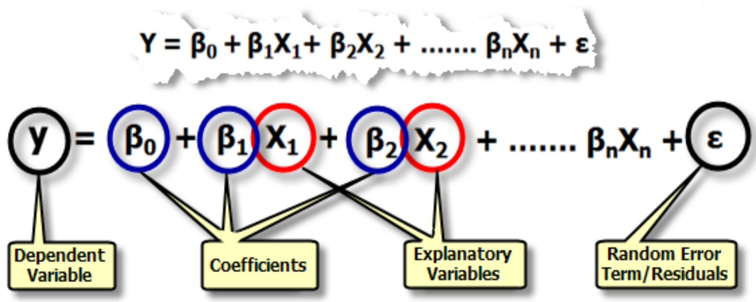
The Analytical hierarchy process (AHP) method has a sound mathematical foundation, which has been widely used in several socioeconomic and engineering applications (Banai-Kashani,1990; Kauko,2004;Maiczewski,1999).It is one of the best known comparative ratings of the important of various factors, which are extracted from stakeholders and then analyzed to produce a set of consensus weights using a fairly common form of matrix algebra (Banai-Kashani,1990).The technique is based on a pairwise comparison of elements (attributes or alternatives), and results in a comparison matrix in which the relative importance of each element or factor is determined numerically .The technique also has a scientific basis through which the consistency of the driving factors evaluation can be judged. Kauko (2004), argued that most of the classical multi-attribute modeling approaches are based on the assumption of explainable utility functions; however, the AHP does not assume that the evaluator is able to express his or her overall elicitation of the problem as one function. Rather, the AHP is based on the assumption that the relevant dominance of one attribute over another can be measured by a pairwise comparison of preferences, systematically made on each level of a hierarchy of factors (Banai-kashani,1990; Malczewski,1999; Satty,1980).

In using AHP to model a problem, one needs a hierarchical structure to represent that problem as well as pairwise comparisons to establish relations with in the structure (satty, 1980).The AHP has been used with absolute or relative types of comparisons to drive ratio scales of measurement (Malczewski,1999;Thape & Murayama,2008). In absolute comparisons, alternatives are compared with a standard that has been developed through one's experience. In relative comparisons, alternatives are compared in pairs according to a common attribute. The relative measurement w_i; i=1,,,,n, of each of n elements is a ratio scale derived by comparing the elements with each other is pairs. In paired comparisons, two elements i and j are compared with respect to common property. The i is used as the unit and the j is estimated as a multiple of that unit in the form $(m_i/m_j)/1$.where an estimate of the ratio m_i/m_j is taken from a fundamental scale of absolute values between 1 and 9 (Saaty, 1980). The numbers are used to represent how many times the larger of two elements dominates the smaller with respect to a common property or criterion.

2.7.2 Spatial Regression Analysis

Spatial regression methods capture spatial dependency in regression analysis, avoiding statistical problems such as unstable parameters and unreliable significance tests, as well as providing information on spatial relationships among the variables involved. Depending on the specific technique, spatial dependency can enter the regression model as relationships between the independent variables and the dependent, between the dependent variables and a spatial lag of itself, or in the error terms. Regression analysis allows you to model, examine, and explore spatial relationships and can help explain the factors behind observed spatial patters. By modeling spatial relationships however, regression analysis can also be used for prediction. The logistic regression model is used to integrate the social, physical, political, and socio economic factors of the study area into the urban growth modeling process. This model demonstrates and explains the relationship of a number of Xs independent variables to a dichotomous single-dependent variable Y, which represents the occurrence or non-occurrence of an event. Logistic regression empirically finds the relationship between the independent variables and the function of the probability of an event happening (Klein Baum and Klein 2010). The use of logistic regression can yield the coefficients of independent variables (both continuous and categorical); the dependent variable is a binary categorical variable with a value of either 1 or 0 and can be computed using the well-known logistic regression equation (Huang et al. 2009). This method provides the probability of the existence or nonexistence of each type of land use/cover in every location based on driving factors. Logistic regression is a powerful empirical method used when the outcome-dependent variable is dichotomous. Spatial urban expansion is the dependent variable represented in a raster binary map. A value of 1 on the produced probability map indicates the presence of urban growth, and a value of 0 indicates the absence of urban growth.

The probability of urbanization for each cell in the raster map was produced based on the following Logistic regression equation:



- **Dependent variable** (y): This is the variable representing the process you are trying to predict or understand. In the regression equation, it appears on the left side of the equal sign. While you can use regression to predict the dependent variable, you always start with a set of known y-values and use these to build (or to calibrate) the regression model. The known y-values are often referred to as observed values.
- **Independent/Explanatory variables** (X): These are the variables used to model or to predict the dependent variable values. In the regression equation, they appear on the right side of the equal sign and are often referred to as explanatory variables. The dependent variable is a function of the explanatory variables.
- **Regression coefficients** (β): Coefficients are computed by the regression tool. They are values, one for each explanatory variable, that represent the strength and the type of relationship the explanatory variable has to the dependent variable. When the relationship is positive, the sign for the associated coefficient is also positive. Coefficients for negative relationships have negative signs. When the relationship is a strong one, the coefficient is relatively large (relative to the units of the explanatory variable it is associated with). Weak relationships are associated with coefficients near zero; β_0 is the regression intercept**.** It represents the expected value for the dependent variable if all the independent (explanatory) variables are zero.
- **Residuals:** These are the unexplained portion of the dependent variable, represented in the regression equation as the random error term ε. Known values for the dependent variable are used to build and to calibrate the regression model. Using known values for the dependent variable (y) and known values for all of the explanatory variables (the Xs),

the regression tool constructs an equation that will predict those known y-values as well as possible. The predicted values will rarely match the observed values exactly, however. The difference between the observed y-values and the predicted y-values are called the residuals. The magnitude of the residuals from a regression equation is one measure of model fit. Large residuals indicate poor model fit.

Building a regression model is an iterative process that involves finding effective independent variables to explain the dependent variable you are trying to model or understand, running the regression tool to determine which variables are effective predictors, then repeatedly removing and/or adding variables until you find the best regression model possible.

From the methods mentioned above spatial regression analysis has its advantage over other methods in embracing a wide range of variables and identifying the relative importance of different factors (Abiodun, 2017). Many authors claimed that logistic regression model has a strong capability to not only incorporate biophysical influence (slope, land use/cover, transport, zoning) but also demographic and social variables to better understand human forces ability in urban growth pattern (Hu and Lo.,2007).Fundamentally, logistic regression model is simple to interpret Field (2013); moore.et al.(2009),suitable approach to evaluate critical areas for future urban development (informal settlement proliferation on urban growth; i.e. areas that will be highly urbanized and not).Dubovyk et al. (2011);Duwal(2013) and as assess the impact of macro-level changes (e.g. major roads, built-up areas etc.) (Lesschen et al.2005).Therefore, in order to comprehensively analyze the driving factors of urban expansion of Adama Town, the spatial regression model is chosen in this study.

2.8 Empirical Literature Review

Many literature studies have been devoted to exploring the driving forces and mechanisms of urbanization .As a product of human activity worldwide, urban expansion is strongly influenced by geophysical, socioeconomic, and institutional conditions. Previous studies have shown that urban expansion is driven by socioeconomic factors (Liu, Zhan, & Deng, 2005).many urban expansion studies have used standard economic factors to investigate the causes of urban expansion.

According to Brueckner and Fanster (1983) have found the fundamental economic factors, including population, income, and agricultural land rent, are of primary importance in determining urban spatial sizes. They further stated that “urban sprawl is the result of an orderly market process rather than a symptom of an economic system out of control.” More recently, McGrath (2005) has confirmed this result, and has further stated that unexplained effects beyond conventional economic factors also contribute to urban expansion. The key determinants of urban expansion in china are population, income, and agricultural land rent, and urban core growth is affected by industrialization (Deng, Huang, Rozelle, &Uchida, 2008).

In addition, Briassoulis (2008) proposed that urban model should consider bio-physical driving forces which consist of characteristics and processes of the natural environment. Suitability of a location to develop can be impacted by bio-physical factors, for instance, slope layer needs to be taken in to consideration in urban expansion model (Verburg et al.2004).Hu and Lo(2007) proposed that steep and elevated areas are less likely to be developed due to the cost of construction and higher risk of land instability. Factors like economic gains and insufficiency of land availability might lead developer to developing despite the high cost and risk of slope and elevation. Apart from that, zoning status or legally protected areas have produced the best result in sensitivity analysis of developed urban model which signify it as one of importance factors of urban expansion (Poelmans & Vanpompaey, 2010).

Another study by Kuang, Chia, Lu and Dou (2014) recognized that urban planning management strategies and polices have become major driving forces that need to be considered in modeling urban growth as they can affect other drivers. China, for example, has experienced unprecedented speed of urbanization rate since government setting up special economic zone which has emerged as chain’s commercial and industrial hub. On the contrary, the united states remained relatively stable urbanization rate due to introduction to variation of distinct zone to manage rural and urban area (Kuang et al.,2014).Instead of exercising land use policy to direct physical development and other goals which indirectly stimulate urban development (Briassoulis, 2008).In addition, the drivers of urban expansion change as the city grows overtime (Aspinall,2004;Li et al.2013).At the early stage of urban growth, location related factors and physical conditions of the sites are more influential, and gradually other factors would increasingly shape the form of the urban area (Li et al.2018). In line with this trend of urban growth, recent studies include the interactions between urban land expansion and the socioeconomic and demographic factors.

Based on the experimental studies by Long et al (2008) ,the effects of spatial planning on urban expansion through quantitative analysis should addressed more widely, since urban expansion is usually due to political divers that can be investigated by qualitative analysis in spatial planning. The development of sustainable policies for urban transformation should be investigated by a mixed approach. Within the advancement of technology regarding the geostatistical dataset, it is easier to verify the amount of land urbanization through land use datasets in different time series, and geospatial data such as altitude and slope can be used in analyzing the effects of physical factors on land urbanization. Converting the socioeconomic statistical data, including GDP and population, and policy- oriented information from urban planning at the regional scale in to spatial data at the land patch scale and combining them with geographic information data will improve the mixed approach to understand drivers of urban expansion.

Aguayo et.al (2007) revealed that urban growth areas are stimulated by distance and density of specific elements which implies proximity and neighborhood are two important driving forces to urban development .It is difficult to develop an area if the road network is not well constructed because roads open many opportunities, especially for business by attracting higher population migration. Resident's desire to live at a location with easy access to other destinations helps to explain not only facilitates residents' daily lives but also reduces construction cost for amenities like shopping malls and hospitals (Li, Zhou &Ouyang, 2013).

2.9 Conceptual Framework

The conceptual framework consists of all these stages of the research. First, classified the remote sensing images to perform built-up expansion analysis. There are various ways of approaching the use of satellite imagery for determining land cover change in urban environments. Martin (1989) divided the methods for change detection into two classes: pixel to pixel comparison and post-classification comparison. Mapping and monitoring land cover have been widely recognized as an important step to better understand and provide solutions for social, economic and environmental problems (Foody, 2002). As a product of human activity worldwide, urban expansion is strongly influenced by physical, socioeconomic, and institutional conditions (Liu, Zhan, & Deng, 2005). At the early stage of urban growth, location related factors and physical condition of the sites are more influential, and gradually other factors would increasingly shape the form of the urban area (Li et al., 2018).

Finally spatial logistic regression model is used to identify factors responsible for changing urban growth morphology. Fundamentally, spatial logistic regression model is simple to interpreter Field (2013); Moore et al., (2009), suitable approach to evaluate critical areas for further urban development.

CHAPTER III. METHODOLOGY

3.1 Description of Study Area

Adama Town is located about 100 km south east of Addis Ababa along the main road to Harar, enclosing between 8^0 26' 15" N to $8^0$37' 00" N latitude and 39^0 11' 57" E to "39^0 21' 15" E longitude at an average altitude of 1620m above sea level. East Showa Zone, in which Adama Town is located, form a part of the mid central plateau physiographic unit. (Wikipedia)

It is found on a nodal location along main national and regional transport lines from the capital Addis Ababa to other important towns. It is also situated close to natural recreational sites such as 'SODORE', "BOKU' etc.

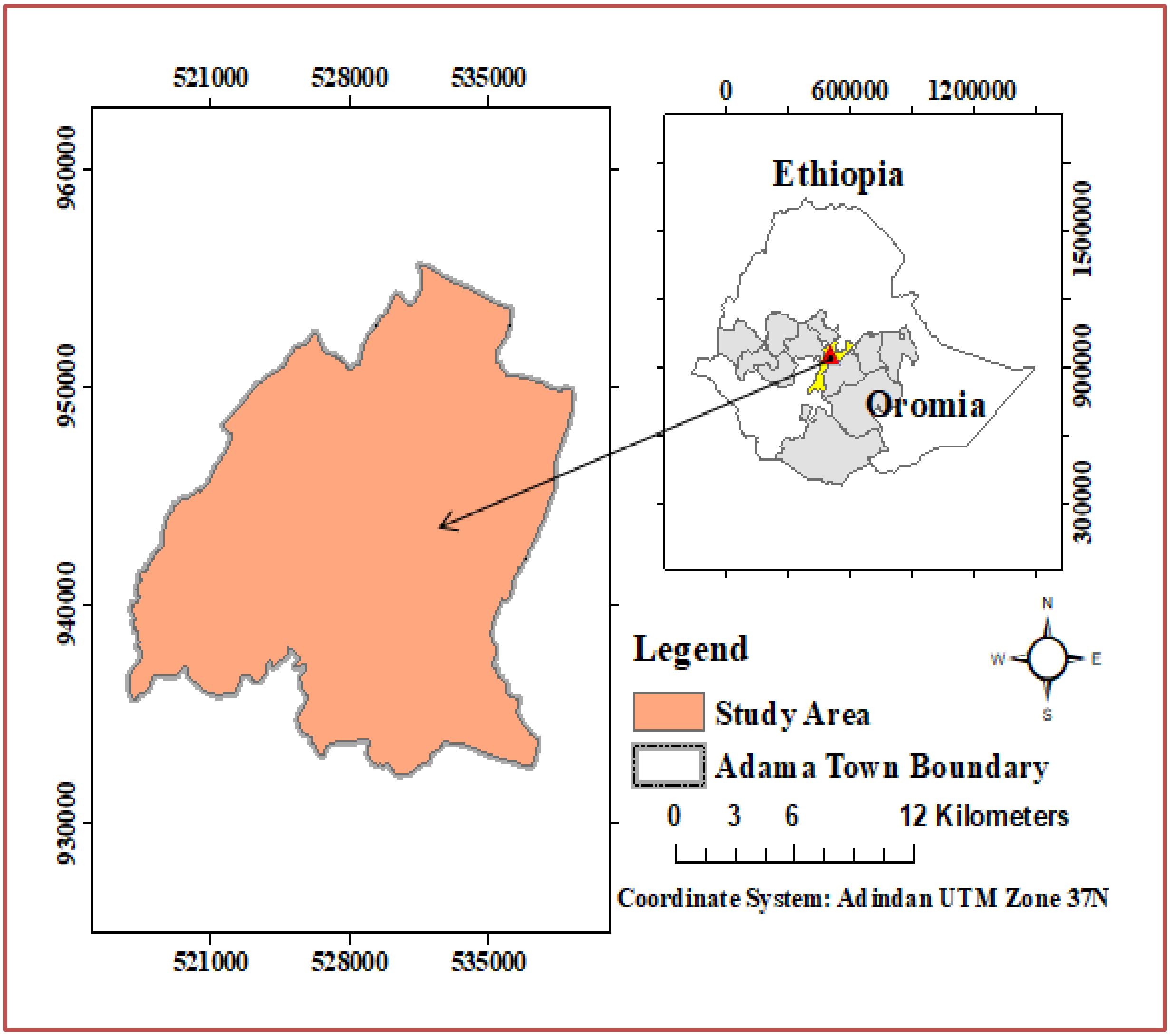


Figure 3. 1 Map of Adama Town Boundary

3.1.1 Population

In 1964, the population of the town was estimated to be 27,812. This figure reached about 39221 in 1977. The results of the 1984 census revealed that the population of Adama reached to 77, 237, while the 1994 census counted a total population of 127,842. Based on the 2007 census conducted by the central statistical agency (CSA) it had 220,212. According to the past population a trend, the town population is expected to grow to 375775 in 2017. From 1994 to 2007 census, the growing population size is 92,370 i.e. the annual increment is 5.56% while, the annual population growth rate of Adama Town in 1990 was 4.6% and reached to 104,464 and in 2000, 2010, and 2019 was 164,716, 260,203, and 429,266 respectively.

3.1.2 Urbanization History of Study Area

Adama was established as a railway station depot in 1916. Its establishment and location have been influenced by many different factors. Conducive economic, social and geographical conditions are the crucial factors for rise and development of the town. The Italian occupation which lasted from 1936-41 made a great deal of contribution to the development of Adama. During their stay in the town, the Italians carried out a number of construction works such as road transportation, communication and likes, which accelerated the grown of the town. The expansion of transportation and communication and the development of infrastructure service and facilities such as education, health, water supply, and electric supply have contribution a lot to the development of the town. The construction and improvement of the roads from Addis Ababa via Adama to Wonji, Assela and Harar made the town a focal point of communication for travelers. It also created a favorable condition for city expansion and has greatly influenced its development pattern.

3.2 Data Collection and Data Source

In order to achieve the desired objective, both primary and secondary data were used in the research. The primary data were gathered through field survey at different places of the study area and the secondary data were obtained from different organization and websites. The data for this study are listed in the following tables.

Table 3. 1 List of data required and its source

No	Data Required	Data Source	Purpose	Year	Data Format
1	Land sat 5 TM	USGS	Land use land cover analysis	2000, 2010, 2019	.tiff
	Land sat 7 ETM+				
	Land sat 8 OLI				
2	Orthophoto	EMA	For digitize input data	2019	.tiff
3	GPS survey	Insitu	For Accuracy Assessment	2019	point
4	Adama master plan	Adama Municipality	To Generate boundary map	2017	.dwg
5	Census data	Adama Municipality	For comparisons of population number	1994, 2007, 2014	numbers
6	Google earth image	Google earth	For comparisons techniques	2000,2010, 2019	image
7	DEM	Free ASTER	slope	2019	GRID

3.3 Software Used

Software is programs which are used for collection, organization, analysis, interpretation and presentation of data. In order to achieve the objective of the study ArcGIS, ERDAS IMAGINE and Microsoft Office software used. ArcGIS is a software application developed by ESRI for working with maps and geographic information. It is used for creating maps and model, compiling geographic data, analyzing spatial information, sharing geographic information and managing geographic information in geo database. ERDAS IMAGINE is an image processing software package that allows users to process geospatial and other imagery as well as vector data and Microsoft office is an application software package with one handle. It includes Microsoft word, Excel, power point etc. to create professional-looking documents, charts, calculations, reports and presentations at high speed and accuracy. List of software and their purpose summarize in figure 3.2.

Table 3. 2 List of software's and their purpose

No	Software	Version	Purpose
1	ArcGIS	10.4.1	For storing, managing, and analyzing spatial information and produce maps.
2	ERDAS IMAGIN	2014	Processing and analyzing satellite images
3	Microsoft Office	2010	Documentation, calculation, chart, and presentation

3.4 Methods of Data Analysis

After collecting all the relevant primary and secondary data and select appropriate software, the next task is describe the methods of the study. Based on the objectives of the study, the first task is image classification of different time land sat image depend on their spectral classes in order to perform change detection. Then identify driving forces of urban growth through literature review by considering the nature of study area this is an input for spatial logistic regression. Finally with the help of ArcGIS tools identify different types of urban growth. Detail explanations of each method of data analysis are given in the subsequent sections.

3.4.1 Image Classification and Accuracy Assessment

Three multi-temporal medium resolution land sat images are used to analyze the urban growth trends and types of Adama Town for the last 19 years. These land sat satellite images of 2000, 2010, and 2019 with 30m spatial resolution down load from United States geological survey (USGS) website. Each image is classified into a set of spectral classes using maximum likelihood algorithm in supervised classification. The land cover maps are composed of two major land cover classes namely: built up and non-built up classes. Each land cover classes comprise different land use classes. The built up area consists of commercial, residential, road and railway networks and other associated lands, parking lots, dumpsite, sport and leisure facilities etc. while the non-built up area includes cropland (agriculture) land, shrub, barren land, grass lands, bear soil and others.

3.4.2 Change Detection

The change detection methods used in this analysis is the post classification comparison techniques in which the GIS overlay of two independently produced classified images in Arc GIS (Alpha et al., 2009).The built-up expansion is analyze using the post classification comparison techniques in which GIS overlay of two independently produced classified images. This method is the most straight forward and intuitive change detection method. Resulting map thus, produced to show the newly built-up area between each subsequent year, i.e. 2000-2010 and 2010-2019 for the study area. Quantitative areal data from the overall built-up area changes, is quantify to analyze the nature and rate of urban growth over time in the study area. The percentage of changes is compute using eq-1.

$$\text{Percentage change} = \frac{\text{A2}-\text{A1}}{\text{A1}}*100 \qquad (1)$$

Where A1 and A2 are areas of built-up in the consecutive years.

3.4.3 Identify Driving Force of Urban Growth

As an empirical estimation model, logistic regression modeling is a data driven rather than a knowledge based approach to the choice of predictor variables (Hu. & Lo, 2007). The method used for this task spatial logistic regression, which is used to analyze the variables that participate in urban growth process. Spatial logistic regression relates the probability of change of dependent binary variable with some independent variables (the variable which are supposed to explain urban growth). Countries like Ethiopia, the choice of independent variable is highly depends on the availability of well-organized and good quality data. Particularly socio-economic data’s are the scarcest data. Probable influential factors for urban growth are note through literature review and contextualize to the study area. Thus, to overcome this challenge, only Road network, CBD, Slope, Institutions, and Industry area are considers as independent variables in this study. The spatial data’s used for independent variables are obtained by digitize from digital orthophoto of the town.

3.4.4 Identifying Three Urban Growth Types

The pattern of urban growth can be categorized into three parts. Infilling, edge-expansion, and outlaying. Wilson et.al. (2003) developed a quantitative method to characterize these tree urban growth categories. With the help of GIS, these three types of urban growth can be identified and quantify in this study. In order to identify urban growth type, the raster maps of existing urban patches associated with newly developed urban patches are firstly converted to vector maps. Following the conversion steps, the boundaries of each existing urban patch is detected. The vector maps of newly developed urban patches are overlaid with the boundaries of each existing urban patch. The urban patch which are existed for two consecutive periods are defined as the old urban patches, whereas the patches which were not existed in the last period are defined as the new urban patches (Sun, Wu, Lv, Yao, & Wei, 2011).

A metric R was defined for calculating the ration between the length of common edge of newly developed urban patches and existing urban patches (Sun et. al., 2011).

$$R = \frac{lc}{l} \tag{2}$$

Where, lc= the length of the common edge between a newly developed urban patch and an existing urban patch.

l = the perimeter of the newly developed urban patch.

The value of R ranges from 0 to 1. The infilling type of urban growth has R>0.5, and refers to the development of newly developed urban patch surrounded by at least 50% old urban area. Edge-expansion urban growth has 0<R<0.5 as it is characterized by the newly developed urban area spreading out from the edge of an existing urban area and surrounded by less than 50% existing urban area. Outlaying growth is the newly developed urban area without any spatial connection to the existing urban area and hence has R=0.

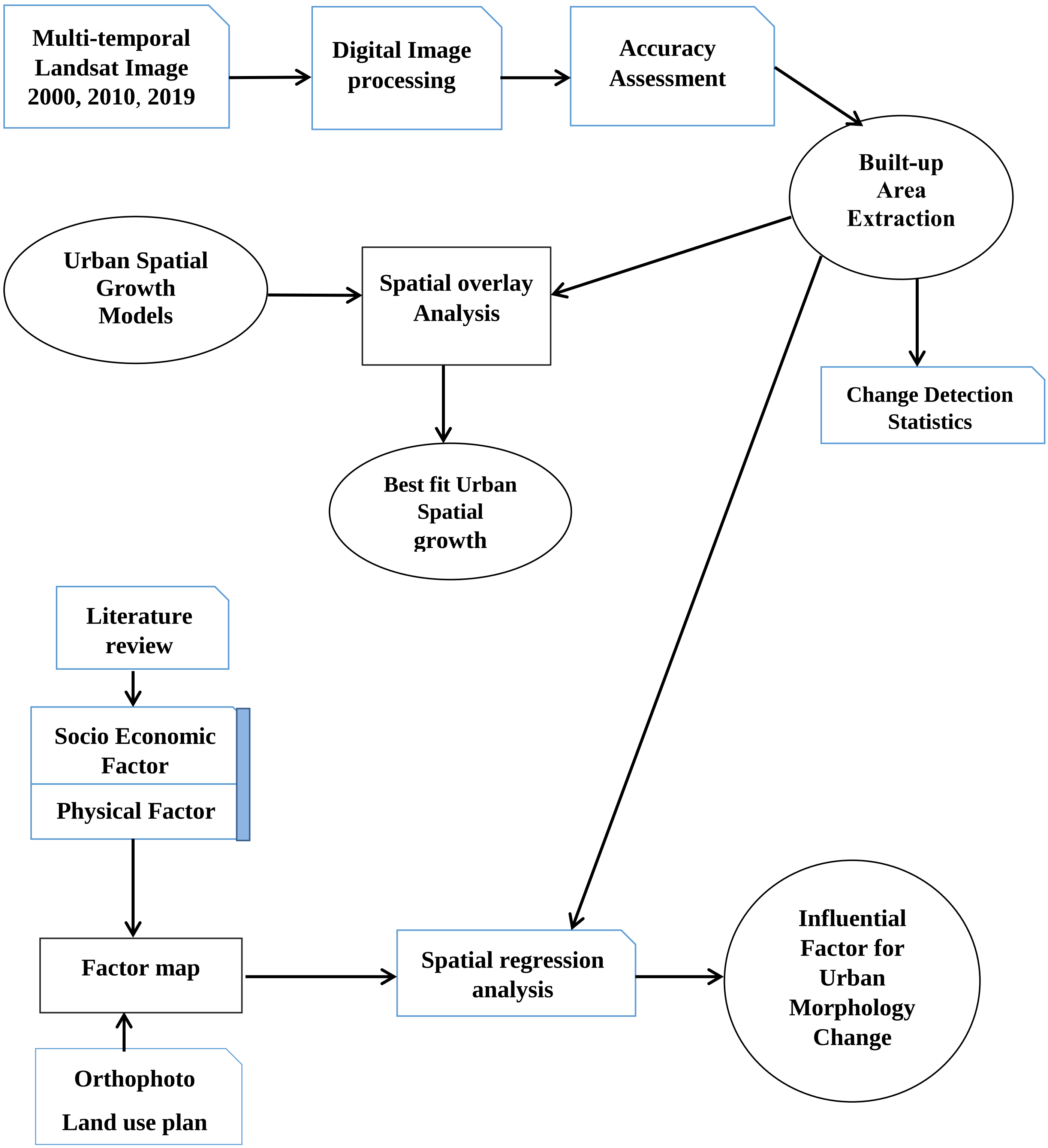


Figure 3. 2 Methodology of the study

CHAPTER IV. DATA ANALYSIS, RESULTS, AND DISCUSSION

4.1 Introduction

This chapter describes the analysis of data followed by results and discussion of the research findings. The finding relates to the research questions that guided the study. Starting from built-up land expansion it goes through finding the most important factors influence the growth morphology of Adama Town using spatial regression model and analyze urban growth type. Most of the results are supported by maps, tables, and illustrative graphs.

4.2 Image Classification and Accuracy Assessment

Land use data for this study were derived from remote sensing images downloaded from United States geological survey (USGS) website with a 30m spatial resolution. Three cloud free land sat images of Adama Town were acquired for May 2000 (TM), April 2010 (ETM+), and May 2019 (OLI). Subsequently, these images are classified by using the maximum likelihood algorithm in supervised classification. The result land cover map contains five major land cover classes (Figure 4.1). Thereafter; they are reclassified into binary files containing built-up area and Non built-up area.

A random stratified sampling method was used to prepare the ground reference data. This sampling method allocates the sample size of each land use based on its spatial extent (Shalaby, A. and Tateishi, R. 2007).Accuracy of land use maps is important in urban studies (Sertel E., Akayss 2015). In thematic mapping from remote sensing data, classification accuracy refers to the level to which the resulting image classification conforms to the truth or agrees with the reality. (Foody, G.M.2002).This is usually undertaken by using information collected from the map and the reference sources. Reference samples data is the class label, which derived from sources that are assumed to be correct, whereas, map sample data refers to be data derived from the map being assessed. A reference sample data for assessing the accuracy of maps created from moderate resolution satellite imagery (e.g., Landsat) can be collected from a variety of sources including previously existing maps, aerial photography, and Google Earth (Fonji SF, Taff GN 2014).

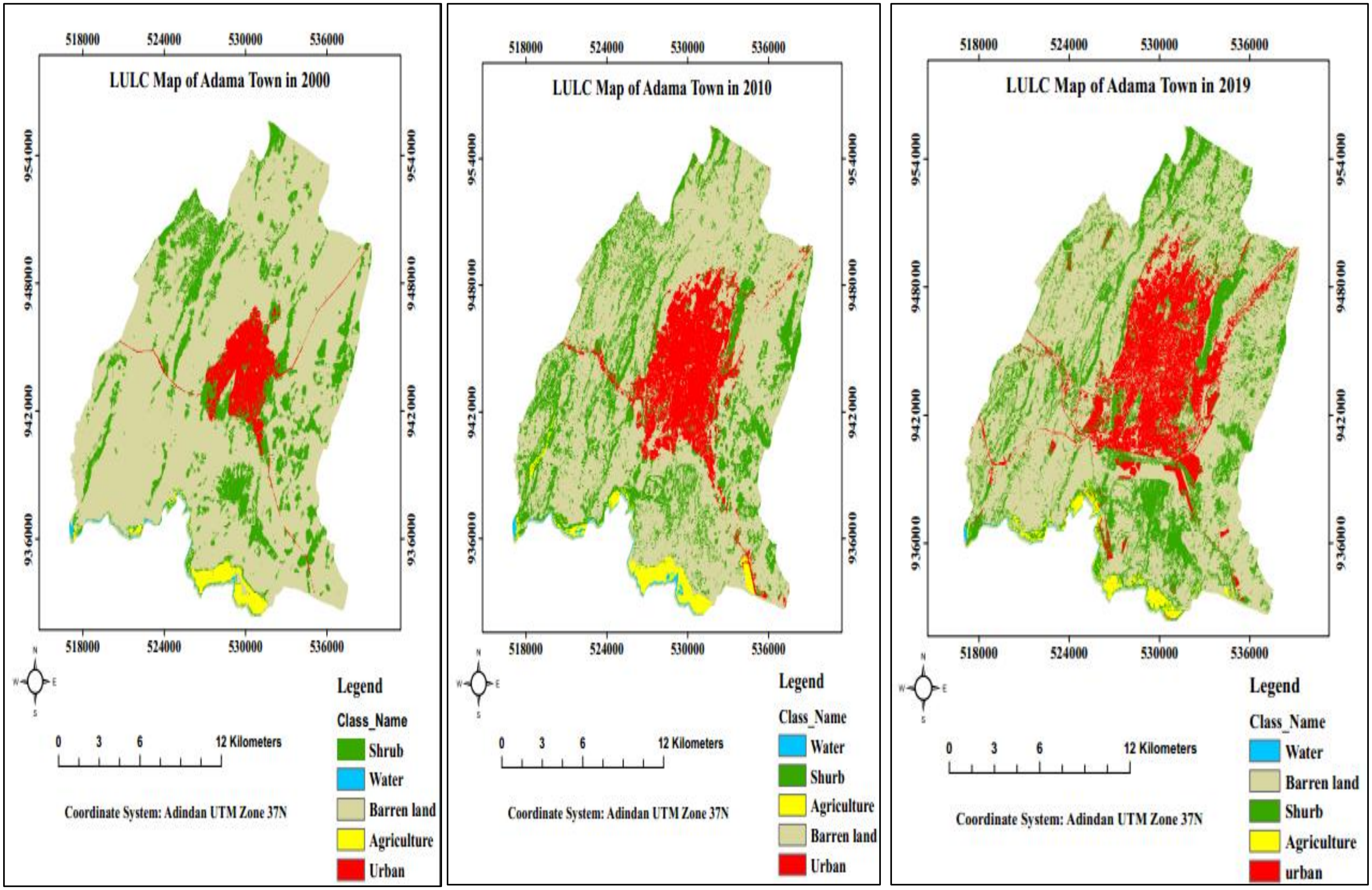


Figure 4.1 Land use/ land cover map of the study area from 2000 to 2019.

In this study, LULC classification accuracy was assessed quantitatively using error matrix which is the commonly used method in LULC classification accuracy assessment (Weng Q., 2010). In this regard, sample pixels were selected from each of classified images through a stratified random sampling method in Erdas Imagine software. This sampling method allocates the sample size of each land use based on its spatial extent (Shalaby, A. and Tateishi, R. 2007). The samples were overlaid with Goggle Earth and Digital Orthophoto to visually interpret and determine their respective classes. Based on the error matrix generated for each year classified map over all classification accuracy and overall Kappa statistics were calculated and summarized in table 4.1. The accuracy requirements for change detection analysis were determined based on the suggestion of Congalton and Green (Congalton RG, Green K., 2009). In this study, the value of the kappa statistics greater than 0.75, indicates strong agreement between the class label on the map and on the reference data.

Table 4. 1 Results of accuracy assessment for each year.

Year	Over all classification accuracy (%)	Over all kappa statistics
2000	88.91	0.75
2010	91.67	0.87
2019	89.21	0.76

4.3 Built-up Land Expansion

The reclassification of classified images into built-up and non-built-up area represented by 1 and 0 respectively for the three different time periods of 2000, 2010, and 2019 summarized in table 4.2. The purpose of the classification was to look at built-up area only where by land cover maps built-up pixels in each time periods were quantified and built-up area of each year and percentage of built- up area increased were derived. Thus, it is possible to interpret the growth directions by visualizing the built-up expansion map.

Table 4. 2 Percentage of built-up area increased from 2000-2019

Year	Class- Name	value	count	Area in m^2	Area in hectare	% of built-up area increased
2000	Non-Built-up	0	329967	296970300	29697.03	
	Built-up	1	17790	16011000	1601.1	
2010	Non-Built-up	0	303001	272700900	27270.09	
	Built-up	1	44756	40280400	4028.04	151.6
2019	Non-Built-up	0	292276	263048400	26304.84	
	Built-up	1	55481	49932900	4993.29	23.96

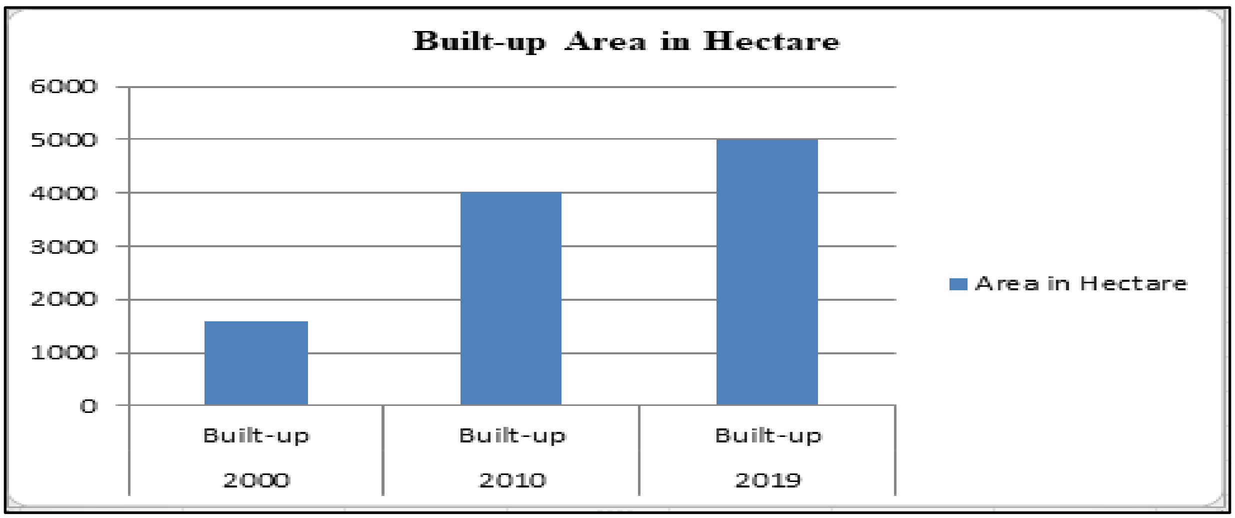
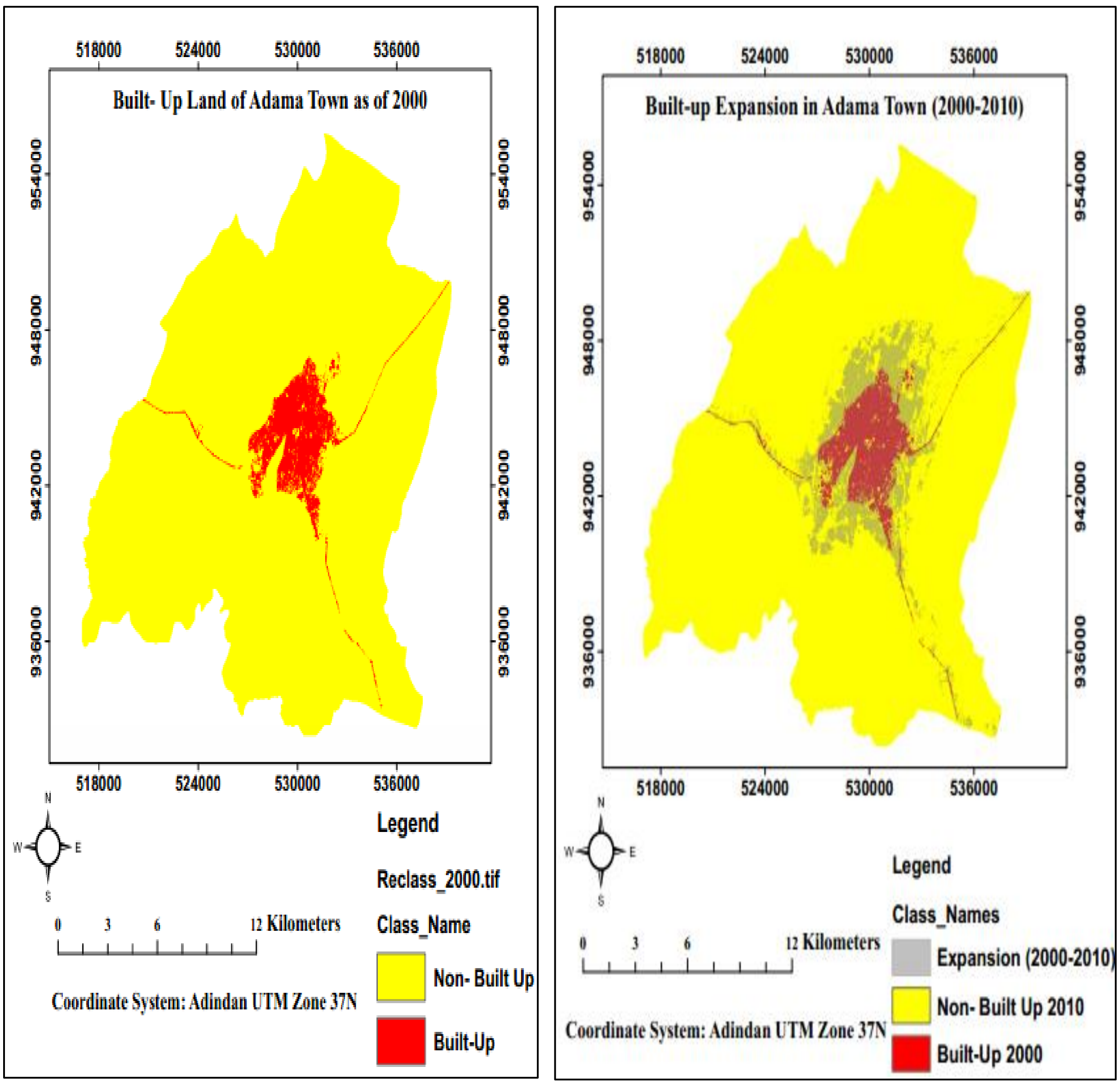


Figure 4. 2 Built-up areas in hectare (2000-2019)

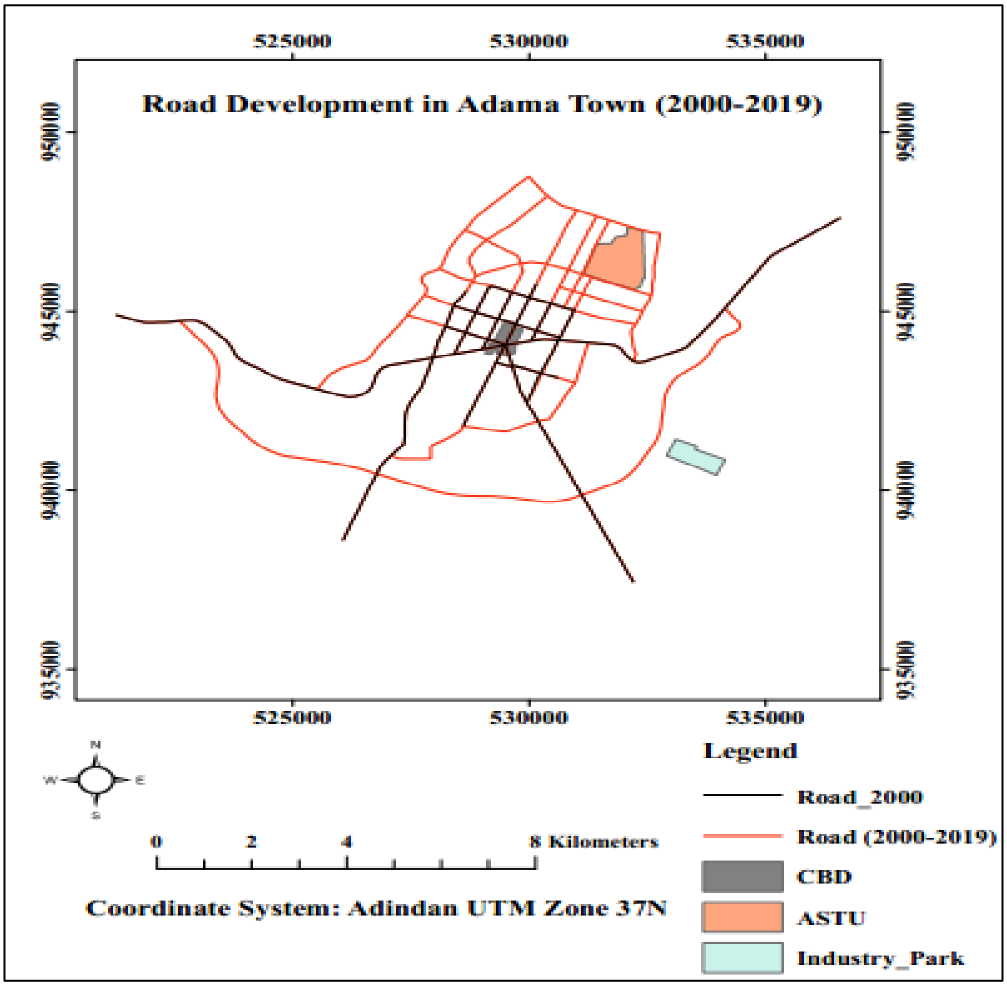
4.3.1 Built-up Expansion from 2000 to 2010

Figure 4.3 b shows that the amount of built-up expansion in Adama Town during 2000-2010 .The significant change has observed and spread from central part towards the peripheral part of the town. It was also clear that the urban /built-up areas occurred to the directions of northern and southern parts of the town. These changes have pointed toward that the spatial pattern of urban expansion has not occurred consistently in all direction but has taken place much faster in certain directions. Furthermore, some new built-up areas appeared in the North-West direction. In addition, analysis of total actual urban growth in the first temporal period reveals that new built-up land 2427 hectare indicating 243 hectare average annual increase of built-up land.

As shown in Figure 4.3c, the development of road indicates that 53 km in 2000 is increased to 116 km in 2019. This development is mainly in northern part where most of built-up expansion occurs. This might be attracted the land development to the area. Besides this, the developments of the road in southern part also encourage built-up expansion and the factors of developments in the area. In addition to this, introduction of office Oromia Broadcast Network (OBN) and Adama Science and Technology University are the potential factors contribute to the development in the area. Moreover, other developments especially the built-up expansion in the North western direction is identified due to proximity to the central city business district (CBD).



(a) (b)

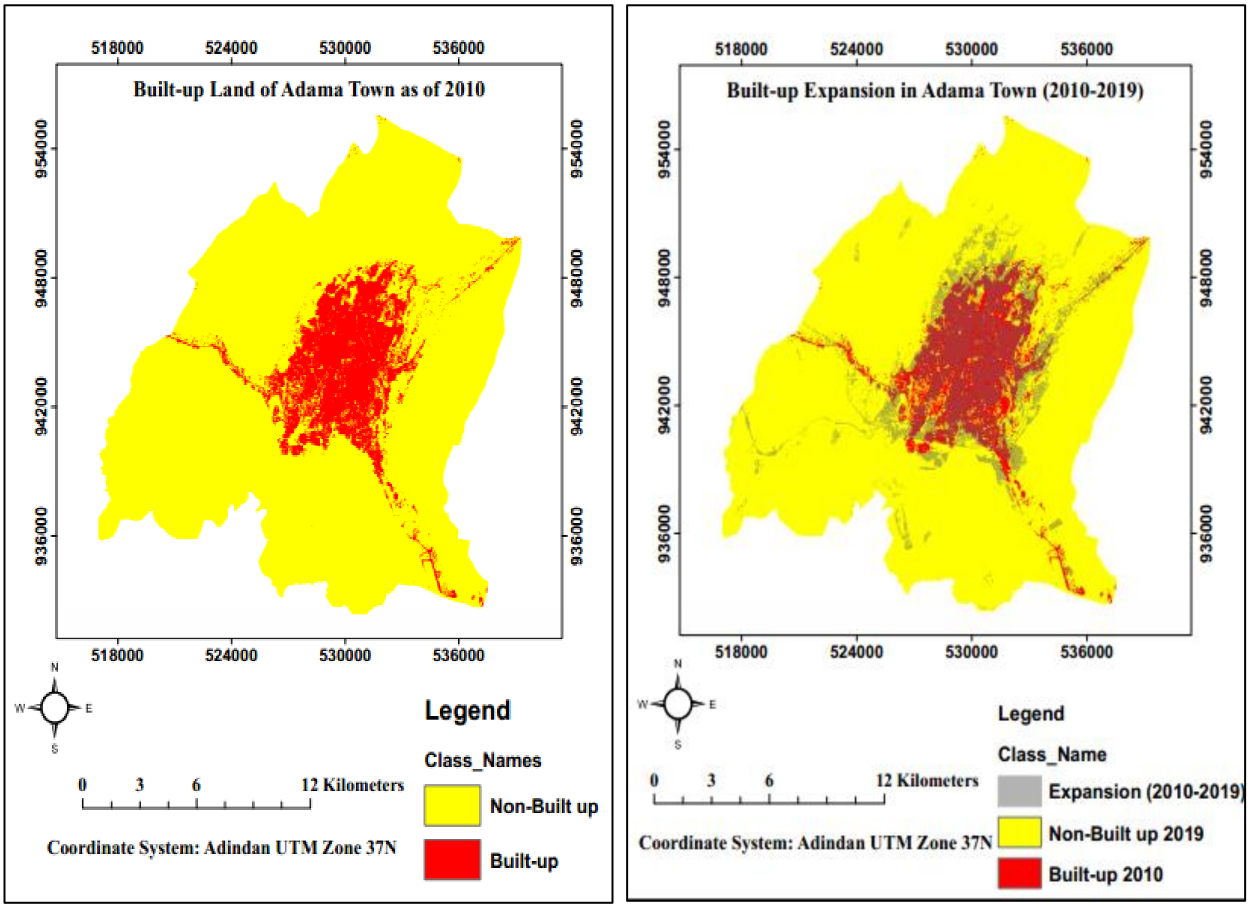


(c)

Figure 4. 3 (a) Built-up as of 2000 (b) Built-up expansion 2000-2010 (c) Road development 2000-2019

4.3.2 Built-up Expansion from 2010 to 2019

As shown in Figure 4.4b, the Built-up expansion of Adama Town during 2010-2019. A noticeable trend of built-up expansion along main transportation route and there is a rapid urban sprawl occurred in eastern and western part following the transportation route. Since the sprawl normally takes places in linear direction along the highway (sudhira et al., 2004). In addition, significant leapfrogging developments away from the dense node were also identified in North-west, South-West, and South-East directions. These are smaller and dispersed built-up patches compared to central urban core development. Analysis of total actual urban growth in the study period reveals that new built-up land 965 hectare indicating 107 hectare average annual increase of built-up land. In addition to this, the beginning of Adama industrial park is the potential factors to the development in the area.



(a) (b)

Figure 4. 4 (a) Built-up land as of 2010 (b) Built-up expansion 2010-2019

4.4 Results of Spatial Regression Analysis

4.4.1 Variables used in the Analysis

In this study, the main purpose of spatial regression analysis is to identify the major driving forces of urban/built-up growth in the study area and statistically quantify the interaction between urban growth and its drivers. In the analysis the built-up expansion map is considered as a dependent variables and maps of selected candidate factors maps as independent variables listed in the table 4.3 below. Each cell in the dependent variables has only two categories, either built up cell (represented by 1) or non-built-up cell (represented by 0) .The numbers of independent variables used for the spatial regression analysis are Road network, CBD, Slope, Institution, and Industry area. Area coverage of built-up land or cell is different for different temporal period.

Table 4. 3 List of variables used in the spatial regression analysis.

Variable	Name	Nature of Variables	Feature type
Dependent	Built-up maps 2000,2010,and 2019	Dichotomous	polygon
Independent	Road network	continuous	Line
	CBD	continuous	point
	Slope	continuous	Line
	Institution	continuous	point
	Industry Area	continuous	Point

4.4.2 Spatial Regression Analysis from 2000 to 2010

Spatial regression analysis allows to model, examine, and explore spatial relationship and can help explain the factors behind observed spatial patterns. As shown in figure 4.5, the result of spatial regression analysis report in GIS environment demonstrates that the coefficient for each explanatory variable reflects both the strength and the type of relationship the explanatory variables has to be dependent variables. When the sign associated with the coefficient is negative, the relationship is negative and the sign is positive the relationship is positive.

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                                             Summary of OLS Results
Variable Coefficient[a] StdError t-Statistic Probability[b]Robust_SE Robust_t  Robust_Pr[b] VIF [c]
Intercept  0.622647     0.001874  315.761624  0.000003*    0.004431  301.440022 0.000002*  --------
FID_Road  -0.000219     0.000028  -84.080911  0.000000*    0.000001 -197.217444 0.000000*  2.512600
FID_CBD   -0.000194     0.000022  -76.127656  0.000005*    0.000004  -52.201726 0.000005*  2.105519
FID_slope  0.000201     0.000018   82.156244  0.000002*    0.000001   81.152031 0.000001*  2.001990
FID_inst. -0.000172     0.000009 -119.565099  0.000008*    0.000002 -115.271722 0.000006*  2.413653
FID_indu. _0.000094     0.000005  -62.121876  0.000011*    0.000003  -59.141219 0.000009*  1.947611


                                               OLS Diagnostics
Input Feature:                          00-10  Dependent Variable:                     00-10GRID_CODE
Number of Observations:                   900  Akaike's Information Criterion (AICc) [d]: 407.210177
Multiple R-Squared [d]:              0.431921  Adjusted R-Squared [d]:                       0.421276
Joint F-Statistic [e]:             142.721927  Prob(>F), (5,870)degrees of freedom:          0.000001*
Joint Wald Statistic [e]:          301.921319  Prob(>chi-squared), (5) degrees of freedom:   0.000001*
Koenker (BP) Statistic [f]:        472.718892  Prob(>chi-squared), (5) degrees of freedom:   0.000001*
Jarque-Bera Statistic [g]:         248.110960  Prob(>chi-squared), (4) degrees of freedom:   0.000005*
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Figure 4. 5 Summary of ordinary least square regression analysis result

According to the result all selected variables except slope are negatively correlated with built-up expansion. For instance, as distance from road increases the chance to a land to be converted to built-up decreases but slope is positively correlated with built up expansion. All variance inflation Factor (VIF) for any of the variables is less than 7.5, which is better result according to ArcGIS Pro documentation it indicates there is no redundancy variables telling the same story which can lead to an over count- type of bias. Two columns, probability and robust probability measure coefficient statistical significance. An asterisk (*) next to the probability tells the coefficient is significant. If a variable is not significant, it is not helping the analysis and we should remove it. When the koenker (BP) statistic is statistically significance, we can only trust the robust probability column to determine if a coefficient is significance or not. Small probabilities are “better” (more significant) than large probabilities. The adjusted R-Squared value ranges from 0.0 to 1.0 and tells how much of the variation in the dependent variables has been explained by the model. According to the result on figure 4.5 the adjusted R-square value is 0.421276. Therefore, the regression equation using the coefficient of five variables can be summarized as,

Built-up exp. = 0.622647 - 0.000219 (Road) - 0.000194 (CBD) + 0.000201 (Slope) -0.000172 (Institution) – 0.000094 (Industry area)

4.4.3 Spatial Regression Analysis from 2010-2019

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Summary of OLS Results

Variable	Coefficient[a]	StdError	t-Statistic	Probability[b]	Robust_SE	Robust_t	Robust_Pr[b]	VIF [c]
Intercept	0.475178	0.001876	222.781611	0.000001*	0.003711	210.114402	0.000000*	--------
FID_Road	-0.000277	0.000012	-71.701219	0.000005*	0.000002	-69.167809	0.000004*	2.110477
FID_CBD	-0.000168	0.000016	-81.107412	0.000011*	0.000009	-77.122987	0.000009*	1.947400
FID_Slope	0.000212	0.000010	84.116942	0.000004*	0.000003	80.191707	0.000001*	2.002798
FID_inst.	-0.000184	0.000017	-108.172144	0.000010*	0.000001	-101.907819	0.000007*	2.461763
FID_indu.	-0.000117	0.000009	-47.121702	0.000102*	0.000090	-44.121821	0.000092*	1.627112

OLS Diagnostics

Input Feature:	10-19	Dependent Variable:	10-19GRID_CODE
Number of Observations:	750	Akaike's Information Criterion (AICc) [d]:	522.111807
Multiple R-Squared [d]:	0.371840	Adjusted R-Squared [d]:	0.351219
Joint F-Statistic [e]:	132.149907	Prob(>F), (5,710) degrees of freedom:	0.000001*
Joint Wald Statistic [e]:	352.144917	Prob(>chi-squared), (5) degrees of freedom:	0.000002*
Koenker (BP) Statistic [f]:	241.184214	Prob(>chi-squared), (5) degrees of freedom:	0.000000*
Jarque-Bera Statistic [g]:	127.121107	Prob(>chi-squared), (4) degrees of freedom:	0.000001*

Figure 4. 6 Summary of ordinary least square regression analysis result

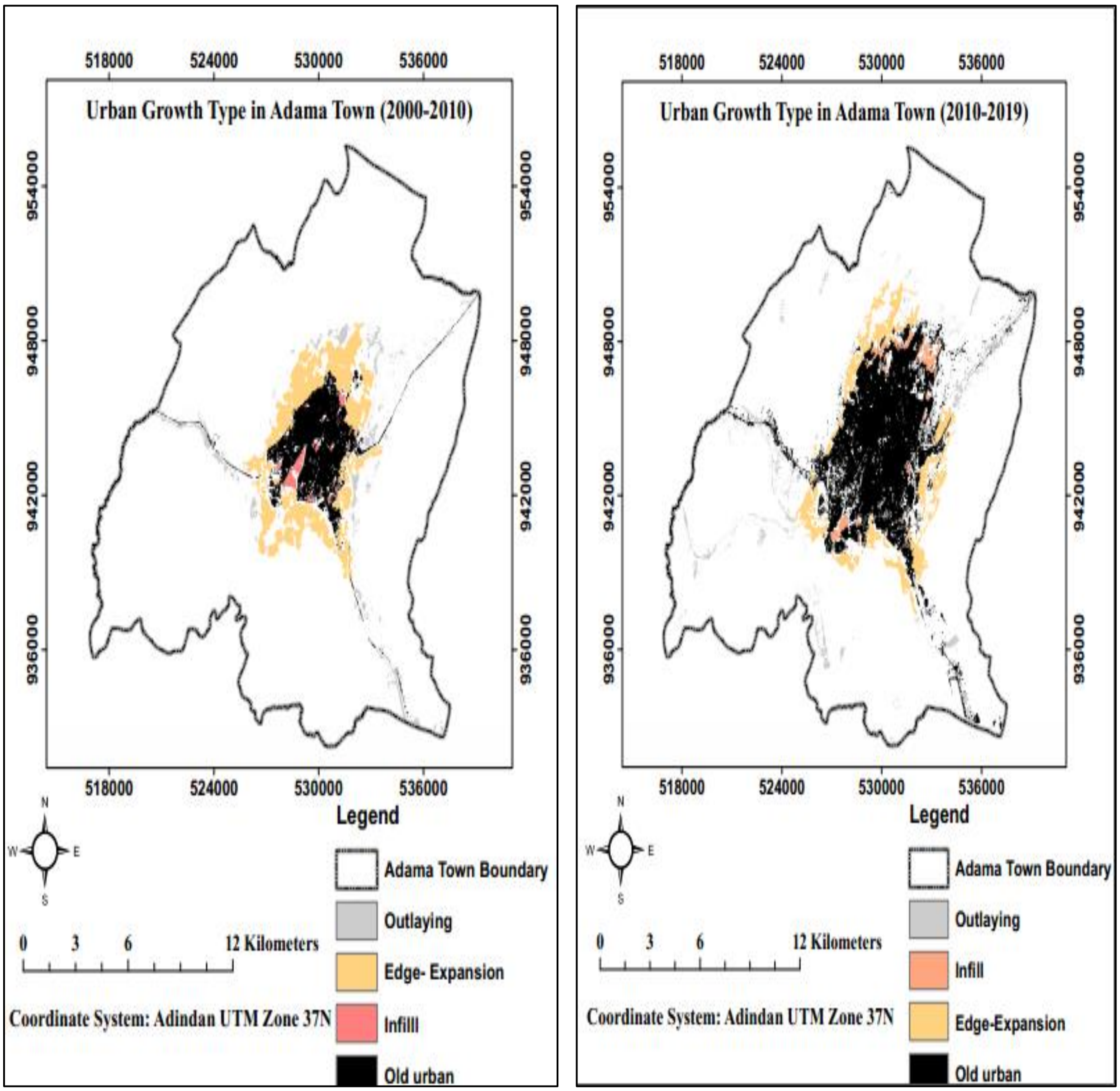
Ordinary least square analysis summarized in figure 4.6, the result of the analysis witnessed that all variables except slope are negatively correlated with built-up expansion means that the higher the distance from these variables the lower is the probability of urban growth to occur or in other words urban growth tends to occur in close proximity to these variables. The analysis revealed that all variance inflection factor (VIF) for all of the variables is less than 7.5 .this shows that there is no redundancy of explanatory variable and maintain the stability of coefficients.

In addition, probability and robust-probability indicates the coefficient statistical significance. The result shows that probability and robust- probability is very small which is the coefficient is statistical significance and an asterisk (*) next to the probability witnessed to the coefficient is significance. Based on ArcGIS Help Documentation the adjusted R-squared values are measures of model performance and possible values of range from 0.0 to 1.0. The result value indicates that 0.351219 which is between 0.0 to 1.0. Therefore, the regression equation using the coefficient of five variables can be summarized as,

Built-up exp. = 0.475178 - 0.000277 (Road) - 0.000168 (CBD) + 0.000212 (Slope) – 0.000184 (Institution) – 0.000117 (Industry area)

4.5 Three Types of Urban Growth

Each type of urban growth leads to different planning and environmental consequences. Thus, identifying the types of growth over time is essential for monitoring and alleviating the consequences of the urbanization process (Luck and Wu, 2002). In this context, three types of growth are measured for each density class. The first type of growth is infill.in this type of growth, the non-urban cells which are completely surrounded by urban cells, are converted to cells corresponding to one of the density classes. Infill growth usually occupies vacant land, where public facilities such as sewer, water and roads already exist (Hoffhine Wilson et al., 2003). The second type of growth is edge-expansion. Where non-urban cells, which adjoin existing urban cells, are converted to one of the density classes. This type represents an expansion of the existing urban patch and has been called urban fringe growth (Wasserman, 2000; Hoffhine Wilson et al., 2003). The final type of urban growth is outlaying in which non-urban cells are being converted to one of the density classes beyond existing growth areas. In order to identify growth type, the raster maps of existing urban patches were firstly converted to vector maps. Following the conversion steps, the boundaries of each existing urban patch were detected. The vector maps (map for each density class) of newly developed urban patch were overlaid with the boundaries of each existing urban patches. Using Analysis tools in ArcGIS, if the newly developed urban patch was within the boundaries of existing urban patch, the patch was categorized as infill growth. If the newly developed urban patch touches the boundary of existing urban patches, the patch was categorized as edge expansion. All other newly urban patches were then classified as outlaying growth.



(a) (b)

Figure 4. 7 Spatial distributions of three urban growth types in the study area.

The spatial distributions of the three urban growth types were mapped for the two temporal periods in Figure 4.7. Although the dominant form was consistently represented edge-expansion growth followed by outlaying and then infilling growth. As in Figure 4.7, distinct urban growth patterns can be shown it is observed that edge-expansion growth type is dominant in the two different temporal periods. To understand a clear detail of the temporal characteristics of urban growth in the study area, the area of the three urban growth types was calculated for the two temporal periods in figure 4.8 shows the dominancy of edge-expansion urban growth in the two temporal periods as said earlier.

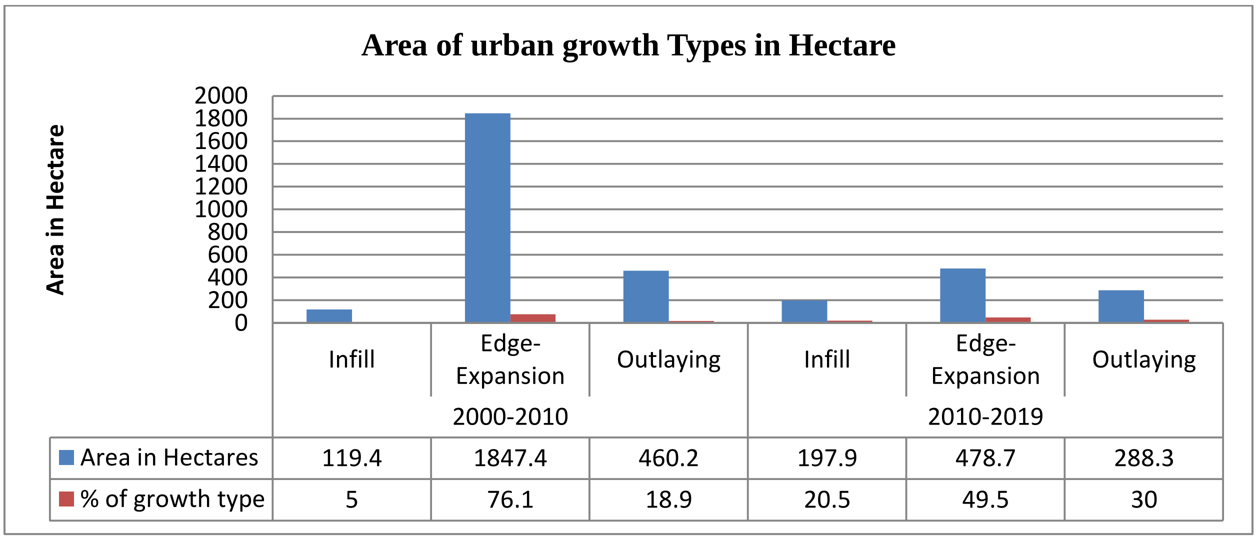


Figure 4. 8: Area of three urban growth types.

In the first temporal period (2000-2010) the edge-expansion covers76.1 % of the newly built-up area and it covers 49.5% area in 2010-2019. It decreased in the second temporal period. As far as the other types of urban growth are concerned, outlaying growth was low in 2000-2010 then it increased in 2010-2019. The outlaying growth type was mostly developed in the North, South, Northwestern, and Southwestern part of the town. A very little portion of the urban area has accounted for infilling type of growth in the first temporal period (2000-2010) which is 5% and it increased in 2010-2019 to 20.5 %.

The increasing trend of edge-expansion urban growth generally reflects the present kind of formation of sprawl whereas infilling growth refers to the agglomerated urban growth. But the high tendency of edge-expansion urban growth in the study area generally portrays the picture of growth of sprawl.

4.6 Discussion

This study analyzed the built-up expansion in Adama Town from 2000-2019 and pinpointed the major potential factors contributes to the existing pattern. As far as this, the study identifies the type of urban growth during the study periods. The findings of this study shows average annual built-up expansion in the first temporal period is 243 ha and 107 ha in the second temporal period. The newly developed land is mostly observed in the Northern and Southern part of the town in the first and second temporal periods. Sinha, et al., (2016), which agrees with this study. Above all, the study shows selected independent variables (Road, CBD, slope, Institution, and Industry area) are found significant as they contributed to physical expansion pattern of the town. This supports arguments of (Huang et al, 2009; Dubovyk, 2010) that noted that proximity factors have a potential to influence development pattern.

Further, these factors are related to dependent variable (built-up expansion) with different strength. Proximity to road network in the town is strongly related to built-up expansion (coefficient values equals to 0.000219) than the proximity to Institution (0.000172), proximity to CBD (0.000194), and proximity to Industry area (0.000094). This implies, even though there is different institution in the study area, development of transport infrastructure is found the most responsible factors for resulted shape of the town in the first temporal periods (2000-2010).

In the second temporal period (2010-2019), the results showed that proximity to road network is (0.000277), proximity to Institution (0.000184), proximity to CBD (0.000168), and proximity to Industry area (0.000117). This implies that, proximity to Industry area is less important than the other factors. Samat et. al, (2011) notice that lowest influence factors when modeling industrial activities in urban growth model. This may be due to people were not comfortable to live in surroundings near to Industrial area and at the same time people prefer to live in an environmental free from commercial or industrial wastes which can affect health of nearby communities.

Slope has been significant and positively related to urban growth in all study periods. This indicating that the higher the slope of an area the higher probability to be occupied by a new built-up cell. This could be attributed to the hilly topographic nature of Adama town, where settlement on lower slope or close to wetlands is unfavorable due to the presence of flood hazards and epidemic diseases like mosquito. Thus, steeper slope were more preferred for settlement than low laying or wetland areas.

The coefficient reflects the expected change in the dependent variable for every 1 unit change in the associated explanatory variable, holding all other variables constant. When the probability or robust probability is very small, the chance of the coefficient being essentially zero is also small. If the koenker (BP) test is statistically significant, use the robust probabilities to assess explanatory variables statistical significance. Statistical significance probabilities have an asterisk "*" next to them and a p-value (probability) smaller than 0.05 indicates a statistically significance model. The variance inflation factor (VIF) measures redundancy among explanatory variables and detects multicollinearity in regression analysis. Multicollinearity is when there is correlation between predictors (i.e. independent variables) in a model it's presence can adversely affect regression results. As a rule of thumb, explanatory variables associated with VIF value larger than about 7.5 should be removed from the regression model because both of these variables are telling the same story. The results of spatial regression analysis witnessed that all VIF values less than 7.5.

Quantification of different urban growth types can be a straight forward spatially explicit approach to assess urban sprawl (Yue et al., 2013) because infilling growth makes an urban area more compact, while outlaying growth leads to opposite feature. During 2000-2010, urban expansion mainly occurred as edge-expansion (1847.4 ha). This implies that the urbanization processes between 2000-2010 were prominently expanded in the urban fringe spaces. At the same temporal period the infilling growth was law percentage area (119.4 ha). This indicates that, small patch size of urban growth takes place. In addition, the degree of outlaying expansion indicates that, low-density expansion was found further from urban cores.

In the second temporal period, infilling growth types shows upward trend (197.9 ha). Most of infill newly urban patches within existing urban area. This implies that, compact and more aggregated urban growth near existing urban area. The edge-expansion growth with in the second temporal period also the dominant growth type occupying 478.7ha of the total newly developed urban lands taking place at sub urban areas. In addition, outlaying growth also upward trend (288.3ha) and causing increased fragmentation and dispersion of urban areas located relatively far from the urban center.

CHAPTER V. CONCLUSION AND RECOMMENDATION

5.1 Introduction

In this chapter the conclusions derived from the findings of this study which means the urban growth in Adama Town from 2000-2010 and 2010-2019 and the major potential factor contributes to the existing morphology of the town. In addition, identify different urban growth type with in the town during the study period are described. The conclusions were based on the purpose, research questions, and the result of the study. The implications of these findings and the resultant recommendations will be explained. Recommendations were based on the conclusions and purpose of the study.

5.2 Conclusion

Analyzing spatial patterns of urban expansion and urbanization rate, as well as exploring the major force driving urbanization, have long been important research topics for understanding the planning and sustainability of urban development. Urbanization was often examined under land cover changes using multi-temporal remote sensed images. This study analyzed the urban growth of and pinpointed the major potential factors contributes to the existing patters of Adama Town, as well as identify different urban growth types and its distribution. Adama Town has been undergoing extensive land cover change. The results indicate that the built-up expansion in Adama Town showed dramatic change speed and the new development have a tendency to replace agricultural lands this might be shortage of providing food and employment opportunity. According to Lwasa (2004) indicates that the process of rapid urbanization take place in developing countries significantly contributes to bring opportunities to new urban development. The problem comes with this rapid urbanization are serious like loss of the surrounding agricultural land, degradation of ecosystem as well as social and environmental changes and along with the urban expansion there is no parallel expansion of urban infrastructure of the urban population.

Significant expansion of built-up area of the town is towards the North and South direction. The main reasons are the development of road, slope, CBD, institutional factors like the presence of Adama Science and Technology University, Oromia Broadcast Network and industry area. These factors have a great influence in the process of the town development and formation. This suggests that the interaction of land use and road network or institutional factors is necessary for the future planning of the town and important to better understand the existing morphology of the town.

In terms of three urban growth types, edge- expansion growth took the predominant role in the built-up expansion process, while a low proportional of infill growth occurred in this study period. This observation demonstrated that the growth of the city tended to be in the formation of sprawl. If this trend continues, fragmented and irregular expansion will increase, which might lead to the inefficient usage of built-up land resources and highly reduces farm land and open spaces.

Finally, this study has confirmed that the use of integrated GIS and Remote Sensing techniques is capable of study urban expansion, driving factors and urban growth types of Adama Town. It can be said that GIS can facilitate the measurement of urban spatial growth and analysis of driving forces; and remote sensing is capable of detecting and measuring a variety of elements relating to the morphology of town, such as the amount, shape, and spread of urban area.

5.3 Recommendation

On the basis of the findings in this study, the researcher makes the following recommendations are put forth to improve and more effectively in order to manage urban expansion and incorporate different factors which are responsible to urban expansion.

- Mostly, the built-up area is expanding in North and South direction. Therefore, in order to maintain uniform distribution of built-up area in all direction and avoid disorder development. The town administration takes different measure to encourage new development in East and west direction.
- The road network of Adama in the expansion area, being based on the nature of the existing network, therefore the municipality should design new road network which cover the entire expansion because road network is major driving force of urban expansion in the study and most built up expansion follow the existing road network.
- Spatial regression model integrates spatial and socio economic factors in an urban growth perspective and it helps the government to design spatial policies to the context to improve plan implementation, to mitigate sprawling and disordered development patterns as well as to conserve environment.

- Besides the factors involved in this study, urban growth is affected by others factors, which are not incorporate in to spatial model due to lack of data. Therefore, it is recommended that more potential variables should be included in the future studies to improve the performance of spatial models and to evaluate the effects of the factors on urban growth.

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APPENDIX

Appendix 1 List of GCP used for Accuracy Assessment.

S/No	Code	Easting	Northing	Land cover type
1	D001	529988.113	951086.665	Shrub
2	D002	528224.374	950875.748	Shrub
3	D003	527988.259	950053.99	Shrub
4	D004	528614.985	950132.092	Shrub
5	D005	529802.074	950187.56	Barren land
6	D006	531132.436	949999.451	Urban
7	D007	532265.764	949862.459	Urban
8	D008	532757.95	949852.507	Barren land
9	D009	534073.021	949839.662	Barren land
10	D010	534965.72	950201.534	Barren land
11	D011	534992.941	948833.745	Barren land
12	D012	534099.213	949086.831	Shrub
13	D013	532781.227	948643.001	Barren land
14	D014	531842.969	949065.183	Urban
15	D015	531015.217	949091.507	Barren land
16	D016	530090.638	948880.918	Barren land
17	D017	529078.535	949014.629	Urban
18	D018	527680.761	949016.845	Shrub
19	D019	526999.814	949006.656	Barren land
20	D020	526640.995	948262.389	Shrub
21	D021	528136.731	947625.197	Barren land
22	D022	529057.405	947887.455	Barren land
23	D023	530112.571	947944.912	Urban
24	D024	530934.841	947914.524	Urban
25	D025	532036.926	948067.827	Urban
26	D026	533255.319	947870.16	Shrub
27	D027	533980.705	948070.546	Shrub
28	D028	534640.264	947757.905	Shrub
29	D029	526174.988	946896.693	Barren land
30	D030	526979.704	946950.432	Barren land
31	D031	528109.546	947129.073	Barren land
32	D032	528991.189	946998.637	Urban
33	D033	530142.281	947044.304	Urban
34	D034	530997.033	946976.003	Urban
35	D035	531979.044	947084.867	Barren land
36	D036	533098.091	946936.298	Urban
37	D037	534239.881	947156.986	Barren land

38	D038	535189.299	947169.448	Barren land
39	D039	536129.161	946865.765	Barren land
40	D040	535951.284	945973.713	Barren land
41	D041	535051.013	946059.816	Barren land
42	D042	533998.883	945922.063	Shrub
43	D043	532905.441	945988.294	Urban
44	D044	531907.311	945641.809	Urban
45	D045	531119.564	945967.332	Urban
46	D046	530315.635	946277.747	Urban
47	D047	529090.799	945657.41	Urban
48	D048	528109.868	946112.111	Urban
49	D049	526796.898	946108.695	Barren land
50	D050	525947.373	945995.659	Barren land
51	D051	525105.021	945921.044	Barren land
52	D052	524734.205	945195.783	Barren land
53	D053	525785.412	945153.817	Barren land
54	D054	526874.274	944945.071	Barren land
55	D055	527747.44	945373.526	Urban
56	D056	528877.061	944884.998	Urban
57	D057	530034.376	945300.045	Urban
58	D058	530996.824	945048.94	Barren land
59	D059	532274.229	944948.428	Urban
60	D060	532805.816	944957.09	Barren land
61	D061	534431.108	944814.183	Urban
62	D062	535009.136	945081.924	Barren land
63	D063	533807.23	943833.099	Urban
64	D064	532968.878	944166.574	Shrub
65	D065	533919.475	942388.875	Barren land
66	D066	533021.651	941998.448	Barren land
67	D067	532066.12	941912.971	Barren land
68	D068	529970.64	942333.067	Urban
69	D069	530809.353	942227.792	Urban
70	D070	528602.278	941967.076	Urban
71	D071	528052.493	942045.138	Shrub
72	D072	527046.238	942038.786	Shrub
73	D073	526142.774	941745.524	Shrub
74	D074	524483.184	941871.046	Barren land
75	D075	524883.312	941851.332	Barren land
76	D076	525913.623	941027.252	Barren land
77	D077	527005.486	940890.487	Urban
78	D078	528042.249	940601.805	Urban
79	D079	528848.185	940890.966	Urban

80	D080	529952.866	940904.337	Urban
81	D081	531098.715	940958.836	Urban
82	D082	531971.245	941084.619	Shrub
83	D083	533024.352	941033.145	Barren land
84	D084	533969.966	940937.465	Barren land
85	D085	531814.779	943974.552	Barren land
86	D086	530840.811	944080.594	Urban
87	D087	530275.246	944145.91	Barren land
88	D088	528949.931	943814.931	Urban
89	D089	528135.427	944064.572	Urban
90	D090	526893.772	944067.658	Urban
91	D091	525913.531	944001.088	Barren land
92	D092	525205.621	943988.92	Shrub
93	D093	524952.254	942993.087	Barren land
94	D094	525795.409	943043.734	Barren land
95	D095	526731.169	942952.273	Urban
96	D096	527758.586	942848.925	Urban
97	D097	528719.415	943106.873	Shrub
98	D098	529839.278	942652.694	Urban
99	D099	530979.33	942969.25	Urban
100	D100	532004.849	942973.533	Urban
101	D101	532976.99	943018.229	Barren land
102	D102	534004.391	942992.962	Barren land
103	D103	523975.127	940000.958	Barren land
104	D104	524678.467	939968.954	Barren land
105	D105	525907.329	940039.604	Barren land
106	D106	527162.233	939815.685	Urban
107	D107	528047.413	940026.58	Shrub
108	D108	528935.933	940165.551	Urban
109	D109	528809.171	939724.953	Barren land
110	D110	531018.971	940025.236	Urban
111	D111	531925.529	940053.683	Shrub
112	D112	533002.489	940017.42	Barren land
113	D113	534009.612	940003.41	Barren land
114	D114	533015.71	938888.87	Barren land
115	D115	532168.147	938943.347	Urban
116	D116	530688.171	939170.756	Barren land
117	D117	529892.278	939017.724	Barren land
118	D118	528817.44	938981.282	Barren land
119	D119	527757.978	938916.856	Shrub
120	D120	526969.816	939130.248	Barren land
121	D121	525984.704	938996.714	Barren land

122	D122	524652.93	939085.612	Barren land
123	D123	525048.27	938316.419	Shrub
124	D124	526411.359	937901.367	Shrub
125	D125	527097.687	937977.109	Shrub
126	D126	527990.381	937935.033	Barren land
127	D127	529007.024	937898.531	Shrub
128	D128	529936.356	938106.794	Shrub
129	D129	530964.031	937993.216	Barren land
130	D130	531874.963	938056.319	Urban
131	D131	531039.987	937045.565	Shrub
132	D132	529825.352	936870.18	Shrub
133	D133	528732.489	937309.409	Shrub
134	D134	528124.201	937191.545	Barren land
135	D135	526907.113	936931.601	Barren land
136	D136	525990.955	936910.962	Urban
137	D137	523069.537	937065.992	Barren land
138	D138	526959.895	936042.776	Barren land
139	D139	527852.279	935803.665	Shrub
140	D140	528659.794	936264.284	Shrub
141	D141	530041.124	936301.464	Shrub
142	D142	528741.876	934838.963	Barren land
143	D143	528037.129	934911.474	Barren land
144	D144	527008.309	934969.415	Barren land
145	D145	525900.444	935049.787	Shrub
146	D146	523989.012	939186.426	Shrub
147	D147	523910.124	937852.226	Barren land
148	D148	532311.081	947932.037	Barren land
149	D149	531437.817	946803.677	Urban
150	D150	528446.038	945057.926	Urban
151	D151	531327.3	945843.559	Barren land
152	D152	527452.929	942278.767	Urban
153	D153	530508.451	941156.936	Shrub
154	D154	530682.935	940732.68	Barren land
155	D155	528890.576	939470.472	Urban
156	D156	532490.014	939473.577	Barren land
157	D157	526549.589	936149.334	Urban
158	D158	528453.412	933968.311	water
159	D159	524271.922	937761.677	water
160	D160	517132.411	936566.544	water
161	D161	526737.661	934258.092	Agriculture
162	D162	534488.822	933612.222	Agriculture
163	D163	517690.912	937381.747	Agriculture