

URBAN LAND USE LAND COVER CHANGE DETECTION:
A CASE STUDY OF ADAMA CITY, ETHIOPIA.



Dejene Mulu Asfaw

A Thesis Submitted to the Department of Geomatics Engineering, School of

Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirements for the Degree of

Master's in Geo-Informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

August, 2021

Adama, Ethiopia

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Co-advisor: Gemechu Kaba (Msc.)

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Declaration

I hereby declare that this Master Thesis entitled “urban land use land cover change detection: a case study of Adama city, Ethiopia.” is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation

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We, the advisor(s) of this thesis, hereby certify that we have read and revised version of thesis entitled “urban land use land cover change detection: a case study of Adama city, Ethiopia.” prepared under our guidance by Dejene Mulu Asfaw submitted in partial fulfillment of the requirements for the degree of Masters of Science in Geo-informatics Engineering. Therefore, we recommend the submission of revised version of the thesis to department following the applicable procedures.

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LIST OF ACRONYM

AHP- Analytical hierarchy process.

AOI- Area of Interest

ARCGIS- Aeronautical Reconnaissance Coverage Geographic Information System

CA_MARKOV- Cellular automata and Markov Model

CORINE: Co-ordination of Information on the Environment

CSA- Central Statistical Agency

DEM - Digital Elevation Model

DN - Digital Number

ERDAS - Earth Resources Data Analysis System

EMA: Ethiopian Mapping Agency

ETM- Enhanced Thematic Mapper

ETM+ - Enhanced Thematic Mapper plus

GCP- Ground Control Points

GIS - Geographical Information System

GPS- Geographic Positioning System

LCM - Land Change Modeler

LULC- Land Use and Land Cover

LULCC- Land Use and Land Cover Change

MCE_ Multi Criteria Evaluation

NASA – National Aeronautics and Space Administration.

OLI- Operational Land Imagery

RS- Remote Sensing

SRTM- Shuttle radar topography mission.

TM - Thematic Mapper

UN- United Nations

USGS –United State Geological Survey

UTM- Universal Trans Mercator

WGS - World Geodetic System

ABSTRACT

This study uses Land Use and Land Cover Change (LULCC) computed from Landsat TM, ETM, ETM+ and OLI datasets of 1990, 2000, 2010 and 2020 respectively. The study aimed to simulate future LULCC using landsat images in the fastest-growing Adama city. Supervised classification and maximum likelihood algorithm was applied to estimate the LULC for years 1990, 2000, 2010, and 2020. These were analyzed by using ArcGIS10.8, Erdas imagine 2015 and IDRISI V.17 to make clear land use structure. The change detection of multiple Landsat images was conducted between 1990 and 2020. A hybrid simulation model that combined the Markov-Chain and Cellular Automata (MC-CA) was used to simulate the future LULC for 2030, 2040 and 2050. The historical LULC change data of 1990–2000, 2000–2010, 2010–2020 and 1990–2020 were used as a baseline. Both transition rules and transition area matrix for the period 1990–2000, 2000–2010, 2010–2020 and 1990–2020 were produced quantitatively using the Markov chain model. After that, the biophysical and socio-economic factors were standardized using fuzzy and determined using the analytic hierarchy process (AHP) and aggregated using weighted linear combination (WLC) under multi-criteria evaluation (MCE) approach was used to produce the transition suitability image. The model was validated using simulated and observed LULC 2020 by using kappa parameters; with the overall kappa index 0.84%; which indicates good kappa index values. The result shows that the proportion of built up area was 2.5% in 1990, this figure rose to just over 17% in 2020, with annual growth rates of 6.4%, 6.2%, and 14.7% in the three study phases, indicates an expansion in built-up area was 4493 ha, resulting in agriculture, barren land, vegetation, and water bodies losing 463 ha, 3760 ha, 223 ha, and 46 ha, respectively from 1990 to 2020. The simulated result indicated that built up area covers 26%, 28% and 30% of the total area coverage according to prediction at 2030, 2040 and 2050 respectively, indicate that these patterns of bare land changing into built-up and vegetation will continue over the next 30 years due to urban expansion and reforestation. It is predicted that the conversions of other land-use types into built-up areas will persist in the southern and northern areas of the city, as east-west growth trend of the city is hampered by the natural barriers of hilly ridges of Kechema in west & Didibisa and Migira in east, despite the city has almost a compact settlement shape. The output of the study provides useful information for land use planners and decision makers to make better decisions in improving future land use policies and formulating management strategies within the framework of sustainable land use planning.

Keywords: Modeling, lulcc, urbanization, simulation, Landsat.

CHAPTER ONE: INTRODUCTION

1.1. Background of the Study

Land use land covers (LULC) are two different terms. Land use defines the human use of land, and land cover represents the physical properties of surface elements. Land-use and land-cover (LULC) change has become important and essential component in current strategies for monitoring environmental changes and managing natural resources (Kumar et al., 2014). In recent decades, notable changes in LULC have been noticed due to rapid urban growth (habitat, 2014). The main consequences of the world's exponential population growth are rapid land use reform, troubling global environmental change and the transition of other fields to urbanized lands (Wu et al., 2006; Guan et al., 2011). The method of urban land use growth is a complex and diverse phenomenon. Interactions of several influences in time and space at different scales such as political, fiscal, social, and cultural factors, among others, define and influence urban land transition (Barredo et al., 2003; He et al., 2006). The pattern of land use change in developing countries is a manifestation of the haphazard distribution of new settlements, which is known as dispersed urban sprawl (Arsanjani et al., 2011). The conversion of agricultural fields to commercial, residential, and industrial land uses, i.e. built up area, has resulted in urban sprawl (Ettema et al., 2007; Al-shalabi et al., 2012; Amous, 2013). Furthermore, urban sprawl and unplanned urban growth degrade the efficiency of the urban climate for people. For improved performance of planning policies sufficient data and appropriate models are needed (Dadhich and Hanaoka 2011; Othman et al., 2013).

However, a large volume of data regarding the research area is needed to conduct a successful investigation, reporting and recording of land use transition. As a result remote sensing technology provides modified land use and land cover data that can be used to collect, analyze, and model land use transition spatially and accurately (Dadhich and Hanaoka 2011; Wakode et al., 2013; Youssef et al., 2011; Biro et al., 2011). According to Yuan (2009), superior spatial analytical technologies such as GIS and remote sensing are very helpful in determining plans and policies. Recently, a lot of research on urban land use transition studies using GIS and remote sensing has been published. Instead of mapping and identifying historical developments the majority of these studies focus on potential urban land use transition modeling (Barredo et al., 2003; He et al., 2008; Kelarestaghi and Jeloudar 2011; Al-shalabi et al., 2012). Furthermore,

population development and related land use transition can be mapped, modelled and analyzed thanks to developments in GIS and the integration of GIS with remote sensing (Araya and Cabral 2010; Kelarestaghi and Jeloudar 2011; Youssef et al., 2011; Kawy and El-Magd, 2012; Wakode et al., 2013). Urban land use transition models, according to Li and Yeh (2002), Deng et al., 2008 and Yang et al., 2012, are highly useful for urban development impact assessment, land transfer management, land use planning, identification of optimal land use change trends, and enabling local planners to create a healthy urban climate. Despite its difficulty, however, the modeling and simulation phase of land use transition is expected (Yang et al., 2012).

Land use models that are used to simulate, test, and forecast possible future scenarios of land use transition can be classified into three categories: (a) statistical and methodological methods, such as logistic regression (Al-sharif and Pradhan, 2013; Al-sharif et al., 2013) and Markov chains (Arsanjani et al., 2011); (b) complex models, such as the agent-based and Cellular Automata (CA) models (Al-shalabi et al. 2012; Q-s and Li 2007); (c) interconnected models, such as the transfer of land use and its impact model (Al-shalabi et al., 2012; Q-s and Li 2007); (CLUE; Verburg et al., 2002). The Markov chain is a popular model which calculates future change based on the past, and Cellular Automata detects the spatial location of change (Rimal et al., 2017). Integrated CA–Markov is recognized as a more powerful and effective modeling technique for the change model (Puertas et al., 2014). CA-based models can model non-linear, spatial and stochastic processes (He et al., 2006). Furthermore, the CA model can model and monitor diverse spatially dispersed systems, as well as provide simple insights into local behaviors and global land use/cover transition trends. However, determining acceptable transformation rules based on training data, which governs the model, is the most important consideration in CA models (Al-shalabi et al., 2012). It's worth noting that the CA model is influenced by parameters such as neighborhood type, neighborhood scale, and cell size; these parameters should be taken into account for the best simulation performance (Wang et al., 2012).

Since remote sensing data and GIS can be proficiently implemented, the combined CA–Markov model is a versatile technique in terms of quantity estimation as well as spatial and temporal dynamic modeling of LUCC. Furthermore, the integrated CA–Markov model will transform the effects of the Markov chain model into spatially explicit outcomes that are necessary for urban planning and design using a CA function (Guan et al., 2011; Arsanjani et al., 2011)., Integration of dynamic modeling models with mathematical and scientific models, on the other hand,

produces models that can transcend the limitations of a single model by complementing each other. Furthermore, advanced models that use many modeling methods can have a greater understanding and enhanced land use transition modeling (Guan et al., 2011). According to Arsanjani et al., (2011), each research area has varying environmental factors and characteristics, so the performance of land use transition models varies depending on the study area. Furthermore, He et al., (2006) reported that there is still a lack of explicit spatial urban development models capable of monitoring the history of urban expansion, predicting potential urban growth scenarios, and assessing and examining urban plans, provided that land use transition models can be seen as realistic tools to assist land use decision makers, urban planners, and to better understand urban planning (Verburg et al., 1999; Chen et al., 2002; He et al., 2006).

In this research, Adama city was chosen as a case study, which has experienced a very rapid dispersed urban growth over the last decades. This growth results in fast continuing other land cover changing to built-up lands. Moreover, an integrated Markov chain and cellular automata model (CA– Markov) has been applied integration with AHP in Adama city and this integrated model was used in this paper to assess its performance.

1.2. Statement of the Problem

The accelerated urban growth with an increase in population in the urban areas has led to various socio-economic demands and change for other land covers in the country. The rapid increase in population and the growth of urban areas due to urbanization has contributed massively to the change in land use land cover patterns and the conversion of farm land and vegetation to land use of different functions (Karimi et al., 2018). However, as it is observed in numerous developing countries, the intensified constraints, following the fast urbanization processes in the country, are unplanned and uncontrolled that resulting in scattered urban growth, loss of farmland, and environmental degradation. In addition, the urban physical growth rate has been faster than the rise in infrastructures and service delivery in Ethiopian cities (MUDHCo, 2014). Unplanned changes in LULC creates negative impact on the environment by increasing land surface temperature (LST) , relative humidity, irregular rainfall, affects water energy balance, soil quality, biodiversity, and ecosystem and increase the surface runoff. Adama city is one of Ethiopia's fastest-growing cities in terms of population, urban built-up areas and economic function. According to Bulti & Sori (2017) Green areas are being shifted to other land uses such as residential, industrial, and commercial developments.

The growth rate of population of Adama city from 2004 to 2016 is about 9% (Bulti & Sori, 2019). This status, largely considered as the main driver for the conversion of urban LULCC of the city. The city today has evolved to be one of the major commercial and business centers in central Ethiopia. The growth of the city has become more prominent due to the identification of the area as a viable economic hub of the country. The use of the CA-Markov model in LULCC studies has advantages such as its dynamic simulation capability; high efficiency with data, scarcity and simple calibration, and ability to simulate multiple land covers and complex patterns (Memarian et al., 2012). It was found that there is little evidence of the research conducted to tackle the urban LULC issues in future though the subject was widely research and highly used as a decision-making tool in both global and local setting of the area. From the above argument, it is imperative that the impact of the city upon surrounding areas is noticeably high and it is likely to be even more soon. Given such urban growth, the detailed study of past to present and future prospects of the city situations has become necessary for urban planners and policymakers to manage the city under the country development policy. Aburas (2017) focusing on CA-based simulation models, it was suggested that the integration of quantitative models such as MC and AHP could improve the accuracy of CA modeling and prediction. It is worth to mention that the CA-Markov model employed in this research was able to model the future LULCC using historical maps, i.e. CA-Markov model is very useful in situations of limited data. However, in case of urban development the land use change will be affected by several factors, for instance; biophysical factors (slope, elevation,....etc.) and socioeconomic factors (distance to road, distance to existing built-up,.....etc.) rather than land use history only. Thus, incorporating these factors in CA-Markov model will improve the understanding of land use change in urban areas and enhance the model ability for future prediction of land use change. Therefore, it is intended to fill this gap by incorporating these factors to the model and evaluating the model performance.

1.3. Objectives

1.3.1. General Objective

The general objective of the study is to analyze the LULC changes of Adama city, Ethiopia, from 1990 to 2020 and model the future city's LULCC pattern in 2030, 2040, and 2050 using the integrated CA-Markov model.

1.3.2. Specific objective

The specific objectives of this study are to:

- ✓ Detect land use land cover change from 1990 to 2050.
- ✓ Quantify the magnitude and rate of built-up area expansion from 1990 to 2020.
- ✓ Model LULC changes of the city using CA-MC model for 2030, 2040, and 2050

1.4. Research Questions

In order to achieve the research objectives, the research questions were formulated as the following:

- ✓ What is the spatial and temporal change of the LULC areas during the study periods?
- ✓ What is the spatio temporal change trend of the built-up area from 1990 to 2020?
- ✓ What will be the future LULC based on the analysis and simulation of past trends?

1.5. Significance of the study

The study's goal is to examine past and future land use land cover changes, both of which have become common in recent years. The final output of this study will provide information for Policymakers, city urban planners, land administration, and environmental protection office: To form and implement more coherent and sustainable urban planning strategies regarding existing and future land use. to Planning, management and monitoring of natural resources. To serve as an input parameter in many fields as geology, hydrology, and environmental studies. Further researcher will be interested in the findings of this analysis because it will add to the current realistic and theoretical knowledge base on the past and future LULCC. Fill in the awareness gap by running simulations and proposing adaptable LULC change model.

1.6. Scope of the study

The Geographical scope of this study is Adama city, Ethiopia, where urban growth is prone in the areas, which cover 312.9 km² and shape area with the current new Administrative boundary. Conceptually, this research focus mainly on LULC change analysis from 1990-2020 and prediction of the future urban land use land cover modeling at (2030, 2040 and 2050) using Geo spatial technologies and giving clue about the importance of developing land use land cover change map for urban planning in Adama city boundary and also the accuracy assessment was

carried out for classified image , change analysis ,validation and future prediction of land use land cover change and finally conclusion and recommendations were raised based on the findings.

1.7. Limitation and assumption of the study

The accuracy and reliability of the predicted urban growth model will ultimately depend on the historical input data and the model calibration. The high spatial resolution of remote sensing data interpretation is required to obtain better simulation results (Chaudhuri & Clarke, 2013). In this study, 30 meter Landsat satellite images obtained from USGS earth explorer website (<https://earthexplorer.usgs.gov/>) has been used. Generating accurate land use the land cover map was a challenge from such images due to a coarse resolution. It was difficult to make a clear distinction between different land use features classes. using High Spatial resolution Satellite image such as Quick bird, IKONOS, Geo Eye, World view, and SPOT will provides better and detail information with good quality to map Land use land cover classes and overall accuracy may greater than the value obtained. The incorporation of major social, economic and political factors which can drive significant changes in LULC into identified models is limited by the availability of data.

1.8. Organization of the research

The whole thesis is divided into five chapters. The first chapter lays the background of the study providing general introduction about the research work including the problem statement, questions and research objectives, the scope and limitations of the study were also highlighted. The second chapter deals with literature survey in which the related works as have been performed by various other researchers are presented. In the third chapter, information about the chosen study area is given and how the several data layer maps are generated, also outlining the methodology of carrying out the task and the data sources utilized. Chapter 4 presents the findings of this research work and a detailed discussion on the results obtained. Finally, in the fifth chapter, a conclusion is drawn based on the results obtained along with future research possible and recommendations.

CHAPTER TWO: LITERATURE REVIEW

2.1. Theoretical Background of the study.

The earth's surface has been changed considerably over the past decades by humans because of urbanization, deforestation and agriculture. Despite the fact that rates of land conversion to agriculture and deforestation vary around the world, the number of people living in cities has been steadily increasing. Since World War II, urbanization has been increasing, showing no signs of slowing down, and is expected to continue into the twenty-first century (Ouz, 2004).

2.2. Land use and Land cover Changes (LULCC).

Because of the existence of many current database systems, the terms land usage and land cover have been used interchangeably in the land use research community. These two words, on the other hand, describe two distinct problems and definitions. The observed biophysical cover on the earth's atmosphere, including trees, barren dirt, rough surfaces, and water bodies, is referred to as land cover. Land use, on the other hand, is the modification of land surface processes such as biogeochemistry, hydrology, and ecology through human activities for the purposes of agriculture, forestry, occupation, and pasture (Di Gregorio and Jansen, 2000).

With the belief that processes on the earth's surface affect temperature, land use and land cover changes became a leading research subject on global environmental change many decades ago. Land use and land cover transition had a significant effect on global warming through the carbon cycle in the early 1980s; with terrestrial habitats acting as both sources and sinks as a result of the changes. Following that, the upcoming volume of the 1991 Climate Change Institute of the Office of Interdisciplinary Earth Studies (OIES) dedicated to land use and land cover changes at the global level by illustrating the main recent patterns of changes, their effects in the atmosphere, human causes on it, as well as data and modeling of changes (Meyer and Turner, 1992).

The scientific group has established three fundamental problems with the support of the International Geosphere and Biosphere Programme (IGBP) and the International Human Dimensions Programme on Global Environmental Change (IHDP) land use and land cover change initiative. Understanding the causes of land use and land cover transitions, quantifying them, and using models to forecast them is among the goals (Lambin et al., 2003).

Meyer and Turner (1992) distinguish between two types of ground cover changes: conversion and alteration. The former is a transition from one kind of land cover to another (e.g from grassland to cropland). However, the latter is a change within a land cover category (e.g thinning of a forest or a change in composition). Land use is driven by changes in land use as a result of human activity, so a similar type of cover may accommodate many uses (forest used for combinations of timbering, slash and burn agriculture, and soil protection). On the other side, a single land-use structure will support multiple covers (as certain farming systems combine cultivated land, improved pasture and settlements).

Changes of land use and land cover resulting from the overt and indirect effects of human activity on the atmosphere in order to improve one's quality of life. One of the direct consequences of humans is population development, which has an influence on land use, especially in developed countries, over longer time scales. Land use and land cover transition is a dynamic phenomenon, according to Lambin et al (2003), and it can be caused by reciprocal relations between environmental and social influences at various spatial and temporal scales. Land use and land cover transition can be classified as either direct (proximate) or indirect (indirect) sources, according to Verburg et al., (2002).

Human actions that may result from the continued use of land and specifically affect land cover are examples of direct causes, indicating that humans are moving factors. They are mostly run at a local level and illustrate how and when humans directly alter local ground cover and ecological processes. Indirect factors, on the other hand, are structural forces that reinforce the more straightforward causes of ground cover changes. The dynamic interaction of societal, political, economic, technical, and biophysical factors has resulted in these triggers. Climate change, hydrology, air quality, and wildlife are also impacted by changes in land use and land cover. Meyer and Turner (1992) reported that it resulted in a variety of microclimatic improvements in their sample. Deforestation is linked to rising global surface temperatures due to changes in land use. This resulted in a significant warming of the local climate, known as an urban heat island. Their research has revealed that water contamination occurs as land cover shifts from agriculture to population (urban areas). Understanding both how people make land-use decisions and how complex environmental and social influences work to affect these decisions is essential for identifying the causes and impacts of land use and land cover transition (Lambin et al., 2001). Land use transition projections are useful for understanding the effects of complex land use and

land cover changes because they offer insight on land use trajectories by projecting into the future. However, models' potential to predict outcomes is critical for improved environmental policy and land use planning (Verburg et al., 2002).

2.3. Urban Land use Changes

Urbanization, in a general sense, is one of the ways that human movements are changing the global ground cover. While the urbanization pattern is global, the United Nations Centre for Human Settlements (Habitat, 2001) states that the most noticeable developments have occurred in developed countries as a result of rural people migrating to cities in search of better opportunities. Following this, it was predicted that between 2000 and 2030, the population of metropolitan areas would rise at a rate of 2.3 % per year on average (Nations, 2001)

Long considered a sign of regional economic viability, urban development, especially the movement of residential and commercial land use to rural areas on the outskirts of metropolitan areas, has been viewed as a sign of regional economic vitality (Yuan et al., 2005). However, with the effects on the environment, increased economic disparities, and social fragmentation, its value has become unbalanced. It can be defined as the rate of increase in urban population. Dynamic processes resulting from urban change, especially the massive global growth of urban population and urbanized area, have an impact on both human and natural systems at all scales (Brockerhoff, 2000). According to Araya and Cabral (2010), population development in Setbal and Sesimbra, Portugal, grew dramatically by 91.11 percent between 1990 and 2000. However, much of this expansion occurred on the outskirts of cities, as a result of the amalgamation of a number of smaller settlements as well as the consumption of farm resources. Development was expected to proceed in the future, with a variety of implications for natural resources. One of the main driving factors for such rapid growth, according to their report, was population growth.

Historically, population analysis has been used to assess the extent of urban sprawl (Carlson and Traci, 2000). Meanwhile, aerial photography is becoming increasingly necessary for updating ground cover maps. Since land cover changes at the regional level are increasingly due to human activities, the changes in the community could not be realized. As a result, reliable and up-to-date data is needed to implement sustainable development plans and enhance city livelihoods. Local governments and policymakers value the opportunity to monitor improvements in urban land cover and land usage. It is now possible to track urban land cover and land use transitions

and urban sprawl in a timely and cost-effective manner thanks to expanded availability and improved accuracy of multi spatio-temporal data and modern analytical techniques (Yang et al., 2003). As a result, satellite data can be used for spatial planning and urban ecology.

2.4. Urbanization

2.4.1. Definition of Urbanization and Urban Growth

Urbanization refers to the growth of towns and cities, often at the expense of rural areas, as people move in to urban centers in search of jobs with the expectation of a better life, enabling cities and towns to grow. It can also be termed as the progressive increase of the number of people living in towns and cities. It is highly influenced by the notion that cities and towns have achieved better economic, political, and social mileages compared to the rural areas (Bhatta et al., 2010). Urban growth is a spatial and demographic process as that refers to the increased importance of towns and cities as a concentration of people with in a particular economy and society (Bhatta et al., 2010). There are at least three different and widely studied concepts of urban growth in the urban and regional planning literature, related to population change, economic performance and the spatial expansion of urban areas (Reis et al., 2015). The socio-demographic dimension of urban growth focuses on demographic trends and migration. The first includes the natural population growth rate, depending mainly on fertility and mortality rates, while the second depends on the capacity of a city to attract residents from other cities or rural settlements (Turok and Mykhnenko, 2007; Rieniets, 2009).

2.4.2. Status of Urban Growth in world

The world is rapidly urbanizing and cities are experiencing the dynamic processes of urbanization and globalization (Monica et al., 2017). According to Xing Quan (2015), prior to 1950, global urbanization trends were calculated based on the transformations that took place in Organization for Economic Cooperation and Development (OECD) countries. The proportion of the world's population, which is urban, has been growing rapidly and currently a larger fraction of the total population lives within cities (UN, 2007). According to United Nations world Urbanization Prospect (UNWUP, 2014) the percentage of urban population in 1950 was 30% , which was increased to 54% in 2014, and estimated to be 66% by 2030. Urbanization is not merely a modern phenomenon, but a rapid and historic transformation of human social roots on a

global scale, whereby predominantly rural culture is being rapidly replaced by urban culture (Pawan, 2016).

2.4.3. Status of Urban Growth in Africa

According to Omoakin Jelil (2012), Africa used to be, and perhaps is still, the least urbanized continent, with growth rates of cities close to, if not the fastest in the world. But, today, in virtually every part of the continent, new cities have been emerged, while the old ones have drastically expanded, some of which have become mega-cities. By 2030, for the first time in the history, more of the continent's people will be living in urban areas than in rural regions and by 2050 an estimated 1.23 billion people, or 60% of all Africans will be city dwellers. Currently, even if the level of urbanization in Africa is low, the rate of urbanization is high due to the population growth, which is one of the most important driving forces of changes in any urban system. If urban population swells, the city must expand upward or outward. Along with economic development and technologies (mainly transport and communication) revolution, rapid urban growth can be characterized by the development of suburban expansion and redevelopment in city centers (Rui, 2013).

2.4.4. Status of Urban Growth in Ethiopia

Ethiopia is the second most populous country in Africa next to Nigeria with a population estimated at 99.39 million in 2015 from which 19.4% live in urban and peri-urban areas (CSA, 2016). Between 2007 and 2015 nineteen million people were added to the population. The population size is growing by 2.9 percent per year and is expected to nearly double in less than 33 years to around 185 million in 2050 (Efrem & Tesfaunegn, 2017). The country is one of the lowest urban dwellers residences compared to Sub - Saharan standards of a percentage of the total population residing in cities and urban settings, despite indications display a rapid rate of urbanization in the pace at which people are relocating to urban centers. Projection made by the Ministry of Urban Development and Housing indicates that, the number of urban population by 2025 is expected to reach between 30-35 million (27 to 30% of a total population). By 2037, the urban population will be 42.2 million (40% of the total population). This means that the urban population of Ethiopia will increase between 2015 and 2037 by as much as 39 million, and that the urban population expansion accounts for around 75% of the total population increase of over 50 million during this period. Date back to the country level of urbanization, it was about 5% in

the 1950s, and 10% in the 1970s and by 1984 was about 13%, and reached 19% in 2014 having grown by 6% between 1984 and 2013 and this reflects an average increase of 2% per decade (Pieper & Hakalin, 2018).

2.4.5. Status of Urban Growth in Adama city.

The construction of the Addis Ababa-Djibouti railway at the start of the 20th century had given impetus to the establishment of several urban centers (such as Adama, Dire Dawa, and Hursso) that started as transport outposts. Adama city is one of the railway urban centers, founded as a railway depot in 1916. According to state of Ethiopian cities report provided by Ministry of Urban Development and Housing (MUDH, 2015) based on 2007 census, the CSA officially had recognized 973 urban centres in Ethiopia. A key feature of the country's urban system is the primacy of Addis Ababa, which was population wise more than ten times larger than the second largest urban centre, Adama in 2014.

2.5. LULC change and drivers.

2.5.1 International Review of Drivers of Land Use Change.

LULC change involves a conversion from one LULC to another or intensification of the present or current LULC (Turner et al., 1994). The changes in LULC are determined by how individual landowners, communities, businesses and governments control land use and make decisions on how to use land. Such decisions are influenced by the interactions between socioeconomic factors such as population and environmental factors (e.g. topography and climate) which vary at different scales (Lambin and Geist, 2007). (Briassoulis, 2000) confirms this and further clarifies that environmental drivers do not have a direct impact on land use change but impacts land cover change which in turn influences land managers decisions. As a result, LULC adjustment can be modeled as a function of socioeconomic and environmental variables. The term "moving forces" is also used to describe these factors. The reasons that drive LULC transition can both be classified as proximate or underlying, with the former referring to direct adjustments made by individuals on a small scale, such as individual farms, and the latter referring to subtle changes that arise at a larger scale (Lambin and Geist, 2007). Proximate driving factors are usually caused by human activities such as infrastructure and agriculture expansion whereas underlying factors are caused by complex interactions between social, political, demographic and environmental variables (Lambin et al., 2001). Briassoulis (2000) describes underlying driving

forces as socio-economic drivers which comprise of demographic, economic, institutional factors, technological and cultural or socio-political.

2.6. Factors of urbanization

There are several factors of urbanization, such as Economic development, innovation of technology, industrial revolution, emergence of large manufacturing factors, job opportunities, availability of infrastructures and migration. Generally, the causes of urbanization and urban expansion are group into three major classes.

2.6.1. Demographic effects

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

2.6.2. Economic effects

It include the level of economic development, difference in household incomes, exposure to globalization, the level of foreign direct investment, the degree of employment, the level finance markets, the level and effectiveness of property taxation and the presence of high inflation and acute shortage of housing (Angel et al., 2005).

2.6.3. Natural /environment effect

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

2.7. Urban Land use land cover of Image Classification

Remote sensing, image processing, and pattern recognition all require image classification. In remote sensing, classification entails grouping/clustering the pixels of an image into a limited number of classes, with pixels in the same class possessing identical properties. The bulk of image classification relies on the identification of land cover class spectral response patterns (Brito & Quintanilha, 2012). Supervised and unsupervised classifications are the two primary methods to differentiate these approaches. Parallelepiped, maximum probability, minimal

lengths, and Fisher classifier methods are some of the sub classification methods in supervised classification. Hard Classifier is the term for these processes. The method of assigning unknown items to one or more known features using training data is referred to as supervised classification. The maximum likelihood (ML) classification algorithm determines the probability that a given pixel belongs to a certain class, assuming that the statistics for each class in each band are normally distributed. The class with the highest probability is allocated to each pixel (i.e., the maximum likelihood). By using more features and training samples from the study field, the supervised classification technique will provide better results. Objects chosen as descriptive examples of known features are referred to as training data.

2.8. Land use land cover Change detection

The method of detecting changes in the status of an object or phenomenon by analyzing them at various times using remote sensing techniques is known as change detection (Singh, 1989). Change detection has a wide range of applications in different disciplines such as change analysis, forest management, vegetation phenology, and seasonal changes in pasture production, risk assessment, urban expansion and other environmental changes (Singh, 1989). To be useful, a change detection study should include the following elements: area change and rate of change, spatial distribution of modified forms, land-cover change trajectories, and precision evaluation of change detection effects.

2.9. Geo-spatial technologies useful for urban LULC change analysis

New tools for sophisticated ecosystem conservation are now available thanks to advances in remote sensing, GIS, and IDRISI. With the advent in technology, data costs have decreased, and historic spatiotemporal data and high definition satellite imagery are now available for use in spatial design, mapping, earth science, traffic planning, environmental planning, emergency response, and study of urban expansion transition.

2.9.1. Remote Sensing

According to Lambin (2004), remote sensing (RS) is described as follows: The science and art of collecting knowledge about the Earth's surface by the study of data collected by a computer located at a distance from the surface is known as remote sensing. Remote sensing is an essential tool of land change science because it facilitates observations across larger extents of Earth's

surface than is possible by ground-based observations by using of cameras, multispectral scanners.

2.9.2. Geographic Information System (GIS)

GIS is a system that combines hardware, software, and data to capture, manage, analyze, and view all types of geographically referenced data (Maguire) (1991). GIS also allows for the convergence of these data sets in order to derive useful information and to output the information derivatives in map or tabular format. Acquisition, editing, manipulation, analysis, simulation, visualization, publication, and storing of geographic data are all supported by GIS. Input, storage, analysis, and output are the four essential subsystems of GIS.

2.9.3. IDRISI Selva

IDRISI is the industry leader in raster, covering the full spectrum of GIS and remote sensing needs from database query, to spatial modeling, to image enhancement and classification. Special facilities are included for environmental monitoring and natural resource management, including land change modeling and time series analysis, multi criteria and multi-objective decision support, uncertainty and risk analysis, simulation modeling, surface interpolation and statistical characterization (IDRISI Selva Manual version 17.01). One advantage of using IDRISI for land-use change modeling is that in one software package you have: 1) the data, 2) the simulation model, and 3) the statistical techniques of goodness-of fit (Pontius 2002).

2.10. Types of LUCC Modeling

Modeling of Land Use Land Cover Change (LUCC) is a rapidly growing research field since land use change is one of the most significant ways that humans affect the climate. Modeling means the process of creating a representation of reality; it could be a map, graph, picture, or mathematical representation. Land use land cover changes modeling defined as the process of creating maps based on the history of Land use land cover, existing information and assumptions of the future. Modeling land use land cover plays a significant role to understand impacts of the changes that occur through time. The Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler (LCM), Earth trend, Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (Eastman, 2006). Since LUCC models can be radically different in a lot of ways, it's difficult to equate their results. For example, some

models, such as IDRISI's GEOMOD, simulate change between two land categories (Silva and Clarke 2002) while others, such as IDRISI's CA_MARKOV, can simulate change among several categories (Pontius and Malanson, 2005). However, it is difficult to compare which one gives more accurate representation (Wu and Webster 2000; Chang, 2006)

2.10.1. Land change Modeler (LCM)

The Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI oriented to the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation (Eastman, 2012). Land Change Models are important tools for environmental and geomatics research concerning LUCC (Pontius, 2015). Monitoring and analysis of changes in LULC are needed in order to provide information on existing land use patterns and changes for decision makers to support sustainable development (Fan, 2007).

LULCC models are used to improve and/or better understand of the alteration of land use that is induced by human activities (Brown, 2004). In LCM, tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, habitat and biodiversity impact assessment, and planning interventions (Eastman, 2012). The actual modeling of transformation sub-models is done in the IDRSIS Run Transition Sub-Model panel. Three methodologies are provided for modeling: a Multi-Layer Perceptron (MLP), Similarity-Weighted Instance-based Machine Learning (SimWeight) and Logistic Regression. Multi-Layer Perceptron and SimWeight procedures perform best in modeling transitions (Eastman, 2012). The MLP option can run multiple transitions, up to 9, per sub-model. But SimWeight and Logistic Regression can only run one transition per sub-model. MLP and SimWeight both exercise with half of the samples (change pixels) and validate with the other half. At each iteration, MLP calculates estimated class memberships for each of the validation pixels and records the overall accuracy as well as an ability ranking. The competence score is the difference between the measured accuracy based on the validation data and the predicted accuracy based on a random guess at the validation pixels' class memberships. SimWeight calculates the mean transition potential among validation pixels that changed (i.e., went through the transition) and the mean transition potential among pixels that did not change (persisted). These numbers reflect the hit and false alarm rates. The Peirce Skill Score is a number between 0 and 1 that represents the difference between them. Logistic regression is a

statistical technique for predicting outcomes. Binomial Logistic Regression is used in this model, as well as the Maximum Likelihood approach for prediction

2.10.2 Earth Trend Modeler (ETM)

Earth observation image time series provide a critically important resource for understanding both the dynamics and evolution of environmental phenomena. As a consequence, Earth Trends Modeler (ETM) is focused on the analysis of trends and dynamic characteristics of these phenomena as evident in time series images. Furthermore, the method is extremely immersive, with the discovery process being essentially an engaging one. The trends and dynamics emphasized include: Inter annual trends, Seasonal trends, Cyclical components, Irregular but recurrent patterns in space/time (recurrent patterns in space/time including a unique form of Wavelet analysis), Tele connections (analysis of climate patterns of variation between widely separated areas of the globe), and variability such as the coupled ocean-atmosphere (Eastman, 2012).

2.10.3 GEOMOD

GEOMOD is a concept that has been widely used to examine deforestation benchmark scenarios (Pontius and Chen, 2006). It is a grid-based land-use and land-cover transition model that simulates the spatial trend of land change in time forwards and backwards. Simulates the change between exactly two land categories denoted as 1(non-developed and 2 (developed), but 1 and 2 could represent any two categories for any particular application (Pontius, 2006). The starting time, finishing time, an image of the beginning time for two land cover forms that must be denoted by 1 and 2, an approximation of the number of cells in each of the two groups at the ending time, and a suitability map are the minimum input criteria. GEOMOD is a program that uses a land use/cover chart to forecast the future of a certain land class. Its advantages need only one time land use map for calibration and its disadvantage can simulate change only in two categories (Pontius & Chen, 2008). GEOMOD was created to take full advantage of data that varies greatly in terms of availability, completeness, precision, currency, and accuracy (Silva and Clarke 2002).

2.10.4 Cellular Automata (CA)

Cellular Automata (CA) is a spatial dynamic model which predicts transitions among any number of LULC categories (Li et al., 2015). In CA model, the transition of a cell from one LULC to another depends on the state of the neighboring cells (Adhikari and Southworth, 2012), which is based on the idea that a cell with higher proximity to a cell will have a higher probability to change in the future. Hence, CA model is very important to study complex geographic phenomena (Wang et al., 2012). Nevertheless, it pays attention merely to the local interactions of cells (Sang et al., 2011).

Mathematically, CA model (Al-sharif and Pradhan, 2013) is expressed as:

$$S(t, t+1) = f(S(t), N) \quad (1)$$

where, S is the states of discrete cellular, t is the time instant, $t+1$ is the coming future time instant, N is the cellular field and f is the transition rule of cellular states in local space.

2.10.5 Markov chain model

Markov is a stochastic model which requires pairs of LULC images (Clark labs, 2012; Eastman, 2012). The model portrays the probability of one state being altered to another state in a so called transition probability matrix (Arsanjani et al., 2011; Li et al., 2015). However, it didn't account any sense of spatial character or geography (Wang et al., 2012; Li et al., 2015) and does not provide clarification about the change processes (Adhikari and Southworth, 2012). Mathematically, the model is expressed (Sang et al., 2011; Adhikari and Southworth, 2012; Alsharif and Pradhan, 2013) as:

$$S(t+1) = P_{ij} \times S(t) \quad (2)$$

$$P_{ij} = \begin{vmatrix} P_{11} & P_{12} \cdots P_{1n} \\ P_{21} & P_{22} \cdots P_{2n} \\ P_{31} & P_{32} \cdots P_{3n} \end{vmatrix} \quad (3)$$
$$0 \leq P_{ij} \leq 1$$

Where, $S(t)$ is the state of the system at time 1, $S(t+1)$ is the state of the system at time 2; P_{ij} is the transition probability matrix in a state, P_n is the number of LULC categories. In the study area the t is LULC map of 2000 and $t+1$ are LULC map of 2010 to predict the 2020. the time period simulation 10 years. According to MARKOV model the relation between 2000 and 2010 has been modeled to be used in the 2020 simulation. The results of the MARKOV model are presented in table 4.15.

2.10.6 CA-Markov Model

Cellular Automata-Markov Cellular Automata-Markov (CA-Markov) is a robust model which integrates the ability of Markov and CA models (Arsanjani et al., 2011; Wang et al., 2012; Li et al., 2015). Hence, CA-Markov predicts not only the trend but also the spatial structure of different LULC categories (Arsanjani et al., 2011; Wang et al., 2012; Li et al., 2015). To predict future LULC conditions, the model requires a basis LULC image (time 2 image), transition probability matrix and suitability images as a group file (Clark labs, 2012; Eastman, 2012). The model is widely applied in LULC change modeling elsewhere (e.g. Kamusoko et al. (2009) in Zimbabwe; Arsanjani et al. (2011) in Iran; Sang et al. (2011) in China; Al-sharif and Pradhan (2013) in Libya; Adhikari and Southworth (2012) and Singh et al. (2015) in India). The strength of CA-MARKOV is that it is simple to create data, that it adds spatial dimension to the model, and that it can simulate change across several categories. Its flaws are that socioeconomic considerations are ignored, and calibrating the model with MCE takes much too long relative to other approaches (Adhikari & Southworth, 2012).

2.11. Model Validation and Future Prediction

The simulated and reference maps are compared during model validation. According to (Eastman, J. 2009), map comparison is critical when analyzing spatial data analytical techniques. To equate two maps, it generates numerical expressions (Vliet, J. V., 2009). Comparing the projected map of time t_2 with the reference map of time t_2 is the easiest way to verify a construct (Pontius, H., 2006). The kappa statistic and multiple-resolution were used to validate the results.

2.12. Literature Review Summary

Several studies have applied this model in different geographical contexts (Lu, Q.;et al;2018). Mosammam (2017), Monitoring land use change and measuring urban sprawl

based on its spatial forms: The case of Qom city, it was found a dramatic increase in the built-up area, mainly occurring along major roads and highways, leading to a huge decrease in agricultural land in Qom, Iran. Aburas (2016), the simulation and prediction of spatio-temporal urban growth trends using cellular automata models: focusing on CA-based simulation models, it was suggested that the integration of quantitative models such as Markov chain (MC) and AHP could improve the accuracy of CA modeling and prediction. Mundia and Murayama (2010), Modeling Spatial Processes of Urban Growth in African Cities: A Case Study of Nairobi City, affirming the applicability of the CA–MC model in developing countries, mainly due to the absence of reliable and accurate data, it has been rarely employed for analyzing Africa’s urban expansion (Bisello,et al;2017). Liping et al., (2018), monitoring and predicting land use land cover changes using remote sensing and GIS techniques in china: The model incorporates the benefits of cellular automata (CA) and Markov chain analysis to simulate future land-use change. It combines the power of the CA model to simulate spatial variations in complex systems and therefore the future predictions of the Markov model. Naboureh et al. (2017) applied the CA-Markov model to predict land cover changes for the purposes of development planning, informing and formulating land use policies in Jiangle County, China, and Penajam Paser Utara Regency, Indonesia, respectively. Sibanda and Ahmed (2021) Modelling historic and future land use/land cover changes and their impact on wetland area in Shashe sub-catchment, Zimbabwe. The CA-Markov model was used to simulate future LULCs in the Shashe sub-catchment, in order to detect their impact on the wetland area in Zimbabwe. Regmi et al. (2017) Geospatial Analysis of Land Use Land Cover Change Modeling in Phewa Lake Watershed of Nepal by Using GEOMOD Model .compared the CA-Markov model with the GEOMOD model to predict future LULC changes in the Phewa Lake Watershed, Nepal, and found that the integration of the CA and Markov models was effective in projecting future LULC scenarios compared to GEOMOD. Memarian et al. (2012), Validation of CA-Markov for Simulation of Land Use and Cover Change in the Langat Basin, Malaysia.CA-Markov model has high efficiency, simple to calibrate and high ability to simulate multiple land covers and complex patterns. In this paper an integrated CA–MC model with an AHP process for the purpose of modeling the urban LULCC in Adama city.

CHAPTER THREE: STUDY AREA, MATERIALS AND METHODS

3.1. Description of the study area

Geographically, Adama city is spatially positioned at crossroads in southeast of Addis Ababa at a distance of 99 km and 84.7 kilometers via old & express road respectively along all-weather road that leads from Addis Ababa to the sea port of Djibouti. It takes only one hour journey on well-constructed asphalt road to reach a national capital/ primate city of the country that serving as a nerve-center of the country. It is situated in Rift valley within Awash River Watershed in Oromia Regional State of Ethiopia & north of Asela town at 75 kilometers distance. Astronomically, it is located at $8^{\circ} 33' N$ latitude and $39^{\circ} 16' E$ longitude. (figure.3.1).

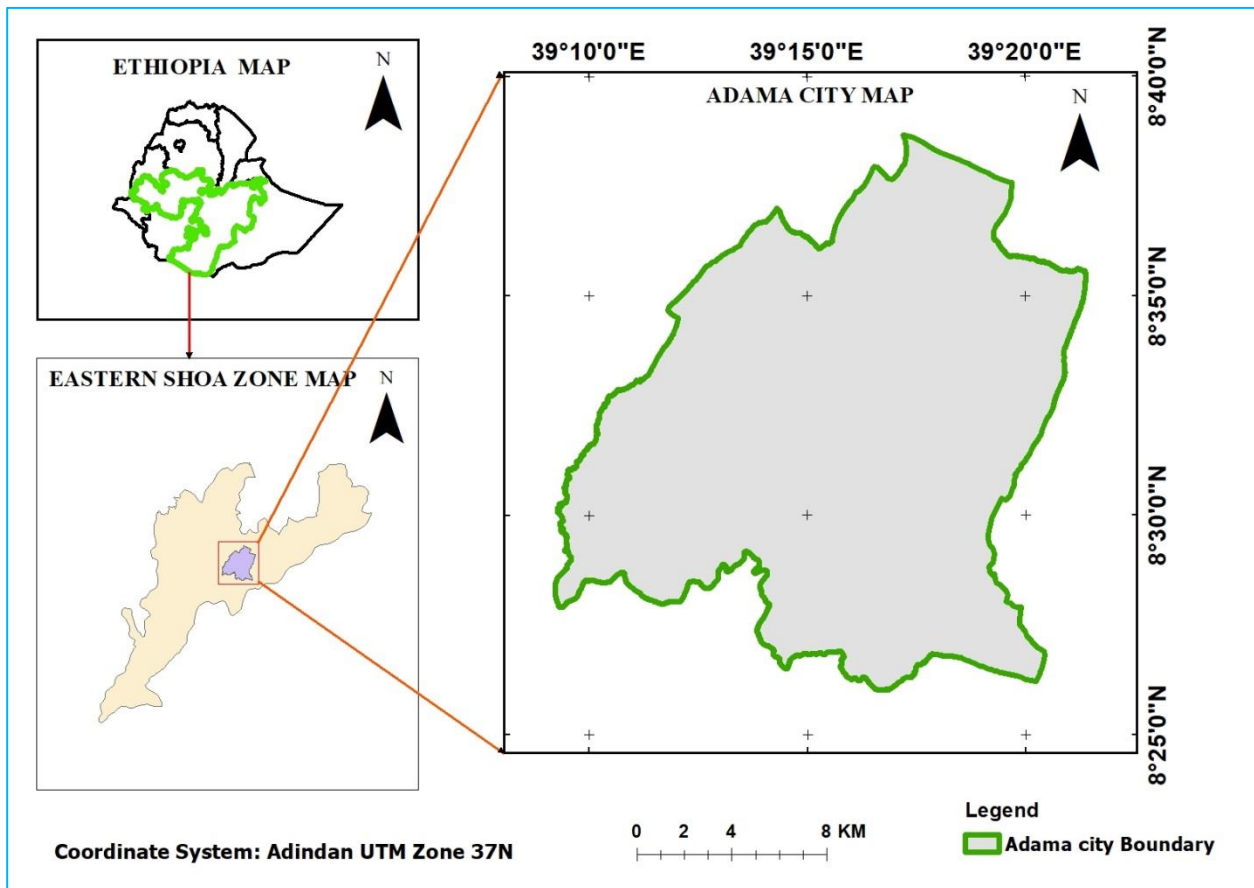


Figure 3.1: Location Map of the study area.

3.1.1. Population

Change in population growth accelerates the demand for land and the dynamics in land-use/land-cover changes. The results of the 1984 census revealed by CSA that the population of Adama city 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 of Ethiopia (CSA), this city has a total population of 220,212, an increase of 72.25% over the population recorded in the 1994 census, of whom 108,872 are men and 111,340 women. According to 2007 census population projection for 2009 the total projected population size of a bustling city of Adama is currently estimated at 373, 661(table 3.1). This factor triggers the ever-growing demands for urban services such as land for residence, economic and industrial activities and public services.

Table 3.1: The projected population size of Adama city year 2007-2011 EC.

city	year	male	Female	Total
Adama	2007	176,487	179,857	356,344
	2008	185,107	188,554	373,661
	2009	193,992	197,605	391,597
	2010	206,153	207,083	413,236
	2011	216,046	217,000	433,046

Source: CSA and projected population

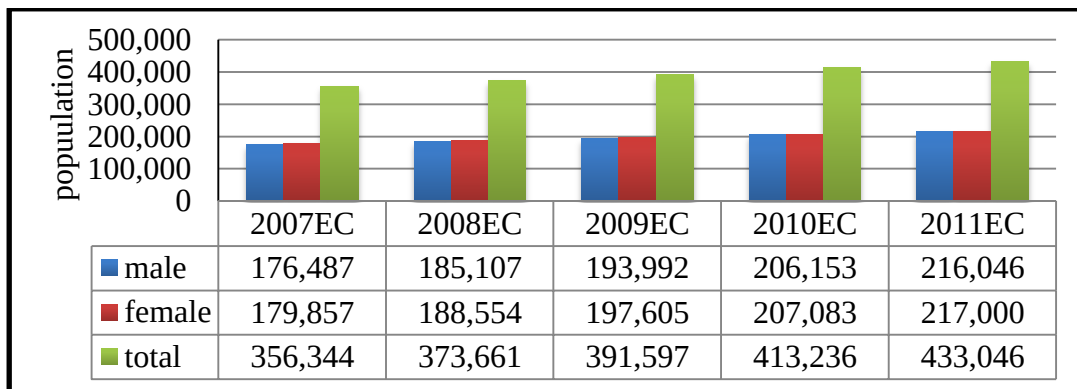
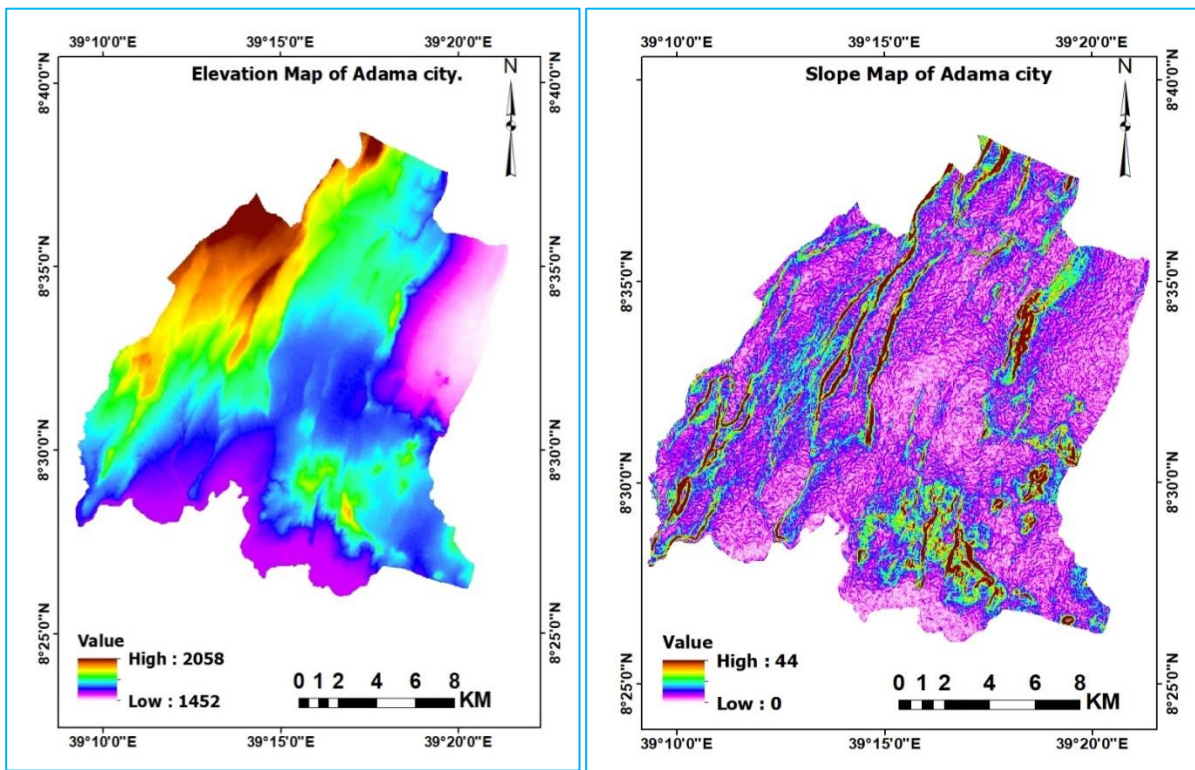


Figure 3.2: trend of Adama city population.

3.1.2. Topography

Topographically, the city is suited in Rift Valley, on flat terrain characteristics and surrounded by mountains and ridged topography. It is bounded by Kechema ridge in the west, Kufagutu peaks on the north, Dibibisa and Migira ridge in the east and Boku ridge in the south. According to the current master plan of the city, the city has demonstrated north-south growth trend as east-west growth trend of the city is hampered by the natural barriers of hilly ridges and altitude of the city ranges from 1,452 meters to 2,058 meters Above Mean Sea Level (m.s.l) in the north. The average elevation is 1,755 meters. The lowest and highest points are located at the extreme east and northwest part of the expansion areas, respectively (Figure 3.3a). The slope in Adama city lies between 0° and 44° lowest and highest points respectively (Figure 3.3b).



(a)

(b)

Figure 3.3: Elevation (a) and slope (b) of Adama city.

3.1.3. Climatic Condition

3.1.3.1. Rainfall and temperature

In respect of climatic condition, the locality of Adama city with very hot temperature & scorching noon time sun is characterized by unreliable rainfall, scarcity of water & dry & hot condition throughout much of the year. The magnificent, pleasant, healthful & congenial climatic condition of Adama city which lays in the Rift crosses the country from north to south is mainly characterized by light & relatively low summer precipitations & winter scorching sunlight. Winter season/Bega (December, January and February) when the overhead sun occurs south of the equator, & spring (March, April and May) when the overhead sun seems to shift its location from south to north. The presence of lovely, fabulous & health-giving climate appeals different people from different parts of the country year round. The city with short rainy season & erratic rain experience bi-modal rainfall which mostly occurs in rainy season (June to September). The amount of temperature significantly drops during the rainy season in the city. The city with short rainy season and erratic rain experience bi-modal rainfall which mostly occurs in rainy season (June to September). The minimum and maximum average annual rainfall of Adama City for years 2007-2011EC was 738.5mm and 976.1mm respectively, whereas the lowest and the highest annual average temperature for years 2007-2011EC was 12.95 and 31.68 respectively (City municipality,2011).

3.2. Materials and software

In this research various software's and materials were used for different purposes in order to achieve the proposed objective. There are a number of different kinds of methods, strategies and techniques to process input data to generate the required output with desired quality. The methodology integrates remote sensing and GIS tools as well as urban LULC modeling using CA- Markov imbedded in DRISI software.

Table 3.2: materials and software used

No.	Software used	Purpose
1	ArcGIS v.10.8.	✓ Visualization, map layout and accuracy assessment for classification.
2	ERDAS v.2015	✓ Digital image preprocessing, layer stacking, radiometric correction and delineation of area of interest (AOI) or subset.
3	IDRISI v.17	✓ For change analysis, multi criteria, multi-objective decision, Support, simulation modeling and predict for the future LULC map.
4	Google Earth pro	✓ Visualization and verification of classification and point data collection for accuracy assessment of 1990, 2000, 2010 & 2020 map.
5	Microsoft office Word v.2016	✓ Writing, chart preparing, graphs and statistical analysis.
6	Microsoft Office Excel V.2010	✓ To display the graphical representation of land use land cover change
7	Handheld GPS	✓ Collect Ground Controls Points (GCPs).

3.3. Data Types and sources

The study's data came from a variety of places, including blogs, associations, and stakeholders. Landsat 5, 7, 8 TM, ETM+, OLI (L1TP product of path 168, row 54) was used for mapping LULC of the study area for year 1990,2000,2010,2020 respectively (table3.3 & 3.4). Despite its medium spatial resolution and mixed pixel challenge the Landsat image is commonly used for urban LULC mapping (Lu & Weng 2005; Chen et al. 2016). It is available for several dates at no cost. The United States Geological Survey included all images from each year with less than 10% cloud pollution (USGS). Since the accuracy of Landsat image recognition during the dry season is better than during the rainy season, all of the photographs were taken during that period (Liu et al. 2015). In urban research land use maps must be accurate geometrically (Sertel & Akay 2015). The National Aeronautics and Space Administration (NASA) use Landsat Level 1 (L1T)

photographs that have been geometrically corrected and ortho rectified (Gutman et al. 2013). The atmospheric effects were minimized by converting raw digital number (DN) values to surface reflectance, which was done in the ERDAS software's radiometric calibration module. A variety of ancillary data was also gathered for this study. The NASA online data portal provided the SRTM Global Digital Elevation Model. Administrative boundaries and population data were also obtained from Adama land administration office. All of the datasets used in the study were geometrically calibrated using WGS 1984_UTM zone 37 North projections.

Table 3.3: Characteristics and properties of the Landsat images used.

Acquisition Date.	Path/Row	Landsat	Sensor	Spatial Resolution	band	Cloud cover
1990/12/18	168/54	Landsat 5	TM	30 m	7	0%
2000/02/05	168/54	Landsat 7	ETM+	30 m	8	0%
2010/01/15	168/54	Landsat 7	ETM+	30 m	8	0%
2020/01/19	168/54	Landsat 8	OLI/TIRS	30 m	11	0.02%

Table 3.4: Data Types and Data Sources of the study.

No.	Input layer	Source.	year	Format.
1	Landsat5TM	USGS earth explorer	1990	Raster.
2	Landsat7ETM		2000	
3	Landsat7ETM+		2010	
4	Landsat8OLI		2020	
5	Population data	Adama city land administration	2020	Number.
6	Road	Derived from Google earth image.	2020	vector
7	Aerial Photograph	EMA	2019	Raster.
8	DEM -SRTM	USGS earth explorer	2020	Raster.
9	Slope	Estimated from DEM.		Raster.
10	GCP	Field Observation	2020	
11	City Master plan & Boundary.	Adama city urban land administration.	2020	CAD.

3.4. Land cover classification Scheme

The land use/land cover classes applied in this paper are adopted from AFRICOVER land use land cover classification scheme which is widely applied in East African Countries (AFRICOVER, 2002). For the sake of simplicity, the researcher modified the descriptions of some of the land use/land cover classes considering the land use/land cover diversity of the study area. Therefore, five major land use/land cover nomenclatures: built up/ urban areas, agricultural lands, vegetated areas, open space and water body are used to produce the final land use/land cover map of the study area (Table 3.5).

Table 3.5: The final land cover classification scheme for study area.

No.	LULC	Descriptions
1	Built-Up	➤ Includes all residential, commercial, and Industrial developments and transportation. Areas under construction are also included.
2	Water	➤ Includes all water bodies (rivers, lakes, gravels, streams, canals and reservoirs.
3	Barren	➤ Includes a surface with no or little vegetation, open land, exposed soil, rocks and sand(eroded gullies)
4	Agricultural	➤ Includes all agricultural lands (both annuals and perennials) and grazing.
5	Vegetation	➤ Includes all forest vegetation types (evergreen, deciduous and wetland), and non-forest vegetation futures that are not typical of forest (pasture grasslands and recreational grasses.

3.5. Methodology

The methodology of this research composed of Image Classification and Change analysis phase, Suitability Analysis phase, modeling the LULC phase.

3.5.1. Image classification and change analysis phase

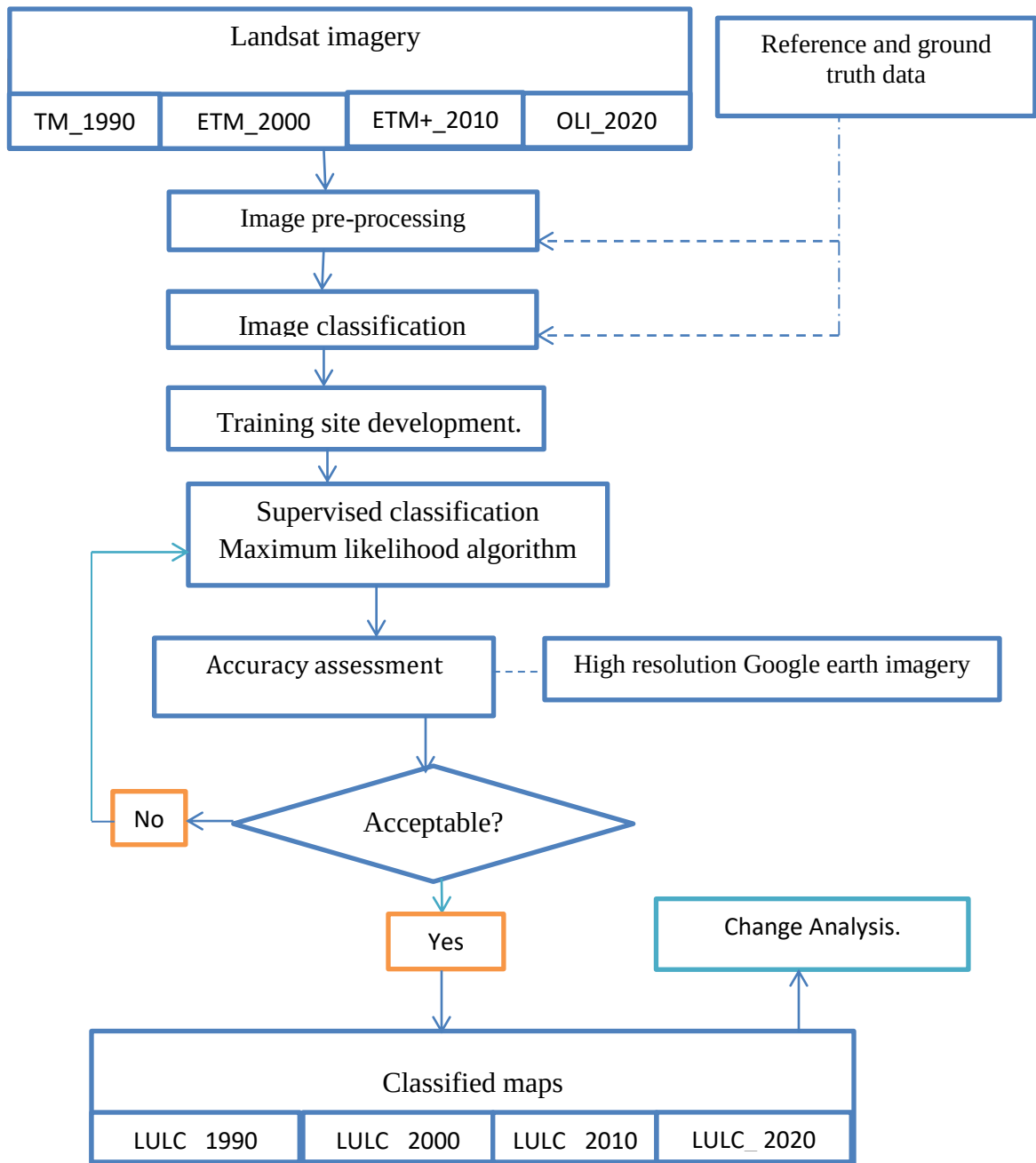


Figure 3.4: Technological scheme.

3.5.2. Suitability Analysis

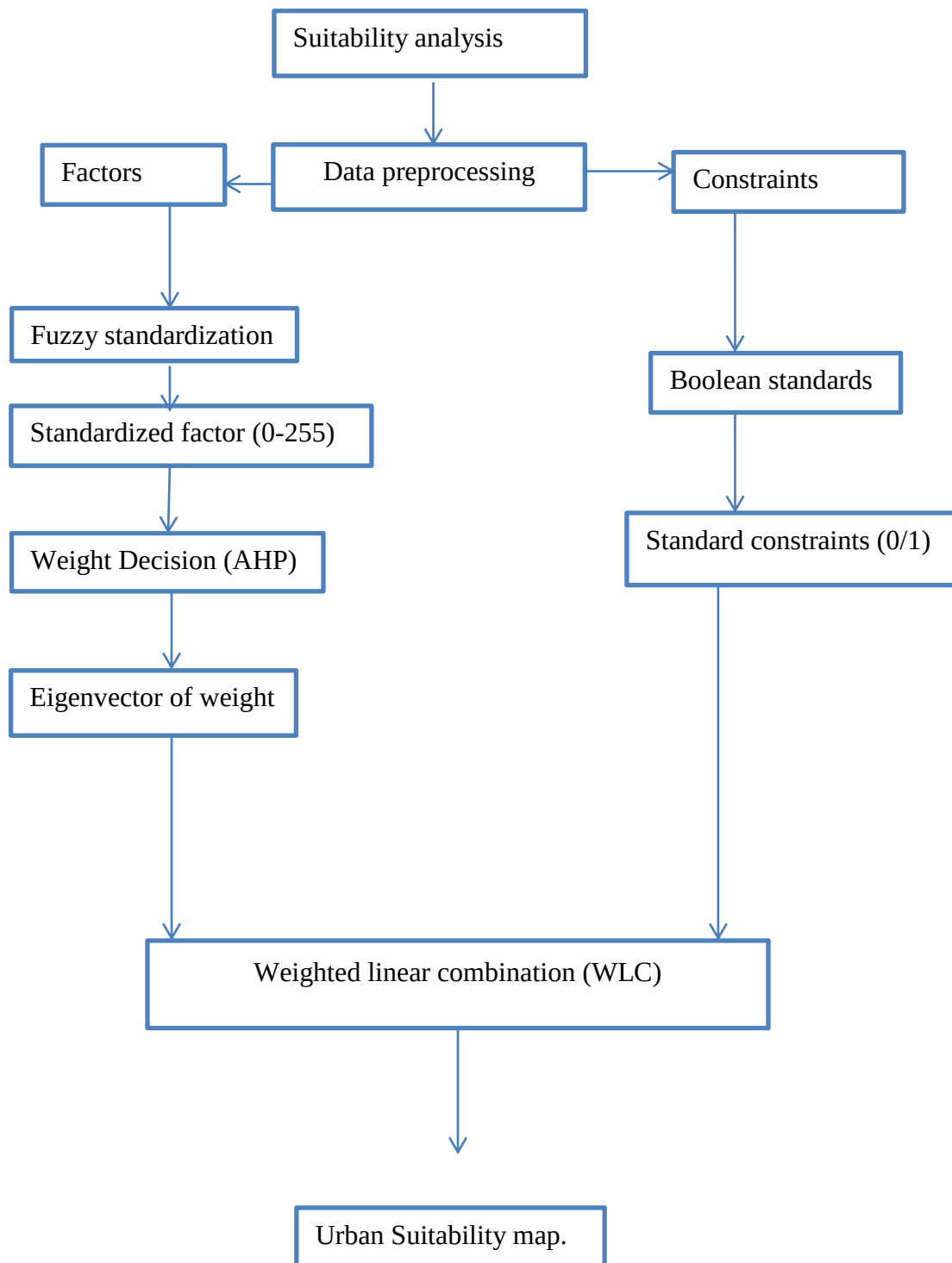


Figure 3.5: Steps used to prepare LULC suitability maps under MCE.

3.5.3. Modeling and Prediction phase

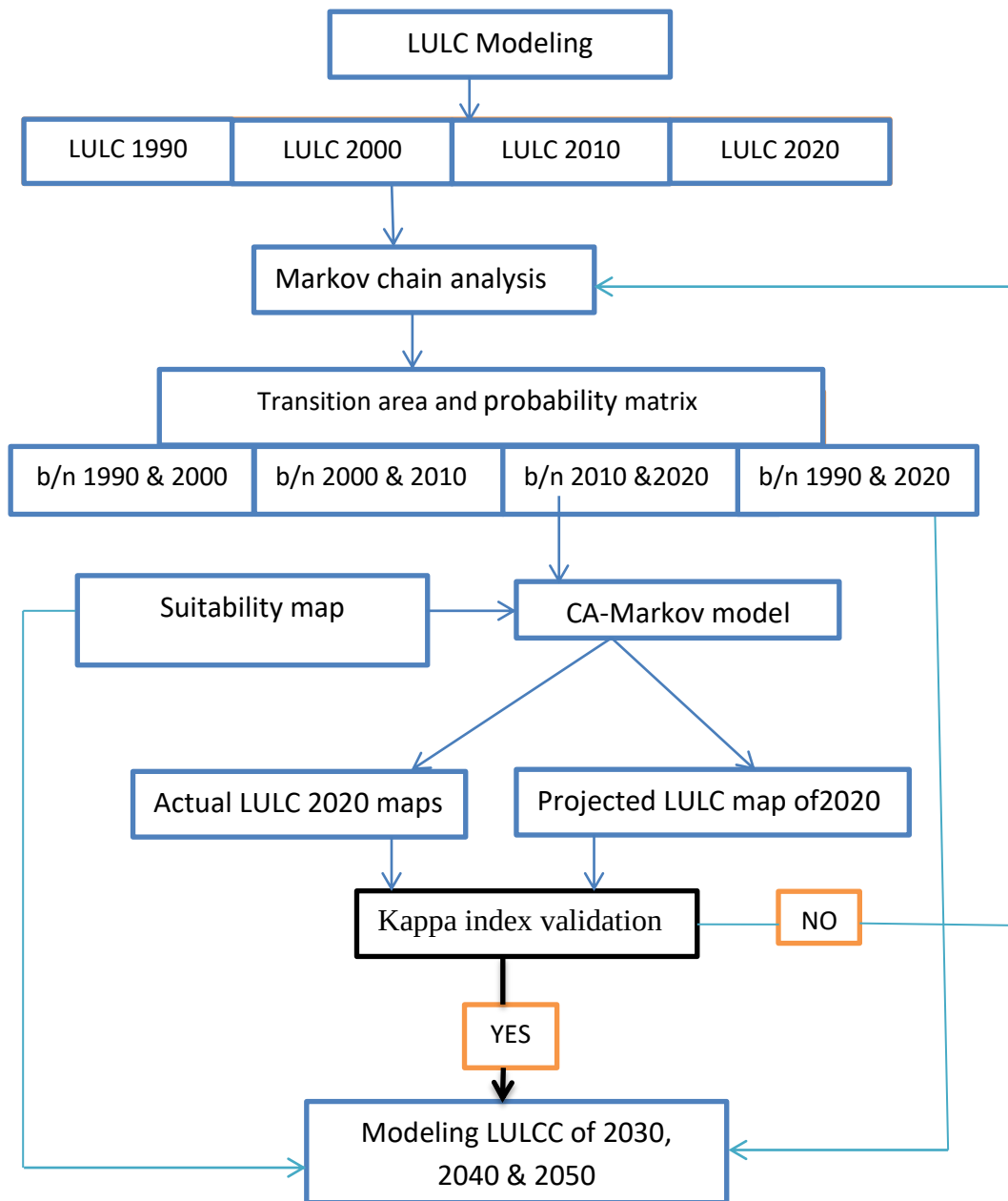


Figure 3.6: Change detection and simulation workflow.

3.6. Methods of Data Analysis

3.6.1. Image preprocessing

The expression "image pre-processing" refers to operations on photographs at the most basic level. If entropy is information metric, these operations do not increase image information quality, but rather reduce it. The aim of pre-processing is to optimize image data by suppressing unwanted distortions or enhancing certain image features that are essential for subsequent processing and study (Kragujevac J. Math, 2009). In this research, some pre-processing techniques of image transformation includes geometric correction or image registration, atmospheric correction and radiometric calibration was used essentially. In addition, image analysis was carryout by using image analysis window such as adjusts the displayed contrast characteristics of image, adjusts the displayed brightness characteristics of image, adjusts the transparency of image, adjusts the gamma transformation applied to all four year Landsat image.

3.6.2. Layer staking

The method of merging several images into a single image is known as layer stacking. To do this, the images must have the same degree (number of rows and columns), which necessitates resampling other bands of different spatial resolutions than the desired resolution. To put it another way, all images/bands must have the same spatial resolution in order to perform layer stacking. Combining images/bands, on the other hand, would increase the final stacked image scale, and therefore the processing time as you perform the research. If you know you won't need any of the images/bands in your study, stacking all of the images into a single image isn't necessary; instead, choose only the images that attract you.

3.6.3. Image Enhancement

The conversion of image quality to a higher and more understandable standard for feature extraction or image analysis is known as image enhancement (Basudeb B.,2011). Image enhancement is a common technique for providing a clear display for image perception (Cetin, 2009). Therefore, in this study, multispectral images were enhanced by using ERDAS software.

3.6.4. Sub-setting of Study area.

Image extraction is the first step of image pre-processing. Any of the image's non-essential elements can be omitted, and the image's emphasis can be narrowed. To minimize the size of the image file and include only the region of interest, it is necessary to remove the project field from the entire image (AOI). This not only removes the unnecessary data from the picture. However, since there is less data to handle, it speeds up the process. When using multiband data, such as Landsat TM imagery, this is critical. Sub setting is the term for this data reduction. ERDAS IMAGINE and Arc GIS Software were critical at this stage. Each Landsat scene was clipped through by the project area during this process (Adama shape file). It must be done after layer stacking or a composite image has been formed.

3.6.5. Training sample selection

Each picture yielded a set of training samples for each level. Consistency in sample collection was maintained to eliminate sampling biases by choosing pixels that appeared constant at various times to train the classifier. First, samples were chosen from a 1990 landsat image (first image). Following that, these samples were used as training samples for the first image and as a foundation for the next image (2000). Second, the base samples were superimposed on the second picture to see if there was a change in class. If some variations were discovered, a new sample from the surrounding area was substituted. Similarly, the same procedures were followed for the rest of the images.

3.6.6. Image classification

There are two types of pixel-based classification: supervised and unsupervised classification (Caetano, 2009). “Supervised classification is a method for detecting spectrally close areas on an image by locating “training” locations of identified targets and extrapolating those spectral signatures to unknown target areas (Mather, 2011). When there are few classes, training sites with ground truth data, or homogeneous regions that represent each class, supervised classification is normally the best option (Erdas Field guide, 2013). The classic classifiers are minimum distance, parallel pipelined and maximum probability methods for supervised classification. The maximum likelihood algorithm determines the probability of a cell belonging to a specific class specified in training sites using a maximum likelihood protocol derived from Bayesian probability theory. The maximum likelihood classifier

calculates class percentages and categorizes the cells with the highest probability (Smith, 2011). If the input samples/clusters have a regular distribution, this classifier is the most reliable. Maximum Likelihood is parametric, which means it depends strongly on the data in each input band having a regular distribution.

Adama city classified land use land cover change using supervised classification method, maximum likely hood algorithm, finally making accuracy assessment for each year classified land use land cover maps.

3.7. Accuracy Assessment

3.7.1. Producer's Accuracy

Producer's accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total). This value represents how well reference pixels of the ground cover type are classified.

$$PA = \frac{\sum TCS_{ij}}{TSC_i} \quad (4)$$

Where; TCS_{ij} is the total number of the correctly classified pixels in rows i and column j , TSC_i is the total number of the correctly classified pixels in row i .

3.7.2. User's Accuracy

Users accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels that were classified in that category of the classified image (row total). It represents the probability that a pixel classified into a given category actually represents that category on the ground.

$$UA = \frac{\sum TCS_{ij}}{TSR_i} \quad (5)$$

Where; TCS_{ij} is the total number of the correctly classified pixels in row i and column j , TSR_i is the total number of pixels in the row i .

3.7.3. Overall Accuracy

It is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix.

$$OA = \frac{\sum TCS_{ij}}{TS} \quad (6)$$

Where; TCS_{ij} is the total number of the correctly classified pixels in rows i and column j , TS is the total reference sample.

3.7.4. Kappa Coefficient

The Kappa Coefficient is used to equate the precision of a grouping to that of simply assigning values at random. The Kappa Coefficient can be somewhere between -1 and 1. The classification is no different than a random classification if the value is 0. The classification is significantly worse than random if the number is negative. A value close to 1 indicates that the classification is significantly better than random. (Jennes et al (2007)).

$$k = \frac{(TS \times TCS) - \sum TSc_j TSr_i}{TS^2 - \sum (TSc_j - TSr_i)} \quad (7)$$

Where; TCS_{ij} is the total number of the correctly classified pixels in row i and column j , TS is the total reference sample, TSc_j is the total number of pixels in column j and TSr_i is the total number of pixels in the row i .

3.8. LULC Change Analysis

Change is assessed between time 1 and time 2 between the two land cover maps. The changes that are identified are transitions from one land cover state to another. It is likely that with many land cover classes the potential combination of transitions can be very large. What is important is to identify the dominant transitions that can be grouped and modeled, termed sub models. Each group, or sub model of transitions can be modeled separately, but ultimately each sub model will be combined with all sub models in the final change prediction. Using change analysis of LCM of the Adama city 1990, 2000, 2010 and 2020 of LULCC in graphs of gains and losses, contributions to net change, transitions of land cover classes between different categories and spatial trend were analyzed.

3.9. Predicted LULC Change

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

3.10. Suitability Analysis

Suitability analysis has importance on LULC change modeling process, because with the assistance of suitability analysis simulation for the longer term are often grounded with the prevailing patterns and drivers. For this research the focus was the urban area expansion and impacts on other categories, because of that the suitability analysis has been done only for Built-up category. In order to use Cellular Automata, a suitability map for every class is taken into account as a pre-requirement. Suitability maps are derived using Multicriteria evaluation (MCE) by combining the information from several criteria to form a single index of evaluation (Eastman 2012; Baysal 2013 ;). The Multicriteria evaluation (MCE) is a common method for assessing and aggregating weighted maps (criterion) based on experts understanding of the interactions and influence of the factors with LULC (Behera et al. 2012; Eastman 2012). These factors are shown in Table 4.11. The factors in Table 4.11 were aggregated using MCE method. Finding the suitable areas for urban suitability requires consideration of different drivers; therefore using a system which evaluates multiple criteria is required. This process combines various criteria (factors and constraints) with different methodologies and then transforms it into a suitability map output (Drobne and Lisec 2009). In order to determine specific class land-use suitability in this research under MCE, several steps were involved. These are: 1 .Identification and development of the criteria. 2. Standardization of the criteria and 3. Aggregate the criteria to arrive at a suitability map of built up class.

3.10.1. Criterion development.

The development of criterion for decision-making to generate the specific built up/urban suitability map images in this research was possible through the knowledge gained from field

survey and insight from literature (Behera et al. 2012; Bürgi, Hersperger, and Weng 2002; Eastman 2012). Different factors and constraints which limit or suit the changing of one LULC class to another over time were identified. Standardized and finally produced suitability maps for built up/urban class using MCE. Euclidean distance for Factor and constraint images was prepared using ArcGIS v.10.8 software (figure 16). Then the images were input in IDRISI Selva v.17 software for further processing. Decision Support Wizard (DSW) in IDRISI Selva, was used to process the factors and constraints standardization using Fuzzy function up to the weighted linear combination (WLC) aggregation step was possible. The factors were extended from 0 to 255 using various fuzzy functions and control points throughout the standardization step (Table 4.7). Constraints are criteria that limit LULC change and are expressed within the sort of Boolean images (0 to 1), with the worth of '0' representing areas restricted for suitability analysis, whereas '1' represents areas suitable for suitability analysis. Some of the fuzzy membership function types are J-shaped, sigmoidal, and linear membership functions (Eastman 2009). For each fuzzy membership function, the suitability of a given landscape for a particular LULC bears different shapes as the value of a factor increases. Monotonically increasing: As the value of the factor increases, the suitability of a land surface for a given LULC class increases. Monotonically decreasing: As the value of the factor increases, the suitability of a land surface for a given LULC class decreases. As the value of the factor increases, the suitability of a land surface for a given LULC class increases from a particular control point, reaches a maximum suitability at a certain point then start decreasing .Since the ultimate determination of suitability of a selected land-use class is achieved through aggregation of the factors and constraints, the overlay requires the standardized factors to be weighted supported their relative importance in influencing the suitability of a particular landscape surface for a given LULC class. There are three ways to do a weighted overlay of factors: utilizing. User defined weights, assigning equal weights, and Analytic hierarchy process (AHP).In this study, the AHP was adopted. The final AHP eigenvector of weights facilitated to perform aggregation of the standardized factors and therefore the standardized constraints employing a WLC algorithm (Malczewski 2000). The Weighted linear combination (WLC) aggregation under the multi criteria evaluation (MCE) generated the standardized suitability maps for built up/urban suitability. The standardized suitability maps are among the essential data input in CA-Markov model.

CHAPTER FOUR: RESULTS AND DISCUSSION.

In this chapter, the results obtained from data analysis as per the study objectives, and discussion on result are presented and described in detail.

4.1 Accuracy assessment of the images.

Classification accuracy was assessed quantitatively using error matrix which is that the commonly used method in LULC classification accuracy assessment (Bulti, 2019). During this regard, sample pixels were selected from each of classified images through a stratified sampling scheme in ARCGIS software. The samples were overlaid with Google earth (for 1990, 2000, 2010 and 2020). supported the error matrix generated for every classified map overall accuracy, user's accuracy, producer's accuracy and overall kappa were calculated. The accuracy requirements for change detection analysis were determined supported the suggestion of Congalton and Green (2009). The values of the general accuracies and kappa coefficients for all the classified LULC maps of 1990, 2000,2010, and 2020 were found to be above 85%, as shown in Table 4.1. This means a reliable and accurate classification of images for analyzing land use/land cover change (see appendix-c).

Table 4.1: land use land cover accuracy assessment.

S/No.	LULC Types	1990		2000		2010		2020	
		PA(%)	UA(%)	PA(%)	UA(%)	PA(%)	UA(%)	PA(%)	UA(%)
1	Built up	87	83	93.33	87.5	88	91.8	92	92
2	Agriculture	84	91	88.46	86.8	92	88.5	90	91.8
3	Vegetation	80	80	82.6	87.8	86.8	90.2	91.8	94
4	Bare land	85	88	83.33	86.5	88	88	92	90.19
5	Water Body	95	93	93.6	91.7	95.7	91.7	92.2	90
	OA	86%		88%		90%		91.6%	
	OK	0.85%		0.85		0.87		0.89	

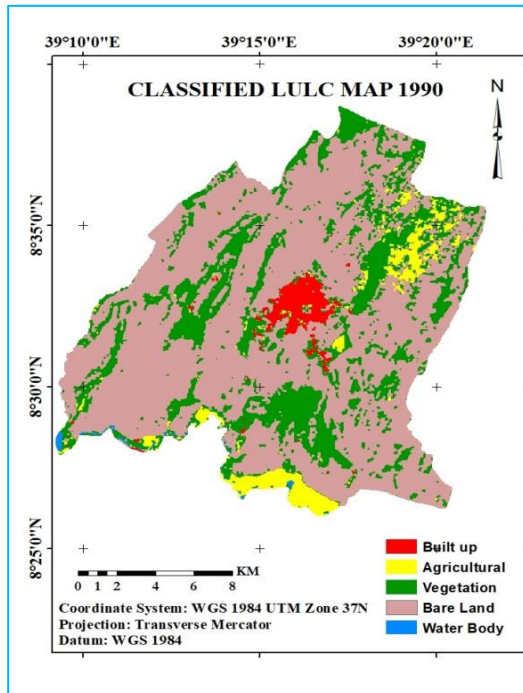
Note: PA, AU, OA and OK-producers accuracy, Users accuracy, overall accuracy and overall kappa respectively.

Table 4.2: Kappa coefficient interpretation

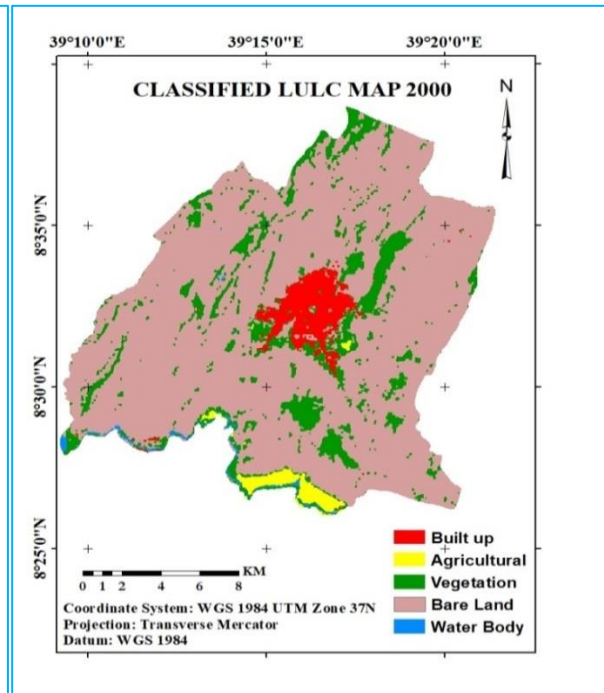
S.No.	Kappa coefficient	Interpretation
1	<0.00	Poor agreement
2	0.01 - 0.20	Slight agreement
3	0.21 - 0.40	Fair agreement
4	0.41 - 0.60	Moderate agreement
5	0.61 - 0.80	Substantial agreement
6	0.81 - 1.00	Almost perfect agreement

4.2. Spatio temporal land use land covers (LULC) change.

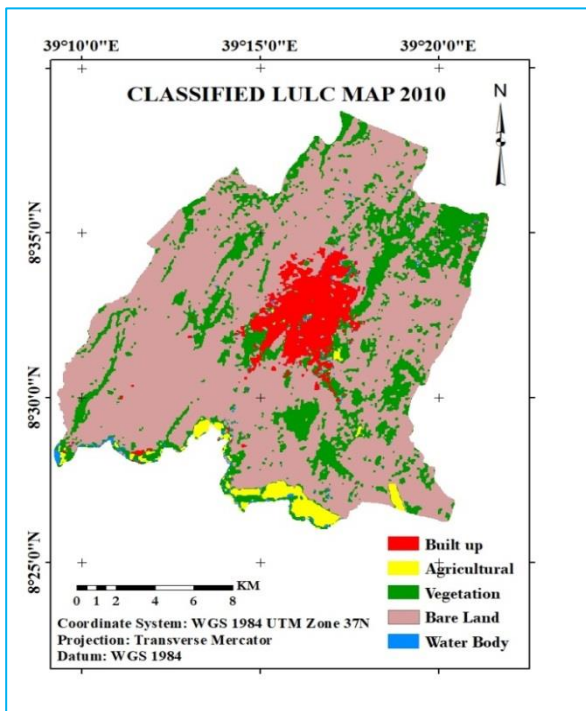
The LULC change analysis results illustrate the historical LULCC and the change dynamics in each land cover class. The study results would significantly help urban planners and decision-makers determine the nature, position, and rate of change in the study area. The classified land use/land cover maps of 1990, 2000, 2010, and 2020 were generated using the supervised maximum likelihood classification. Five LULC classes were identified in the study area for the specified period 1990–2020. Training samples for each class were collected from each image. The outcome displays that the land use land cover pattern of Adama city has changed radically between 1990 and 2020, with the built-up areas experiencing continuous growth over the last study periods, and agriculture, vegetation, bare land, and water bodies decreased during the period. Figure 4.2 displays the spatial distribution of each LULC in 1990, 2000, 2010, and 2020. Figure 4.1 depicts the maps of various stages each land cover class has undergone, with each stage having a different rate and quantity of change. The quantitative result is presented in Table 4.3, which shows the statistics of the five LULC classes and the change dynamics during the four-time periods.



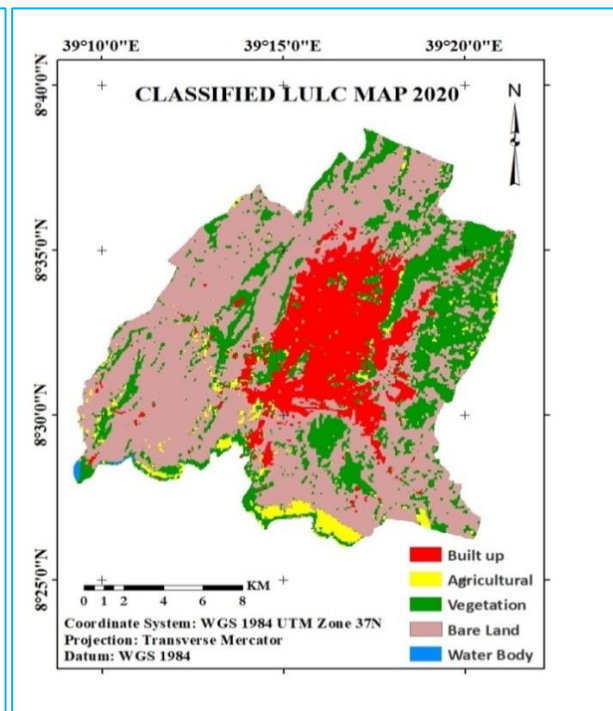
a)



(b)



(c)



(d)

Figure 4.1: Adama city LULC of 1990(a), 2000(b), 2010(c) and 2020(d)

Table 4.3: Quantitative Distribution of LULC in 1990, 2000, 2010 and 2020.

No.	Year	1990		2000		2010		2020	
	LULC types	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area	%
1	Built up	802	2.5	1320	5	2137	7	5294	17
2	Agriculture	1513	4.8	517	1.7	725	2.3	1049	3.4
3	Vegetation	7680	24.5	4105	13.1	6553	20.94	7457	23.8
4	Bare land	21180	67.68	25152	80.3	21615	69	17421	55.6
5	Water Body	115	0.36	196	0.6	260	0.8	68.76	0.2
Total(ha)		31,290	100	31,290	100	31,290	100	31,290	100

Table 4.4: Dynamics of Land Use/Land Cover Change between 1990 and 2020.

No.	Year	LULCC 1990-2000		LULCC 2000-2010		LULCC 2010-2020		LULCC 1990-2020	
	LULC types	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
1	Built up	518	1.7	817	2.6	3157	10.1	4492	14.3
2	Agriculture	-996	-3.2	208	0.7	324	1	-464	-1.48
3	Vegetation	-3575	-11.4	2448	7.8	904	2.9	-223	-0.7
4	Bare land	3,972	12.7	-3537	-11.3	-4194	-13.4	-3759	-12
5	Water Body	81	0.26	64	0.2	-191.2	-0.6	-46.24	-0.1

The study reveals that steady growth in the Adama city's built-up area and significant changes in other LULC classes between 1990 and 2020. It indicates an increase in built-up area from 802ha in 1990 to 1320 ha in 2000 to 2137 ha in 2010 and further increased to 5294 ha in 2020, this is an increase from 2.5% to 5% to 7% to 17% of the total area during 1990, 2000, 2010 and 2020 respectively. Indicating a growth of 1.7% 2.6% and 10.1% during the first, second and third periods respectively. The result reveals an increase from 802 ha (2.5%) of the total area in 1990 to 5294 ha (17%) in 2020, which indicates the expansion of the built-up area with about 14.3% between 1990 and 2020. The city's agriculture, vegetation and barren land perceived an inconsistent change during the study period. The agriculture decreased from 1513 ha (4.8%) in 1990 to 517 ha (1.7%) in 2000 to 725 ha (2.3%) in 2010 and 1049 ha (3.4%) in 2020. This indicates a decrease from 4.8% of the total area in 1990 to 3.4% in 2020. The vegetation decreased from 7680 ha in 1990 to 4105 ha in 2000 to 6553 ha and 7457 ha in 2010 and 2020 respectively. This indicates reduction from 7680 ha (24.5%) of the total area in 1990 to 7457 ha (23.8%) in 2020. The barren land increased drastically from 21180 ha in 1990 to 25152 ha

in 2000, to 21615 ha in 2010, and decreased to 17421 ha in 2020. The result indicates a decrease from 67.68% of the total area in 1990 to 55.6% in 2020. The water bodies decreased from 115 ha (0.36% of the total area) in 1990 to 68.76 ha (0.2% of the total area) in 2020. The growth in Adama city's built-up area can be attributed to the city's rapid increase in population due to rural-urban migration, economic growth and infrastructure. The historical land use/land cover results in 1990, 2000, 2010, and 2020 are illustrated graphically in Figure 8.

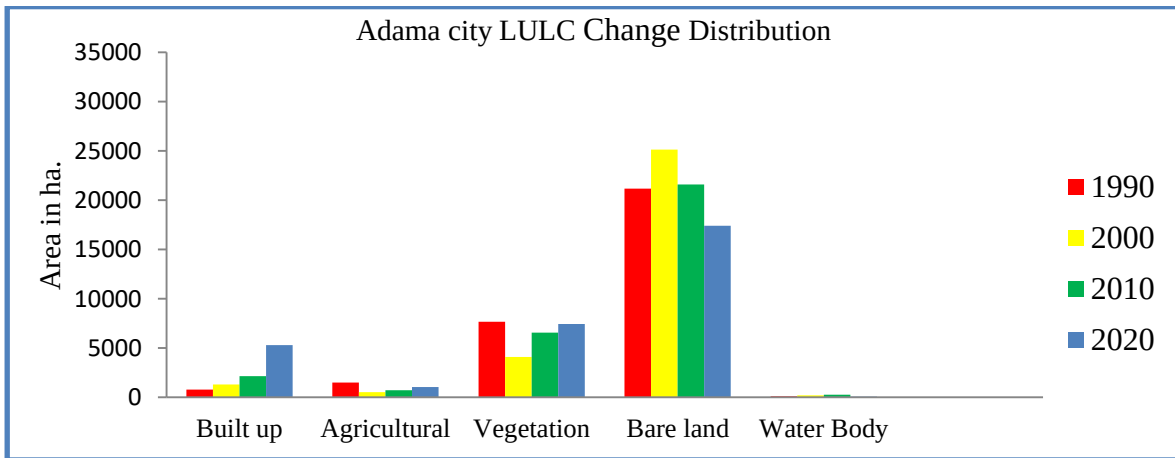


Figure 4.2: Comparative change of LULC in Adama city between 1990 and 2020.

4.3. Rate and Magnitude of Built up Area Expansion (1990-2020)

As a result of population and infrastructure increment the development of Adama City urban expansion from time to time has played a major influence for the expansion of built up areas. The built-up area in a span of 30 years between 1990 and 2020 were compared to find the changes (table 4.9). The built up area expansion of the city between 1990 and 2000 was 518 ha which was a 65% expansion and annual rate of growth was also 52 ha/yr (Table 4.9). The built up area expansion of the city between 2000 and 2010 was 817 ha which is nearly 62% expansion and annual rate of growth was also approximates about 82 ha / yr (Table 4.5). The built up area expansion of the city between 2010 and 2020 was 3157 ha which is nearly 148% expansion and annual rate of growth was also approximates about 316 ha per year. This indicated that, the built-up area has increased at an average annual growth rate of 6.4%, 6.2% and 14.7% during the period's 1990 to 2000, 2000-2010, and 2010 to 2020 respectively, in the study area.

Table 4.5: Rate and Magnitude Built-up Area Expansion (1990-2020).

No	Study period	Time span	Change expansion		Annual growth rate	
			ha	%	ha	%
1	1990-2000	10	518	64.5	52	6.45
2	2000-2010	10	817	62	82	6.2
3	2010-2020	10	3157	147.7	316	14.7

4.4. Built up proportion in Adama city

In order to visualize and examine the spatial expansion of the built up areas during the four time periods, the LULC map was reclassified into built up and non-built up area (Figure 10). These maps show a clear pattern of increased urban expansion prolonging both from urban center to adjoining non-built up areas along transportation corridors. The maps show the spatiotemporal urban growth pattern in the study area. As clearly seen in table 4.6, the proportion of built up areas in 1990 was 2.5% of the entire study area. In 2000 the percentage of built up areas increased to 4.2 %, 2010 the percentage of built up area covers 7% of the total area and in 2020 it reached to 17% of area coverage.

Table 4.6: Built and non-built-up areas (1990- 2020).

No.	Land cover class	1990		2000		2010		2020	
		Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
1	Built up	802	2.5	1320	5	2137	7	5294	17
2	Non Built up	30,488	97.4	29,970	95.8	29,153	93	25,996	83
Total (ha)		31,290	100	31,290	100	31,290	100	31,290	100

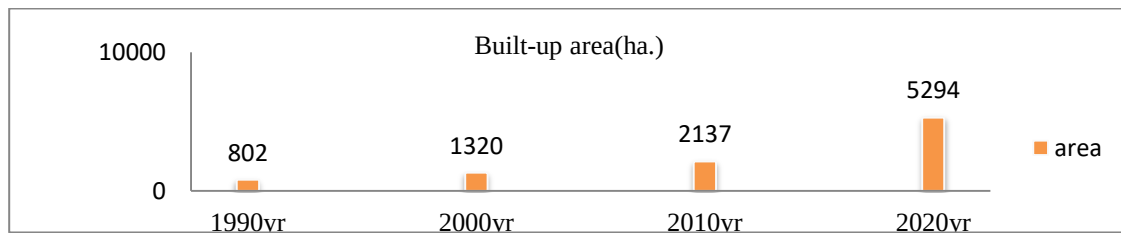
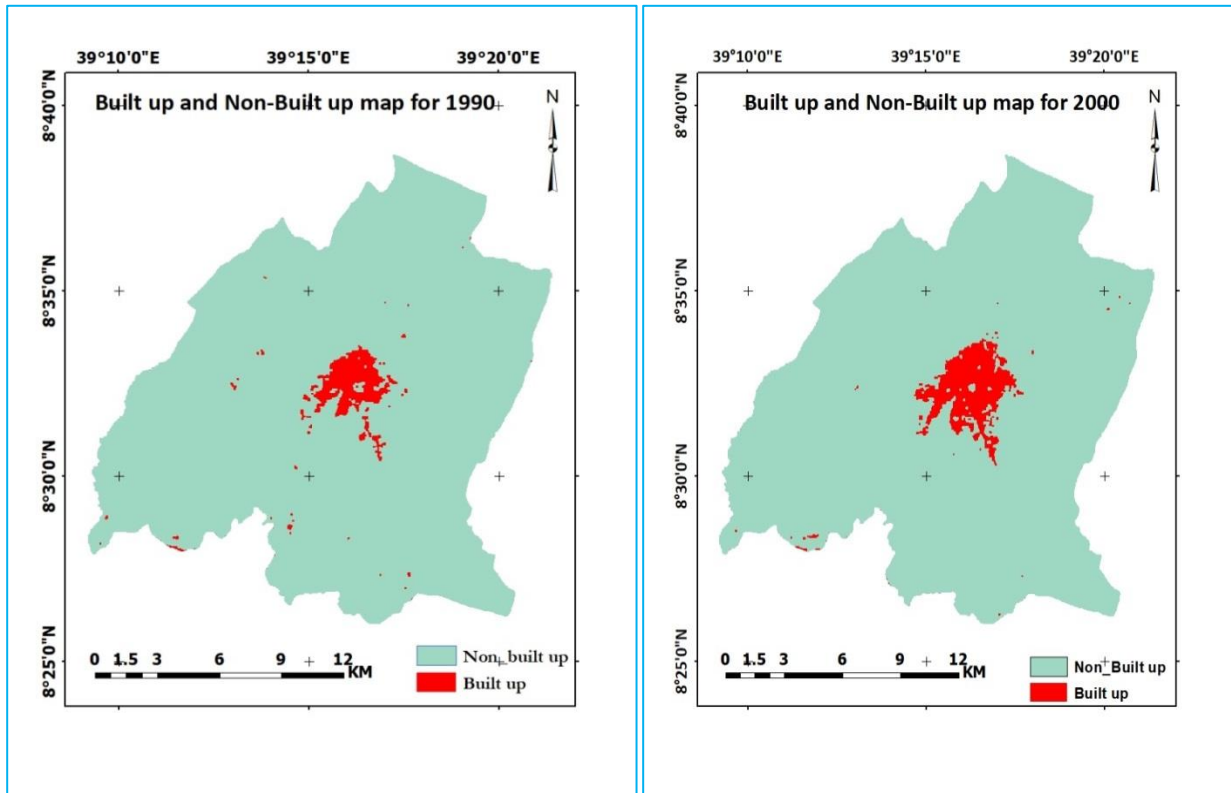


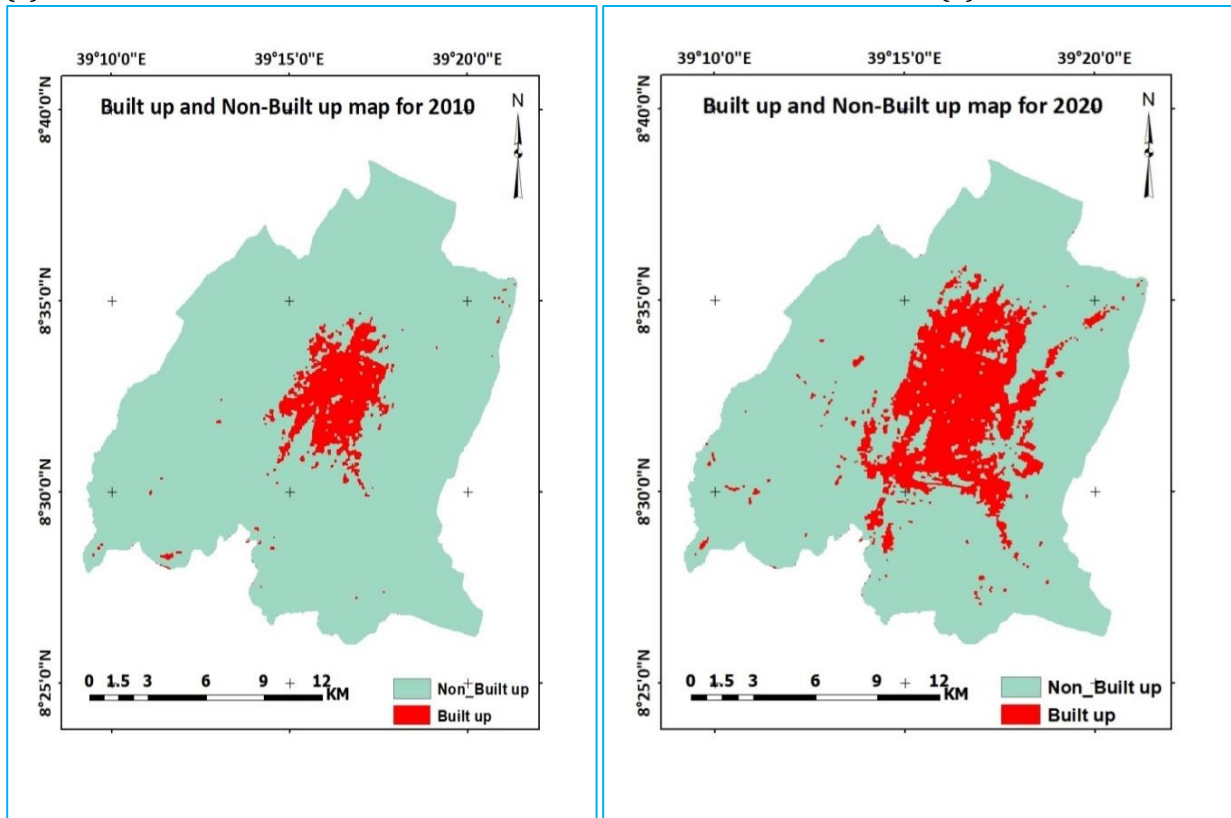
Figure 4.3: Change Trend of built-up area expansion between 1990 and 2020.

Figure 4.3 depict that the study area has experienced spatial increase on different land use and land cover classes such as; built up areas, due to the corresponding horizontal expansion as well as conversion of other land cover classes during the distinct study periods. The reclassified images in figure 4.4 showed that there had been a rapid land cover change from non-built up areas to built-up areas.



(a)

(b)



(c)

(d)

Figure 4.4: built up and non built up map of 1990(a),2000(b),2010(c), and 2020(d)

4.5. LULC Change Analysis

The Change Analysis panel provides three graphs of land cover change between the two land cover maps specified in the Project Parameters panel. The first graph shows a rapid quantitative assessment of change by graphing gains and losses by land cover category. The second option, net change by category, shows the result of taking the earlier land cover areas, adding the gains and then subtracting the losses. The third option, contributors to net change, examines the contributions to changes experienced by a single land cover. The results of the cross-tabulation comparison of both land use and land cover maps below showed that there have been marked changes in all land use and land cover classes between 1990, 2000, 2010 and 2020.

4.5.1. LULCC between 1990 and 2000

During the first period between 1990 and 2000, the built-up/urban area gained 589ha (44.6%) and lost 71ha (0.14%), witnessing a net gain of 519ha (39.28%). agricultural cover gained 14ha (0.07%) and lost 1011ha (4.5%), having a net loss of 996 (4.64%). Vegetation cover gained 1391ha (33.89%) and lost -4966ha (64.66%), having a net loss of 3575 (87.06%). Barren land lost 1484ha (7.01%) and gained 5455ha (21.69%), witnessing a net gain of 3971ha (15.79%). Water bodies lost 29ha (25.04%) and gained 110 ha (56.19%), having a net loss of 82 ha (41.56%) (Table 4.7). The different LULC classes that added to the Contribution to net change in built-up areas during the period between 1990 and 2000 include the change of 364 ha (1.72%) of barren lands to built-up areas and the conversion of 108 ha (1.41%) of vegetation cover, and 48 ha (0.22%) of agricultural to the built-up area. simultaneously, nearly 3710 ha (48.3%) of vegetation and 625 ha (2.78%) of agricultural cover contributed to the gain of barren land. Vegetation cover experienced the most significant loss during this period. This decline can be mainly due to the factors contributing to the reduction in vegetation cover between 1990 and 2000 include inadequate legislation, institutional weakness, unaccountability, and uncontrolled human activities.

Table 4.7: Losses, gains, and net changes of LULC classes between 1990 and 2000 (in ha.).

No.	LULC Types	Gain, losses and net change between 1990&2000							
		Gains		Losses		Net change		Contribution to net change In built-up	
		Ha	%	Ha	%	Ha	%	ha	%
1	Built-up area	589	44.6	-71	-8.81	519	39.28	-	-
2	Agricultural	14	0.07	-1011	-4.50	-996	-4.64	48	0.22
3	Vegetation	1391	33.89	-4966	-64.66	-3575	-87.06	108	1.41
4	Barren land	5455	21.69	-1484	-7.01	3971	15.79	364	1.72
5	Water body	110	56.19	-29	-25.04	82	41.56	-8	-2.28

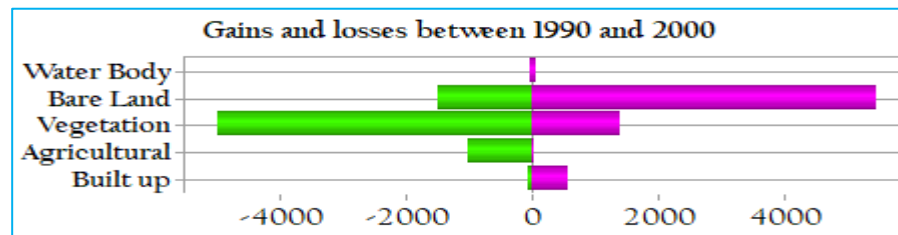


Figure 4.5: Gain and losses between 1990 and 2000 in ha.

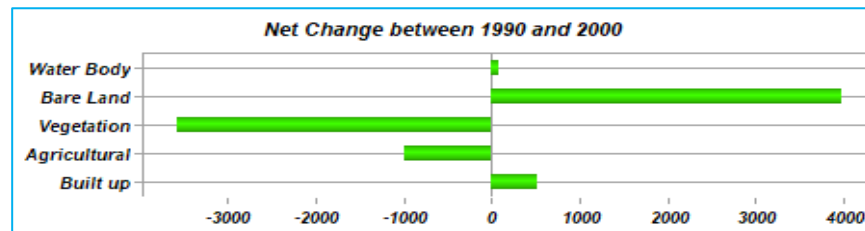


Figure 4.6: Net change between 1990 and 2000 in ha.

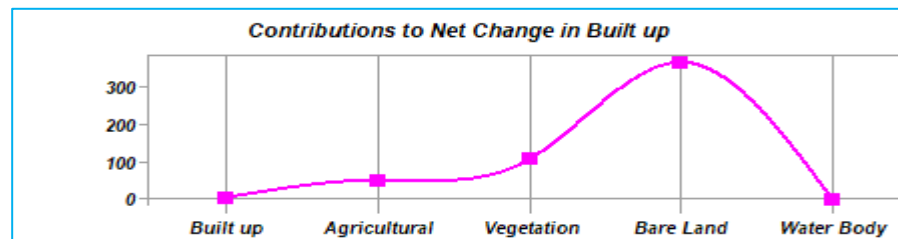


Figure 4.7: contribution to net change in built-up area between 1990 and 2000 in ha.

4.5.2. LULCC between 2000 and 2010

During the this period between 2000 and 2010, the built-up lost 71 ha (5.35%) and gained 888 ha (41.53%), witnessing a net gain of 817 ha (38.23%). agricultural cover lost 95 ha (0.44%) and gained 303ha (1.4%), witnessing a net gain of 209ha (0.96%).Vegetation cover lost 1422 ha (34.63%) and gained 3869ha (59%), witnessing a net gain of 2447 ha (37.35%). Barren land lost 4542ha (18.07%) and gained 1008ha (4.6%), having a net loss of 3537 ha (16.35%). Water bodies lost 108 ha (54.95%) and gained 172 ha (66%), witnessing a net gain of 64 ha (24.6%). the various land cover classes that contributed to the net gains in built-up areas during the period between 2000 and 2010 include the transfer of 653 ha (2.6%) of barren lands to built-up areas and the conversion of 177 ha (4.3%) of vegetation to the built-up area. Similarly, the conversion of 20ha (9.95%) of water areas to vegetation cover and the transfer of 2686 ha (10.68%) of barren to vegetation lands contributed to the net increases in vegetation land during this time. Between 2000 and 2010, the amount of barren land decreased, while vegetation increased dramatically.

Table 4.8: Losses, gains, and net changes of LULC classes between 2000 and 2010 (in ha.).

No.	LULC Types	Gain, losses and net change between 2000&2010							
		Gains		Losses		Net change		Contribution to net change In built-up.	
		Ha	%	Ha	%	Ha	%	ha	%
1	Built-up area	888	41.53	-71	-5.35	817	38.23	-	-
2	Agricultural	303	1.40	-95	-0.44	209	0.96	-6	-0.03
3	Vegetation	3869	59.04	-1422	-34.63	2447	37.35	177	4.30
4	Barren land	1008	4.66	-4542	-18.07	-3537	-16.36	653	2.60
5	Water body	172	66.04	-108	-54.95	64	24.62	-7	-3.49

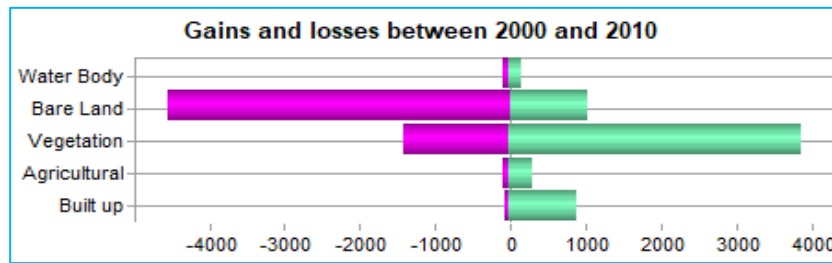


Figure 4.8: Gain and losses between 2000 and 2010 in ha.

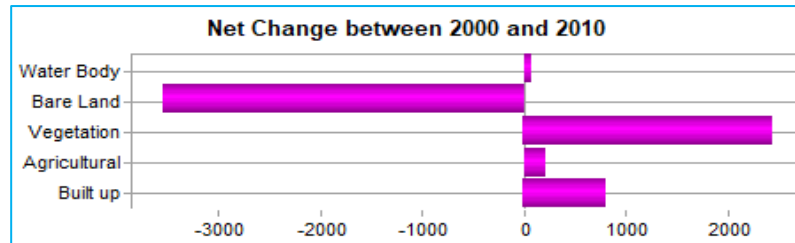


Figure 4.9: Net change between 2000 and 2010 in ha

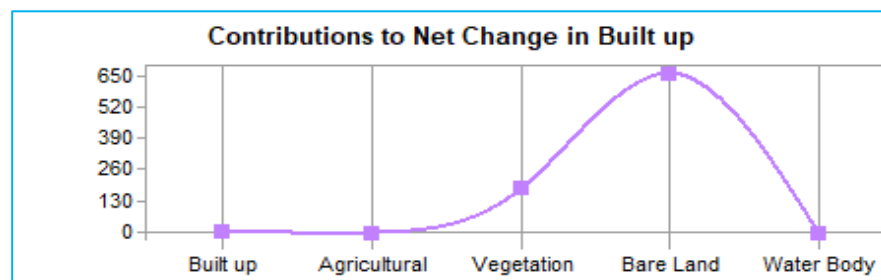


Figure 4.10: contribution to net change in built-up area between 2000 and 2010 in ha

4.5.3. LULCC between 2010 and 2020

During the third period between 2010 and 2020, the built-up/urban area gained 3227ha (60.95%) and lost 70ha (3.27%), witnessing a net gain of 3157ha (59.63%). agricultural cover gained 605ha (2.75%) and lost 281ha (1.3%), having a net gain of 324ha (1.47%). Vegetation cover gained 3502ha (46.96%) and lost 2598ha (39.64%), having a net loss of 904 (12.12%). Barren land lost 6034ha (27.91%) and gained 1840 ha (10.56%), witnessing a net loss of 4197ha (24.07%). Water bodies lost 214ha (82.16%) and gained 22ha (32.46%), having a net loss of 192 ha (278.5%). The different LULC classes that added to the Contribution to net change in built-up/urban areas during the period between 2010 and 2020 include the change of 4 ha (0.02%) of agricultural lands to built-up areas and the conversion of 608ha (9.29%) of vegetation cover, 2475ha (11.45%) of barren land and 70ha (27.01%) of water bodies to the built-up area. Barren land cover experienced the most significant loss during this period.1514ha and 73ha of barren

land and water bodies were the main contributors to net change experienced by vegetation. This decrement can be mainly interrelated to the city's urban built up expansion and development due to population growth.

Table 4.9: Losses, gains, and net changes of LULC classes between 2010 and 2020 (in ha.).

No.	LULC Types	Gain, losses and net change between 2010&2020							
		Gains		Losses		Net change		Contribution to net change in built-up.	
		Ha	%	Ha	%	Ha	%	ha	%
1	Built-up area	3227	60.95	-70	-3.27	3157	59.63	-	-
2	Agricultural	605	2.75	-281	-1.3	324	1.47	4	0.02
3	Vegetation	3502	46.96	-2598	-39.64	904	12.12	608	9.29
4	Barren land	1840	10.56	-6034	-27.91	-4197	-24.07	2475	11.45
5	Water body	22	32.46	-214	-82.16	-192	-278.5	70	27.01



Figure 4.11: Gain and losses between 2010 and 2020 in ha.

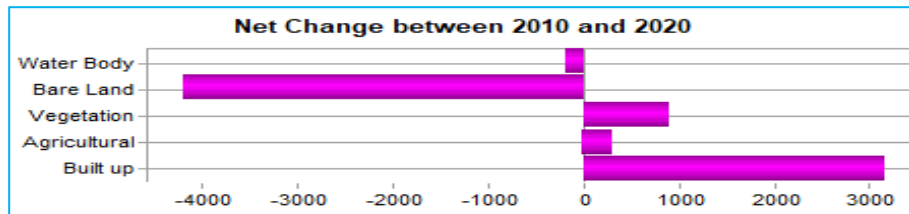


Figure 4.12: Net change between 2010 and 2020 in ha

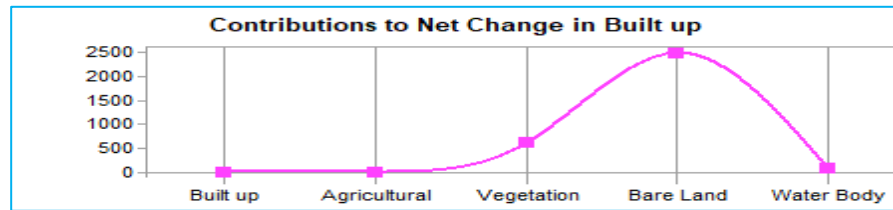


Figure 4.13: contribution to net change in built-up area between 2010 and 2020 in ha

4.5.4. LULCC between 1990 and 2020

During the fourth period between 1990 and 2020, the built-up/urban area lost 47 ha (5.91%) and gained 4540 ha (85.75%), witnessing a net gain of 4493ha (84.86%). agricultural cover lost 1052 ha (4.68%) and gained 588 ha (2.68%), witnessing a net gain of 463 ha (2.11%). Vegetation cover lost 3804 ha (49.53%) and gained 3581 ha (48.02%), witnessing a net loss of 223 ha (2.99%). Barren land lost 5871 ha (32.44%) and gained 3111 ha (17.86%), having a net loss of 3760 ha (21.58%). Water bodies lost 64 ha (55.89%) and gained 18 ha (26.44%), having a net loss of 46 ha (66.75%). The different LULC classes that added to the net gains in built-up areas during the period 1990 and 2020 include the transfer of 97 ha (0.43%) of agricultural to built-up areas and the conversion of 728 ha (9.47%) of vegetation, 3666 ha (17.31%) of barren land and 2 ha (1.65%) water bodies to built-up areas. whilst, 388 ha (1.73%) of agriculture land, 70 ha (0.33 %) of barren land and 45ha (39.64%) water bodies changed to vegetation cover during this period. The LULC change study revealed significant transitions and changes among the various LULC types. It implies that between 1990 and 2020, the built-up area has seen the most significant development in the previous 30 years. This study reveal that the different gains and losses in each land use/land type (in hectares) and the net change in additions to built-up areas (in hectares) during study periods in Table 4.10 and Figure 4.14-16.

Table 4.10: Losses, gains, and net changes of LULC classes between 1990 and 2020 (in ha.).

No.	LULC Types	Gain, losses and net change between 1990&2020							
		Gains		Losses		Net change		Contribution to net change in built-up	
		Ha	%	Ha	%	Ha	%	Ha	%
1	Built-up area	4540	85.75	-47	-5.91	4493	84.86	-	-
2	Agricultural	588	2.68	-1052	-4.68	-463	-2.11	97	0.43
3	Vegetation	3581	48.02	-3804	-49.53	-223	-2.99	728	9.47
4	Barren land	3111	17.86	-6871	-32.44	-3760	-21.58	3666	17.31
5	Water body	18	26.44	-64	-55.89	-46	-66.75	2	1.65

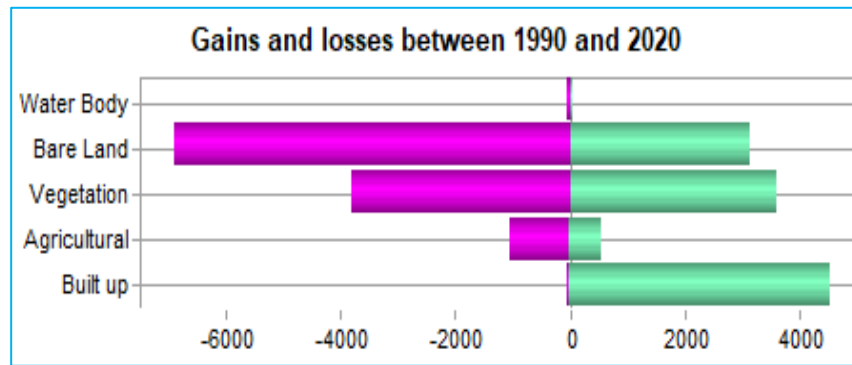


Figure 4.14: Gain and losses between 1990 and 2020 in ha.

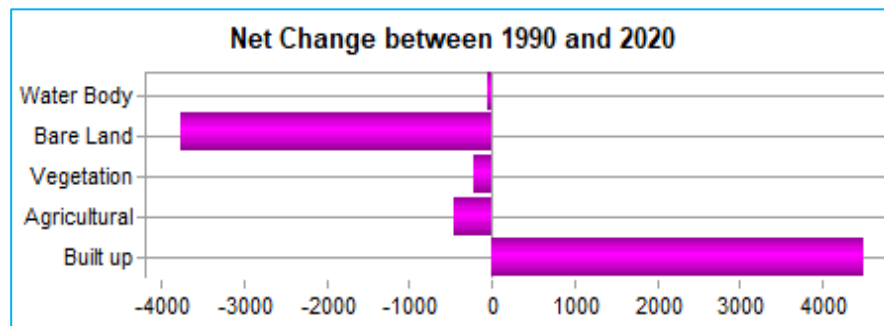


Figure 4.15: Net change between 1990 and 2020 in ha.

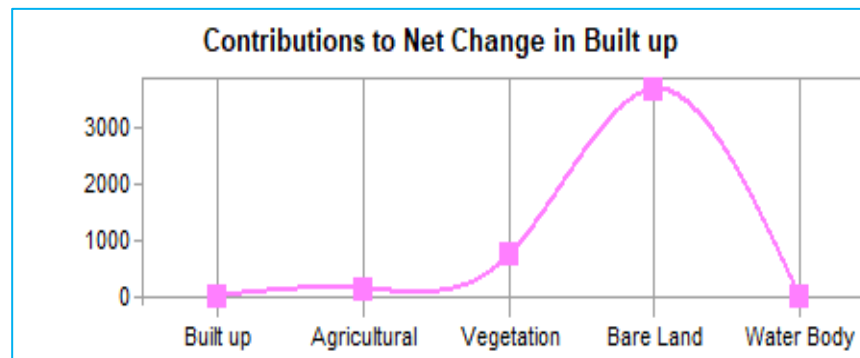


Figure 4.16: contribution to net change in built-up area between 1990 and 2020 in ha.

In Adama city for the last 30 years, Built up area is increased by 4493Ha (84.86%) and the agricultural 463Ha (2.11%), Barren land 3760ha (21.58%), vegetation 223Ha (2.9%) and water body 46ha (66.75%) are decreased.

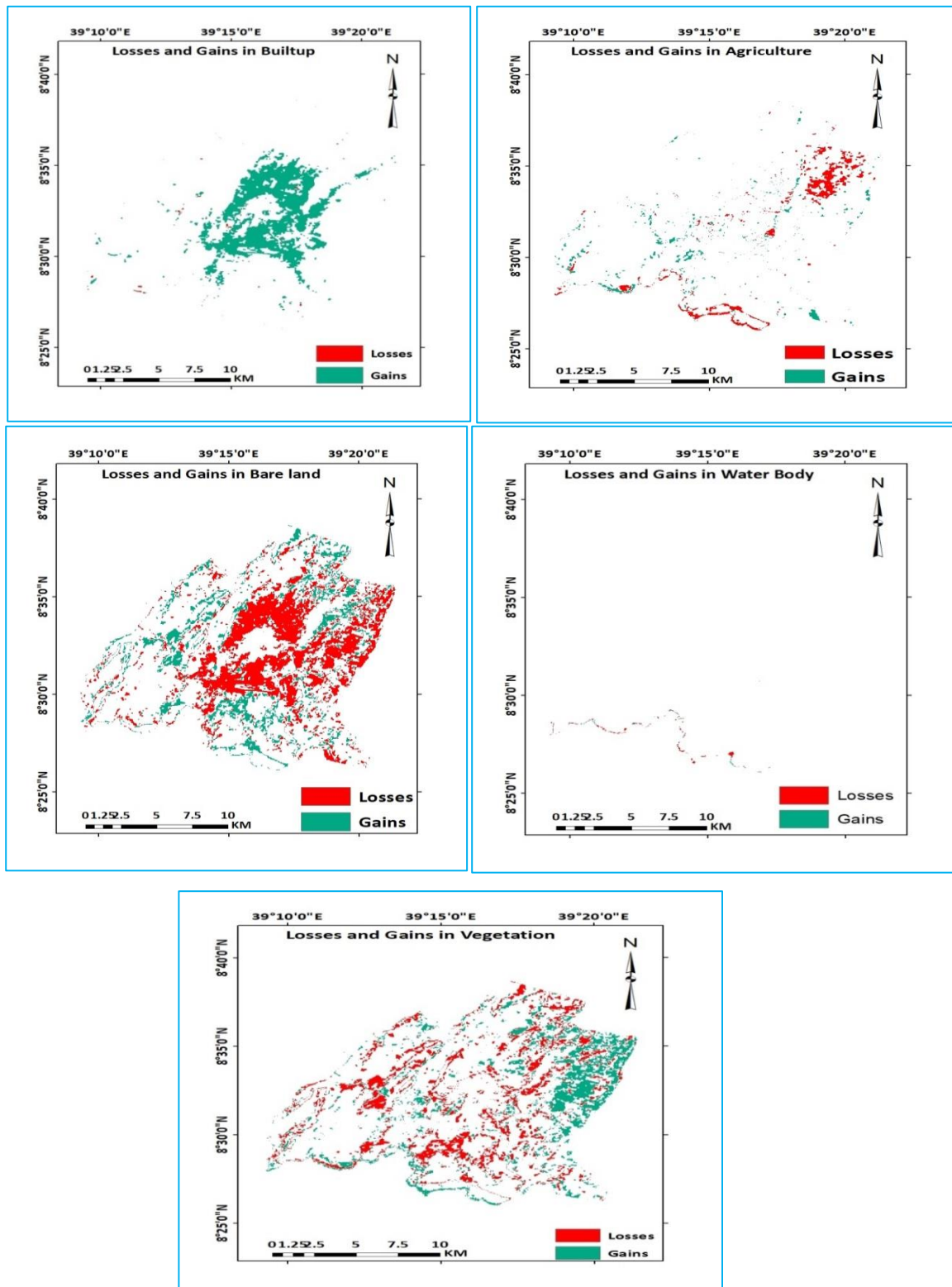


Figure 4.17: Losses and gains in the different LULC classes from 1990 and 2020.

4.6. Built up suitability maps preparation.

Table 4.11 shows Factors, constraints, membership functions and control points used for preparation of suitability maps. Control points of Distance from built-up, Distance from roads, Distance from water bodies, and DEM is given by meter and slope is given in degree. Figure 4.18 show that the Euclidean distance of the factor and constraints, and figure 4.19 shows fuzzy standardized factors.

Table 4.11: Factors, constraints, membership functions and control points used for preparation of suitability maps.

No.	Change drivers/factors	Membership function shape	Membership function	Control points	Constraints
1	Distance to nearest built-up	MD	linear	C=0,d=3692	water bodies(0/1)
2	Distance to nearest roads	Symmetric	linear	a=0,b=25, c=25, d=9236.54	
3	Slope	MD	sigmoid	C=0,d=20	
4	DEM	MD	sigmoid	C=500,d=1900	
5	Distance to nearest m water bodies	MI	Linear	A=500,b=14629	

Note: MD: Monotonically Decreasing. MI: Monotonically increasing.

Monotonically decreasing would indicate that the smallest distance value has the highest suitability score.

Monotonically increasing would mean that small distance values have small suitability values and that at some distance; the highest level of suitability is attained and exists for all greater distance values.

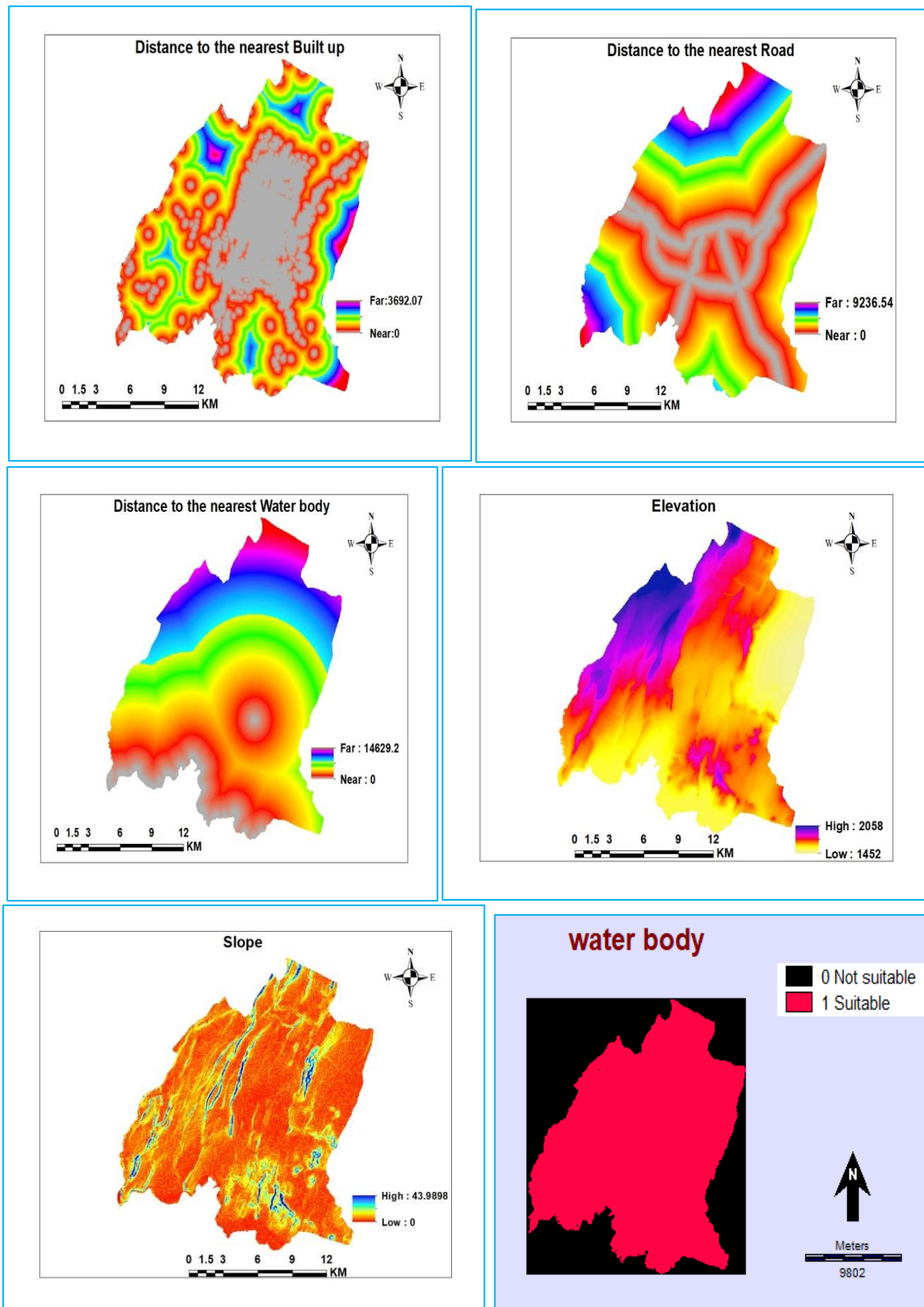


Figure 4.18: Euclidean distance of urban growth contributing factors and constraints.

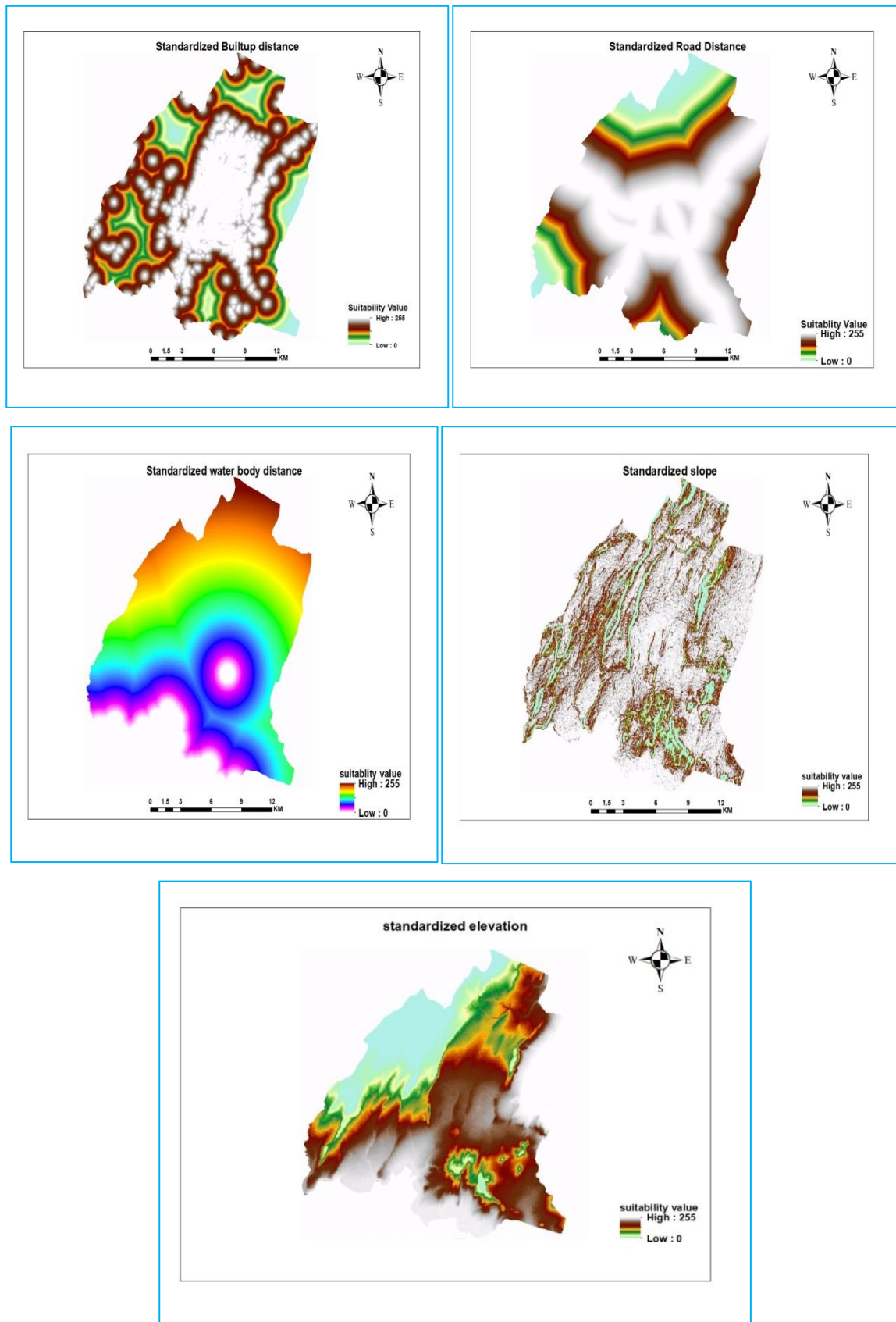


Figure 4.19: fuzzy Standardized factors with scale of suitability.

After defining the factors and constraints and standardize them the next step is to define the weights of the factors. In order to decide the importance of each factor urban planning expert's opinions were used.

4.7. Analytical Hierarchy Process (AHP).

AHP is a multi-criteria evaluation tool used to determine the relative weights of factors using pairwise comparisons (Halmy et al., 2015). Using the responses of these experts in the form of an AHP matrix, the study computed the expansion factor weights using the multi-criteria evaluation (MCE) module in IDRISI. According to Saaty (1977), the relative weights set by the experts have to be consistent, which can be measured using a consistency ratio (CR). We computed the CR as the ratio between the consistency index (CI) and the random index (RI) (Saaty, 1977). In an $n \times n$ AHP matrix, RI is the average consistency index based on the given matrix order by Saaty (1977).

$$CR = CI/RI \quad (10)$$

$$CI = ((\lambda_{\max} - n)/(n-1)) \quad (11)$$

Where, $\lambda_{\max}$ is the principal eigenvalue of the analytical hierarchy process (AHP) pairwise matrix. According to Saaty, (1977), for reliable expert judgment, the consistency ratio (CR) value should be less than 0.1

Table 4.12: Pairwise comparison matrix

No.	Factors	Distance to nearest roads	Distance to nearest built-up	Slope	Elevation	Distance to nearest water.
1	Distance to nearest roads.	1				
2	Distance to nearest Built-up.	1/3	1			
3	Slope.	1/5	1/3	1		
4	Elevation.	1/7	1/5	1/3	1	
5	Distance to nearest water.	1/9	1/7	1/5	1/3	1

According to this pairwise comparison table 4.12 the eigenvector of weights were computed. The weight of the each factor can be observed in table 4.13.

Table 4.13: Weight of Factors

No.	Factors	weights
1	Distance to nearest roads	0.5128
2	Distance to nearest built-up	0.2615
3	Slope	0.1290
4	Elevation	0.0634
5	Distance to nearest water	0.0333
*Consistency ratio = 0.05 Consistency is acceptable.		

* A measure of how far a matrix is from consistency is performed by Consistency Ratio (CR) (Kordi, 2008). If $CR > 0.10$, then some pairwise values needs to be reconsidered and the process is repeated till the desired value of $CR < 0.10$ is reached.

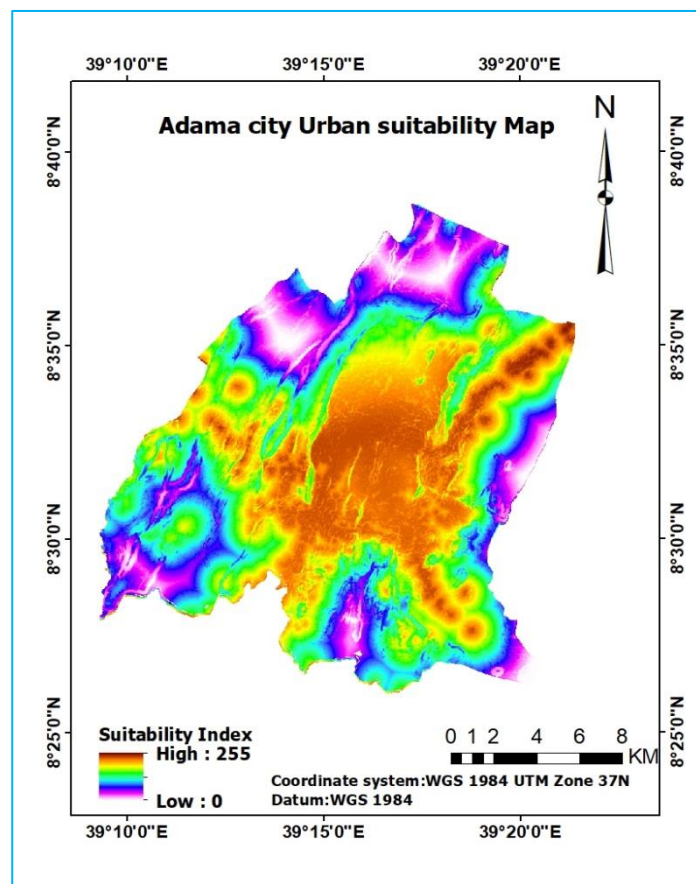


Figure 4.20: Adama city built-up suitability maps.

This suitability map will be used in modeling process in order to ground the model with existing patterns. This might help us to increase the accuracy of the model.

4.8. Factors of Urban Expansion.

Based on the experts' responses, urban expansions are mainly driven by distance to major roads and the existing built-up, followed by the physical factor of slope, elevation and distance to water. The AHP relative weights for these expansion factors are distance to major roads (0.512), distance to built-up, (0.261), slope (0.129), elevation (0.06) and distance to water bodies (0.03). And obtained a consistency ratio of 0.05, which is well below the maximum acceptable value by Saaty (1977), indicating that the experts' judgments were broadly consistent in the identification process.

4.9. Transition potential modeling.

Transition Potential modeling, is probability that determine the potential of land to transition from one state to other state see table below. In order to observe the transformation from all land cover to Built-up figure 27 and table 4.14 prepared. The result indicated that 102.15 ha of agriculture, 754.65 ha of vegetation, 3680.73ha of bare land, and 1.98 ha of water body were converted to built-up class respectively (Table 4.14.).

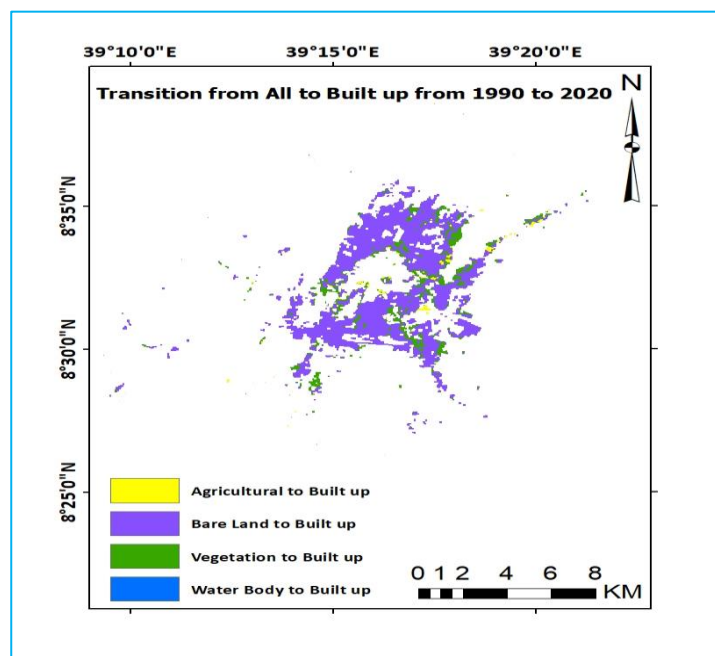


Figure 4.21: Transition from All to Built up class from 1990 to 2020.

Table 4.14: transition from all to built-up (1990 to 2020)

No.	Transition	Area (ha)
1	Agriculture to Built-up	102.51
2	Vegetation to Built-up	754.65
3	Bare land to Built-up	3680.73
4	Water body to Built-up	1.98

4.10. Spatial Trend of Change

The spatial trend analysis tool in LCM was used to compute maps of transition trends from all land cover categories to built up areas between 1990 and 2020. 3rd order of polynomial, which is best fit to the pattern of change, in LCM was used. The numeric values produced don't have any special significance (Eastman, 2012). Thus, the result is interpreted as: the lower the value, indicate less changes and the higher the value indicates more changes. The resulting map is presented in figure 28 below which provides a means of generalizing transition trends of built up areas for easy interpreting complex land change patterns. From figure 4.22 it is evident that the transition intensity of built up areas was more intense in the center of the study area, with the highly changed value (0.309) and less change at the value of (-0.205). The trend has shown a growing (sprawling) of built up areas towards the north and towards south relative to other directions. Thus, the trend and extent of changes in built up areas are likely to continue with the rapid development of infrastructure, economy and increasing of population.

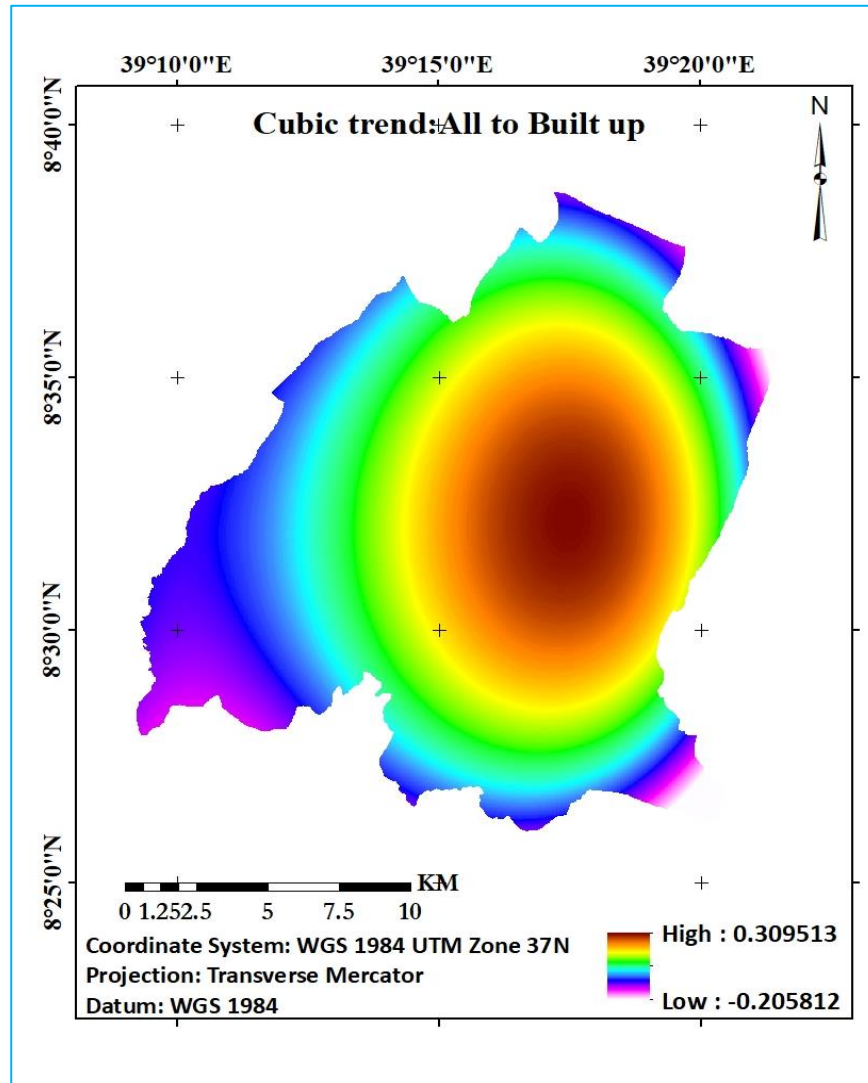


Figure 4.22: Map of spatial trend of changes All to Built-up between 1990 and 2020.

4.11. Modeling and Predicting Land Use/Land Cover Changes

4.11.1. Markov Transition Matrix Analysis.

The transition probability matrix was generated for the time periods of 1990–2000, 2000–2010, 2010–2020, and 1990–2020 to demonstrate the probability that each land cover type was projected to change (Table 4.15). The values on the diagonal of the matrix reflect the likelihood of a land cover type remaining in its original condition, while the values on the non-diagonal represent the likelihood of a land cover type changing to another kind. It can be observed from the matrix that the future change likelihood of barren land to built-up areas increased from 5.5% in 1990–2000 to 22.8% in 1990–2020. The likelihood of vegetation changing to built-up areas

increased reasonably from 2% in 1990–2000 to 11.3% in 1990–2020. This increase in the possibility of barren land and vegetation changing to built-up areas can be credited to the city’s historical setting and rapid population growth. The fast increase in the city’s population also led to an increased demand for urban infrastructures and services, which contributes to the expansion of built-up areas. During the entire period the probability of agriculture, vegetation, bare land and water bodies cover changing to the built-up area were 7.2%, 11.3%, 22.8% and 1% respectively and only 25.9% of agriculture remained unconverted (table 4.15). The change probabilities during the entire periods suggest rapid urban growth and a gradual decrease in agricultural lands due to urbanization. Therefore, the modeling of future scenarios is required to monitor and analyze LULC trends in 2030, 2040 and 2050. The transition probabilities derived from this are then used to compute the likely changes for future land use changes: the 2000–2010 probability matrix was used to calculate the land use changes for 2020, 2010–2020 for 2030, 2000–2020 for 2040, and 1990–2020 for 2050.

Table 4.15: Markov probability matrix for LULC changes during the periods from 1990 to 2000, 2000 to 2010, 2010 to 2020 and 1990 to 2020.

period	category	Built up	Agriculture	vegetation	bare land	Water body
1990-2000	Built up	0.7751	0.0043	0.1146	0.0966	0.0095
	Agriculture	0.0353	0.2823	0.1878	0.4472	0.0474
	Vegetation	0.0204	0.0010	0.3004	0.6740	0.0043
	bare land	0.0557	0.0006	0.1518	0.7905	0.0014
	Water body	0.0045	0.0205	0.2047	0.1331	0.6372
2000-2010 For 2020.	Built up	0.8045	0.0202	0.1108	0.0396	0.0249
	Agriculture	0.0047	0.6943	0.2888	0.0049	0.0073
	Vegetation	0.0677	0.0535	0.5556	0.3079	0.0153
	Bare land	0.0446	0.0063	0.2452	0.6964	0.0075
	Water body	0.0124	0.1746	0.3915	0.0386	0.3829
2010-2020 For 2030	Built up	0.8222	0.0245	0.1140	0.0378	0.0016
	Agriculture	0.0224	0.5209	0.2852	0.1585	0.0131
	Vegetation	0.1225	0.0453	0.5130	0.3169	0.0023
	Bare land	0.1598	0.0217	0.2057	0.6127	0.0001
	Water body	0.2814	0.0618	0.3396	0.1657	0.1517
1990-2020 For 2050	Built up	0.7998	0.0240	0.1142	0.0617	0.0004
	Agriculture	0.0722	0.2590	0.4502	0.2112	0.0074
	vegetation	0.1133	0.0376	0.5020	0.4192	0.0009
	Bare land	0.2281	0.0202	0.1774	0.5743	0.0001
	Water body	0.0193	0.0667	0.5048	0.0342	0.3750
2000-2020 For 2040	Built up	0.8291	0.0484	0.0978	0.0242	0.0005
	Agriculture	0.0201	0.6336	0.1645	0.1806	0.0013
	vegetation	0.2035	0.0619	0.5259	0.2071	0.0016
	Bare land	0.1707	0.0225	0.2434	0.5629	0.0004
	Water body	0.0486	0.0685	0.5862	0.0578	0.2390

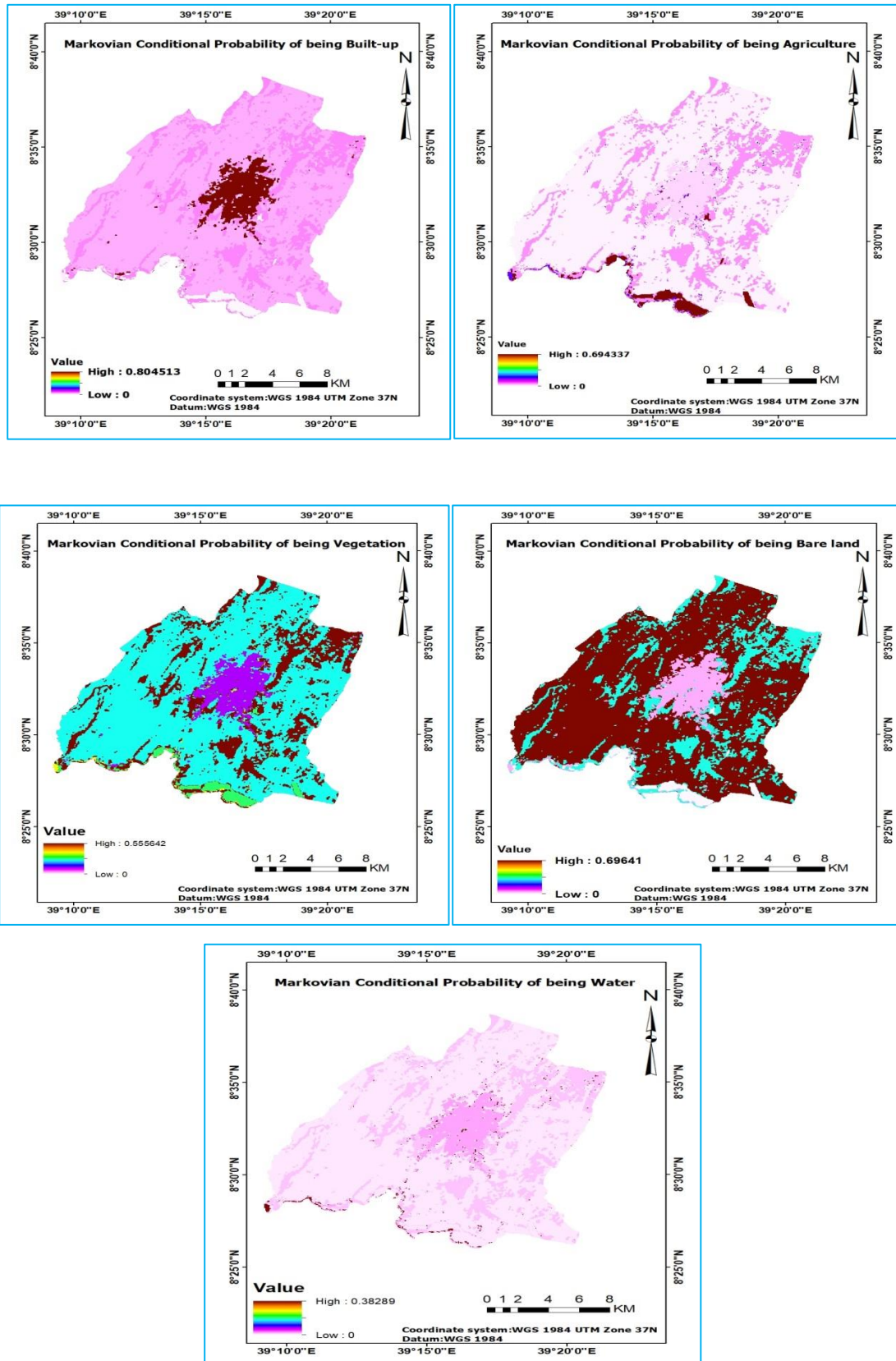


Figure 4.23: markovian conditional probability images to simulate 2020.

4.12. Model Simulations and Validations

4.12.1. CA-Markov model validation

The state transition area matrix and state transition probability matrix are created according to land use maps in 2000 and 2010, which can be obtained by running the CA-Markov model in IDRISI software based on the suitability map that has already been created. The predictive results map for 2020 is obtained with a 5×5 contiguity filter, whose running cycle is 10 years. The next step is to employ IDRISI's CROSSTAB module. Predictive results are analyzed by overlaying the land use map of 2020 that is truly classified. If the Kappa value is less than or equal to 0.4, the land uses have typically changed dramatically, with little consistency between the two pictures. If the Kappa index is between 0.4 and 0.75, there are broad similarities and differences between the two pictures. Aside from that, there is a lot of consistency between the two pictures (Yousheng et al., 2011). Kappa values typically range from 0 to 1. The performance of the CA-Markov model was also assessed based on three more statistics: 1) Kappa index of agreement (denoted K_{standard}); 2) Kappa for no information (denoted K_{no}), and 3) Kappa for grid-cell level location (denoted K_{location}) (table 4.16). Here, the Kappa index between the predicted map and the observed map of 2020 is 0.8424, which is above 0.75, illustrating that the results are reliable. The actual observed findings and the predicted results are quite consistent. The precision for correct predictions is relatively high; therefore, this method can be used to predict the results in 2030, 2040 and 2050. Table 4.16 confirmed that the accuracy assessment of the classified data of 2020 is acceptable and reasonable for any applications based on KIA. All K index values above the minimum acceptable level and were more than 80%, (appendix-F) indicating that the projected and real LULC maps were in good agreement (Mishra et al., 2014).

Table 4.16: Validation results of the CA-Markov model.

Year.	Kappa parameters				
	K_{location}	K_{no}	$K_{\text{location Strata}}$	k_{standard}	Overall Kappa
2020	0.9562	0.8648	0.9562	0.8424	0.8424

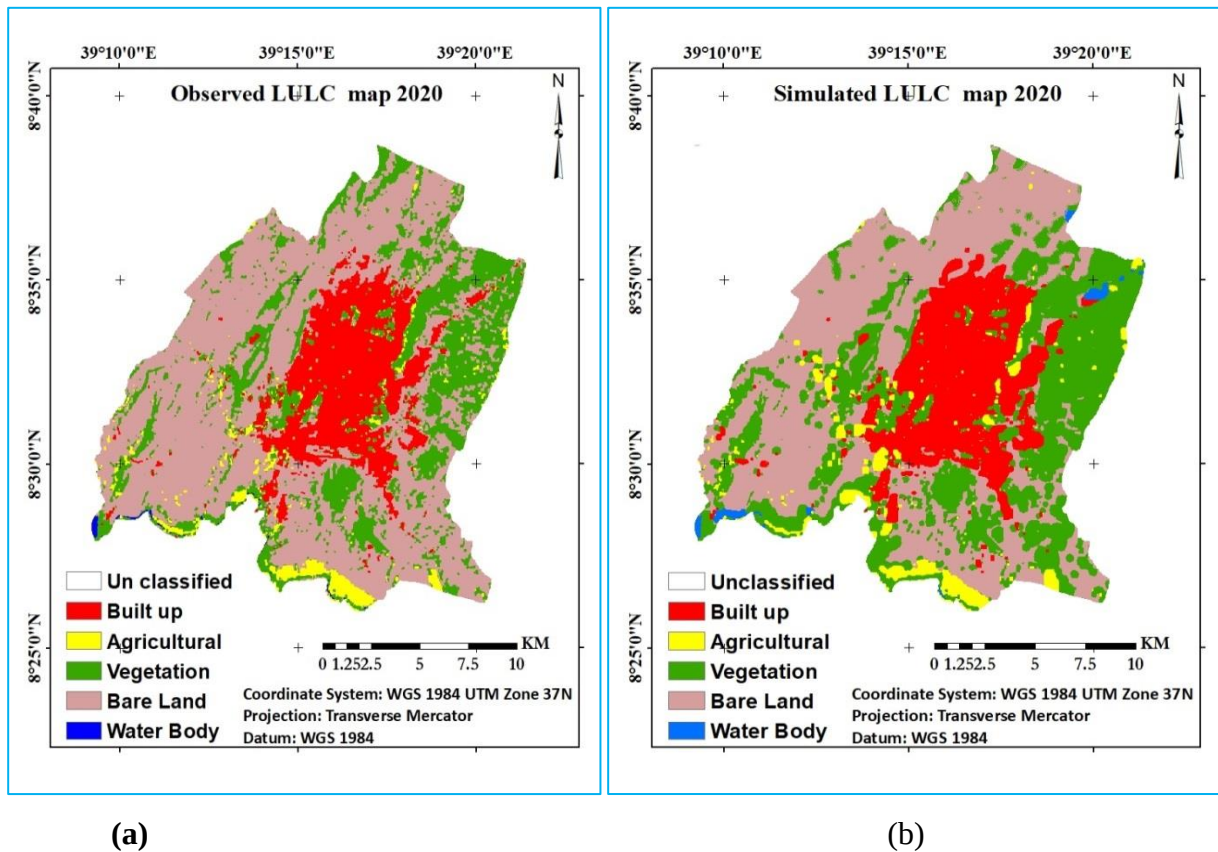


Figure 4.24: 2020 LULC observed (a) and simulated (b)

Table 4.17: Adama cities observed and simulated LULC 2020.

No.	Category	simulated LULC map of 2020		Observed LULC map of 2020		Change in Area (%)
		Area(ha)	%	Area(ha)	%	
1	Built up	6291.36	20	5294.16	17	-3
2	Agricultural	1402.20	4.4	1049.40	3.35	-1.05
3	Vegetation	10393.56	33.2	7456.86	23.8	-9.4
4	Bare Land	12975.12	41.4	17421.12	55.6	-14.2
5	Water Body	228.87	0.7	68.76	0.2	0.5

4.13. Future LULC modeling and change analysis.

4.13.1. Change between 2020 and 2030

The simulation results of the CA–Markov model predicted that the built-up area will increase from 5294.16ha in 2020 to approximately 8094.06ha in 2030. Agriculture cover will increase

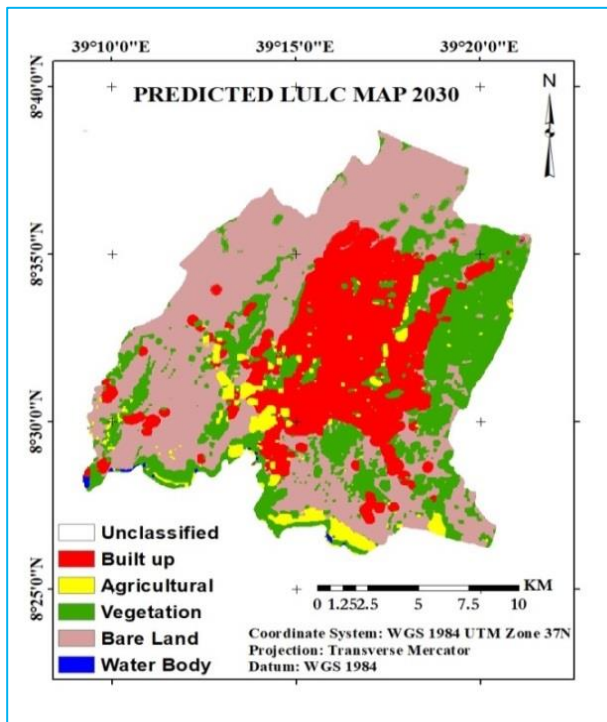
from 1049.40ha in 2020 to about 1396.8ha in 2030. The vegetation cover will increase from 7456.86ha to about 8333.46ha during the period between 2020 and 2030. The area of barren land will decrease from 17421.12ha in 2020 to around 13407.39ha in 2030. The city's water bodies will decrease from 68.76ha to about 59.7 ha between 2020 and 2030.

4.13.2. Change between 2020 and 2040

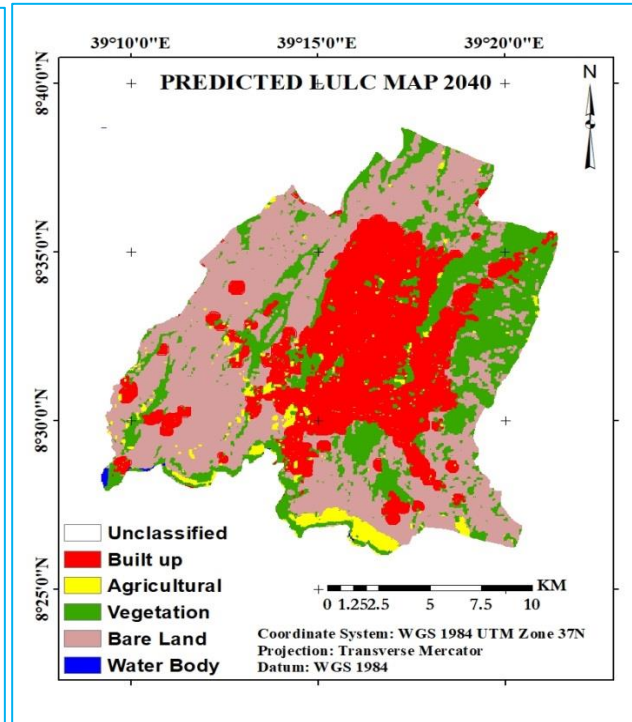
Similarly, the simulation model for 2040 revealed a predicted built-up area will increase from 5294.16 ha in 2020 to approximately 8906.1 ha in 2040. Agriculture cover will increase from 1049.40 ha in 2020 to about 1780.2ha in 2040. The area of vegetation cover will increase from 7456.86ha in 2020 to nearly 8893.2ha in 2040. Barren land will decrease considerably from 17421.12 ha to about 11674.9 ha, signifying a decline of 18.4% between 2020 and 2040. Water bodies will decrease from 68.76 ha in 2020 to approximately 36.4 ha in 2040.

4.13.3. Change between 2020 and 2050

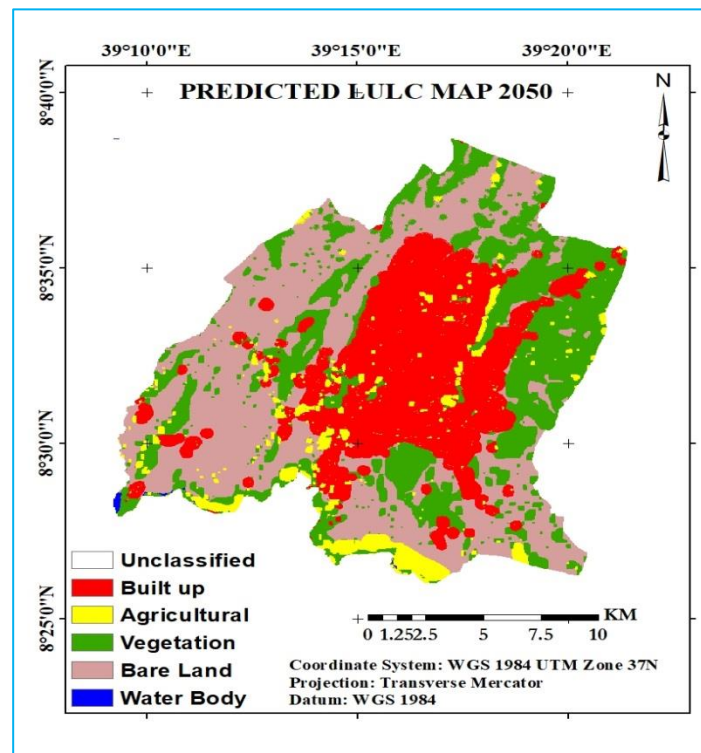
According to the model estimations 2050, built-up area increase from 5294.16 ha in 2020 to approximately 9129.96ha in 2050 signifying the increment of 12.3%. Agriculture cover will decrease from 1049.40ha in 2020 to about 1035ha in 2050. The area of vegetation cover will increase from 7456.86 ha in 2020 to nearly 7402.68 ha in 2050. Barren land will decrease considerably from 17421.12 ha to about 13681.08 ha, signifying a decline of 11.95% between 2020 and 2050. Water bodies will decrease from 68.76 ha in 2020 to approximately 42.30ha in 2050. This result suggests that the increase in built-up areas and the continuous reforestation programs will contribute to the expected reduction in barren lands. The availability of infrastructural, educational, and medical facilities in these city will significantly increase the urban population and alter the city's land uses, affecting the natural environment and further expected to experience an unsustainable natural environment shifting into built-up areas in the future due to excessive human activities. Therefore, in order to balance the expansion of urban areas and conserve the natural environment in Adama city, certain policies that necessitate rapid urban growth and expansion without providing a harmonious association between human activities and the ecological environment need to be amended. This will help urban planners and local authorities effectively to manage land uses and maintain their complex change dynamics.



(a)



(b)



(c)

Figure 4.25: Modeled LULC 2030(a), 2040(b) and 2050(c)

Table 4.18: Statistical distribution of the modeled LULC in 2030, 2040 and 2050.

	Year	2020		2030		2040		2050	
No	LULC	Area(ha)	%	Area (ha)	%	Area(ha)	%	Area(ha)	%
1	Built up	5294.16	17	8094.06	26	8906.1	28	9130	30
2	Agriculture	1049.40	3.35	1396.8	4.4	1780.2	5.6	1035	3.3
3	Vegetation	7403	24	8333.46	26	8893.2	28	7456	23
4	Bare land	17421	55.6	13407.39	42.8	11674.9	37.3	13681.1	43.7
5	Water body	68.76	0.2	59.76	0.19	36.450	0.1	42.30	0.13
LULC Change between									
		2020–2030		2020-2040		2020-2050			
No.	LULC	Area (ha.)	%	Area (ha.)	%	Area (ha.)	%		
1	Built up	2,799.9	9	3,611.94	11	3,835.8	13		
2	Agriculture	347.4	1	730.8	2.2	-14.4	-1		
3	Vegetation	876.6	2.2	1,436.34	4.2	53	-1		
4	Bare land	-4,013.73	-12.8	-5,746.22	-18.3	-3,740.04	-11.9		
5	Water body	-9	-0.02	-32.31	-0.1	-26.46	-0.07		

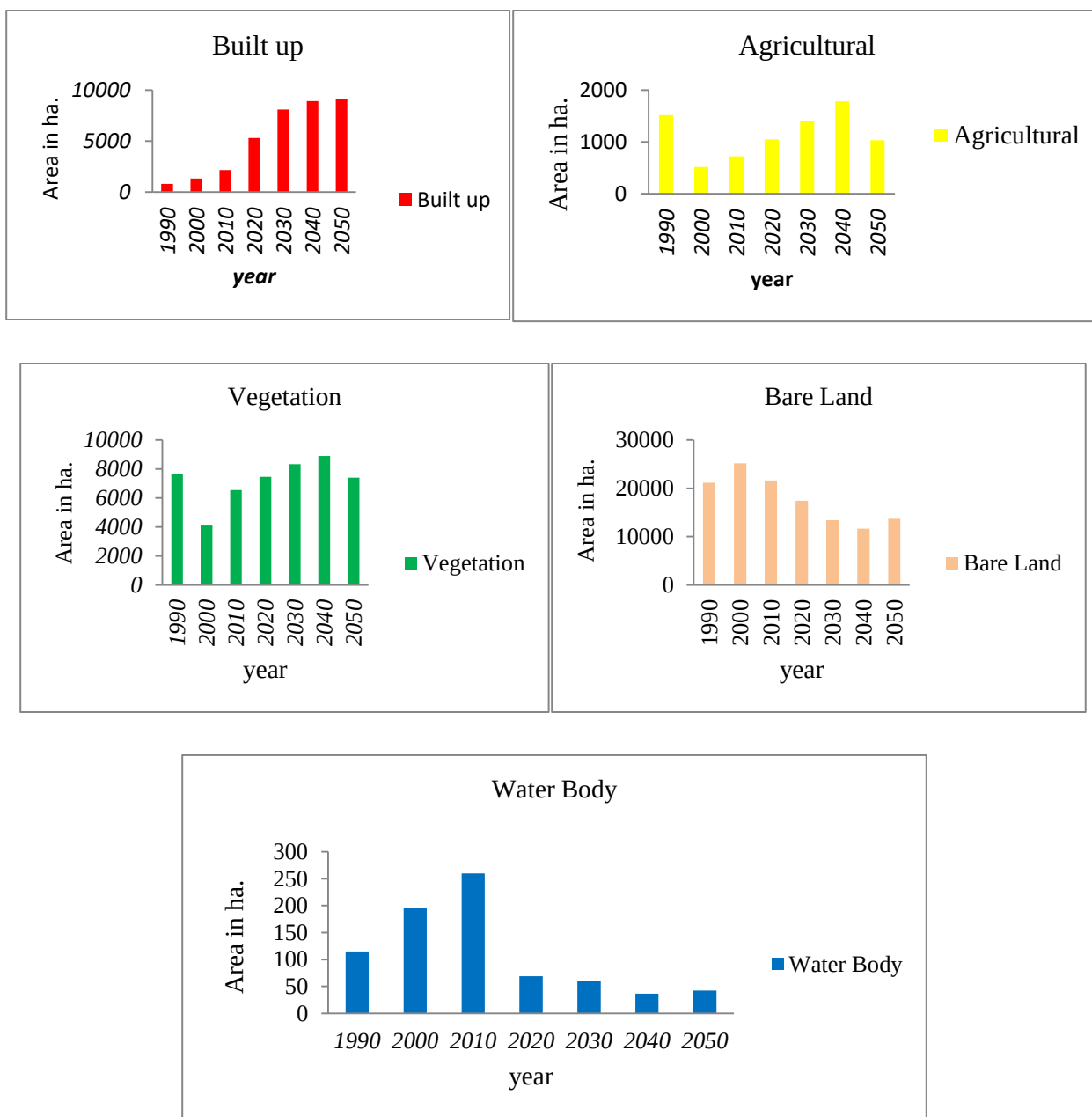


Figure 4.26: Land use land covers change trends in 1990–2050

From the above bar graph the result of study concluded that there is a significant increase in built up area from 1990 to 2050; while barren land decreased, and there has been an observable increasing and decreasing trend of change in the other land cover classes of agriculture, vegetation and water body during study period between 1990 and 2050.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION.

5.1 Conclusion.

The study used geospatial techniques to detect and predict land use and land cover change in Adama city over a 30-year period through an integrated CA–Markov that combined the advantages of cellular automata and the Markov chain model. Multi-temporal satellite data and GIS techniques were employed to monitor the city’s historical land use/land cover pattern using the land cover maps of 1990, 2000, 2010 and 2020. In this study, the land cover maps were classified into five major Land use land cover classes (built-up area, agriculture, vegetation, barren land, and water bodies). This was to comprehensively understand the city’s Land use land cover changes and predict the future. The model was validated using simulated and observed LULC 2020 by using kappa parameters; with the overall kappa index 0.84%; which indicates good kappa index values to predict the future Land use land cover change changes in 2030, 2040 and 2050. The result of this study presented noticeable changes in the spatial and quantitative distribution of land use/land cover. It revealed that the city’s built-up area have to grow continuously between 1990 and 2020, while other land class decreased during the study period. The result shows that the proportion of built up area was 2.5% in 1990,5% in 2000,7% in 2010, and this figure rose to just 17% in 2020, with annual growth rates of 6.4%(52ha) from1990 to 2000, 6.2%(82ha) from 2000 to 2010 and 14.7%(316ha) from 2010-2020., indicates an expansion in built-up area was 4493ha for the entire period from 1990 to 2020, resulting in agriculture, barren land, vegetation, and water bodies losing 463 ha, 3760 ha, 223 ha, and 46 ha, respectively from 1990 to 2020.

The outcome of the LULC change prediction will reveal increase in built-up areas, expected that 8094ha, 8906ha, and 9130ha in 2030, 2040, and 2050; indicates the expansion of 9% from 2020-2030, 11% from 2020-2040, and 13% from 2020-2050, while the agriculture, vegetation, barren land, and water body will decrease by 1%,1%,11.9%,and 0.1% next 30 years from 2020-2050. The findings of the study shown the historical LULCC and highlight the future change in the next 30 years. The study successfully demonstrated the CA–Markov model’s efficiency, using remotely sensed data and GIS techniques to monitor spatio-temporal Land use land cover changes and predict future land cover patterns. Such data are vital for informed decision-making in urban planning, providing the potential information required monitoring growth and improving environmental sustainability. Although the

present study effectively predicted the expected Land use land cover of 2030, 2040 and 2050. This study makes a significant addition by integrating biophysical and socioeconomic factors to assess LUC as a result of fast urbanization: distance to road, distance to built-up areas, and distance to water bodies, as well as slope and elevation. The AHP relative weights for these expansion factors are distance to major roads (0.512), distance to built-up, (0.261), slope (0.129), elevation (0.06) and distance to water bodies (0.03); with this value urban expansions are mainly driven by distance to major roads and the existing built-up based on the current available data. The result predicted that the conversions of other land-use types into built-up areas will persist in the southern and northern areas of the city; this type of future LULC picture forecasting can be useful for urban environmental management planning.

5.2. Recommendations.

On the basis of this research following future prospects and recommendation can be made:

- ✓ From the research, urbanization of Adama city from 1990 to 2050 is expected to causing severe impact on socio economic, environmental aspects and other land covers. It is high time for planner and policy makers to develop urbanization not only in horizontal dimension but in vertical dimension as well. Furthermore, implementation of building bylaws and land use plans is highly recommended.
- ✓ The use of high resolution imageries such as IKONOS and Quick Bird are important in generating good quality of land cover maps. Because urban areas have complex and heterogonous features, high resolution imagery provides better information by mapping these areas. Moreover, the use of ancillary data as ground truth helps for better accuracy of an image classification.
- ✓ Consistent multi-temporal Landsat data for each year provides detail comparison of images, change analysis and modeling. Especially for Markov chain method, it is a requirement of equal interval of images acquisition although there have been uneven temporal availability of data.
- ✓ Political factor, technology, land policy, biophysical and social factor could improve the performance of the models for future predictions. Hence, it is important to the urban planners and decision makers.

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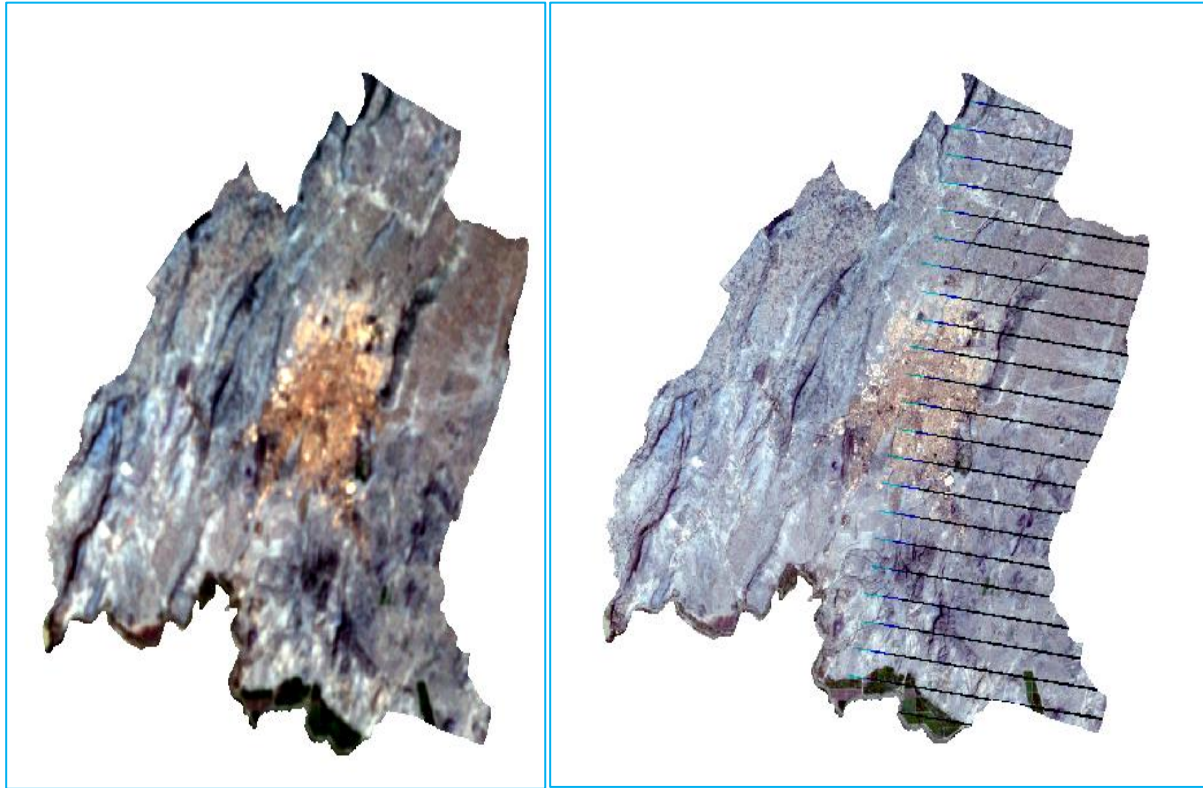
APPENDICES

Appendix-A: Ground control point (GCP) used for validation of the model

Northing	Easting	Class Name
946148.16 m	529329.76 m	builtup
946051.37 m	529490.30 m	builtup
945929.22 m	529366.30 m	builtup
946603.11 m	531239.91 m	builtup
947564.88 m	531593.23 m	builtup
948167.56 m	531845.20 m	builtup
948813.80 m	530505.56 m	builtup
949580.67 m	530886.85 m	builtup
942190.40 m	531147.18 m	builtup
943176.11 m	532329.45 m	builtup
939636.45 m	531818.44 m	builtup
938345.52 m	525877.62 m	builtup
948138.55 m	528951.28 m	builtup
948854.00 m	529197.55 m	builtup
940869.32 m	526867.40 m	builtup
941720.59 m	527151.91 m	builtup
949206.17 m	527843.66 m	vegetation
942458.80 m	526937.04 m	vegetation
942764.56 m	528564.49 m	vegetation
945712.10 m	533210.02 m	vegetation
948212.26 m	534407.41 m	vegetation
938663.90 m	529602.69 m	vegetation
937714.56 m	529655.07 m	vegetation
936746.75 m	530767.95 m	vegetation
935653.82 m	531538.88 m	vegetation
939203.07 m	518417.60 m	vegetation

940155.23 m	519363.14 m	vegetation
936629.13 m	517168.62 m	water body
936676.58 m	518102.10 m	water body
936891.67 m	519093.61 m	water body
937299.80 m	519792.30 m	water body
936516.96 m	520444.05 m	water body
936011.78 m	521606.13 m	water body
936209.90 m	522347.17 m	water body
936970.98 m	522814.07 m	water body
933834.14 m	529149.34 m	water body
932720.59 m	530197.83 m	water body
934221.52	528561.46 m	agriculture
934024.16	529440.54 m	agriculture
932829.00	530390.59 m	agriculture
941958.18 m	531791.63 m	agriculture
938215.15 m	524678.92 m	agriculture
937570.92 m	525804.56 m	agriculture
936744.44 m	525835.37 m	agriculture
935965.24 m	526139.81 m	agriculture
934387.31 m	526670.72 m	agriculture
934826.35 m	526782.34 m	bareland
935505.00 m	529631.65 m	bareland
936836.14 m	530169.59 m	bareland
949887.67 m	532369.55 m	bareland
949275.73 m	531134.34 m	bareland
942314.41 m	528331.23 m	bareland
939392.05 m	521967.14 m	bareland
934903.63 m	529803.82 m	bareland
934455.32 m	531402.93 m	bareland
947394.39 m	525199.58 m	bareland

Appendix-B: Gap-filling of Landsat 7 ETM+ Image scans line error by using Landsat toolbox.



Appendix- C: LULC error matric table.

	REFERENCE DATA (1990)							
	LULC	Built-up	Agriculture	Vegetation	Barren Land	Water body	Total Points	U. A (100%)
CLASSIFIED DATA (1990)	Built-up area	41	1	2	0	5	49	83.67
	Agriculture	0	42	0	1	3	46	91.3
	Vegetation	0	0	44	3	0	47	93.6
	Barren Land	3	0	0	46	3	52	88.46
	Water body	3	7	0	4	42	56	75
	Total points	47	50	46	54	53	250	
	P. A (100%)	87.23	84	95.65	85.185	79.245		
	Overall Accuracy =86%							
	Kappa Coefficient (K) =0.82							

	REFERENCE DATA (2000)							
CLASSIFIED DATA (2000)	LULC	Built-up	Agriculture	Vegetation	Barren Land	Water body	Total Points	U.A (100%)
	Built-up	42	0	2	2	2	48	87.5
	Agriculture	0	46	0	3	4	53	86.79
	Vegetation	0	1	44	3	0	48	91.666
	Barren Land	1	3	0	45	3	52	86.53
	Water body	2	2	1	1	43	49	87.75
	Total points	45	52	47	54	52	250	
	P. A (100%)	93.33	88.46	93.6	83.33	82.69		
	Overall Accuracy =88%							
	Kappa Coefficient (K) =0.8499							

	Reference Data (2010)							
Classified Data (2010)	LULC	Built-up	Agriculture	Vegetation	Barren Land	Water body	Total points	U.A (100%)
	Built-up area	45	1	1	1	1	49	91.8
	Agriculture	2	46	0	1	3	52	88.46
	Vegetation	1	0	44	2	1	48	91.666
	Barren Land	2	2	0	44	2	50	88
	Water body	1	1	1	2	46	51	90.19
	Total points	51	50	46	50	53	250	
	P. A (100%)	88.23	92	86.7	88	95.65		
	Overall Accuracy =90%							
	Kappa Coefficient (K) =0.87							

	REFERENCE DATA (2020)							
CLASSIFIED DATA (2020)	LULC	Built-up	Agriculture	Vegetation	Barren Land	Water body	Total Points	U.A (100%)
	Built-up	46	2	0	1	1	50	92
	Agriculture	1	45	0	2	1	49	91.8
	Vegetation	1	0	47	0	2	50	94
	Barren Land	1	1	3	46	0	51	90.19
	Water body	1	2	1	1	45	50	90
	Total points	50	50	51	50	49	250	
	P.A (100%)	92	90	92.156	92	91.83		
	Overall Accuracy =91.6%							
	Kappa Coefficient (K) =0.895							

Appendix- D: Questionnaire forms filled by experts for suitability analysis of Adama city.

No.	Factors	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Sum	Average
1	Distance to nearest Built-up	16	14	18	19	20	18	105	17
2	Distance to nearest roads	19	13	19	17	20	19	107	18
3	Slope	20	20	15	13	16	15	99	16
4	Distance to nearest Water Body.	14	15	16	13	17	16	91	15
5	Elevation	16	15	17	14	16	15	93	15

Appendix-E: AHP method weight derivation.

WEIGHT - AHP weight derivation

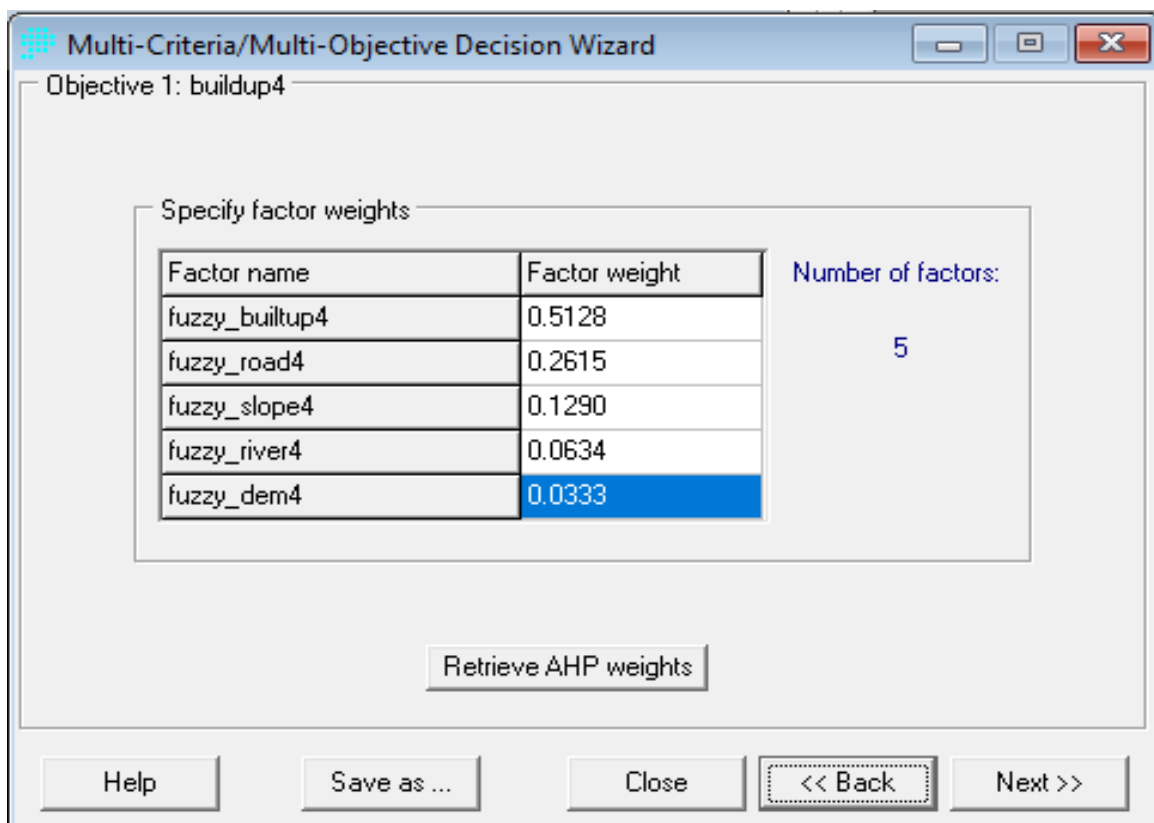
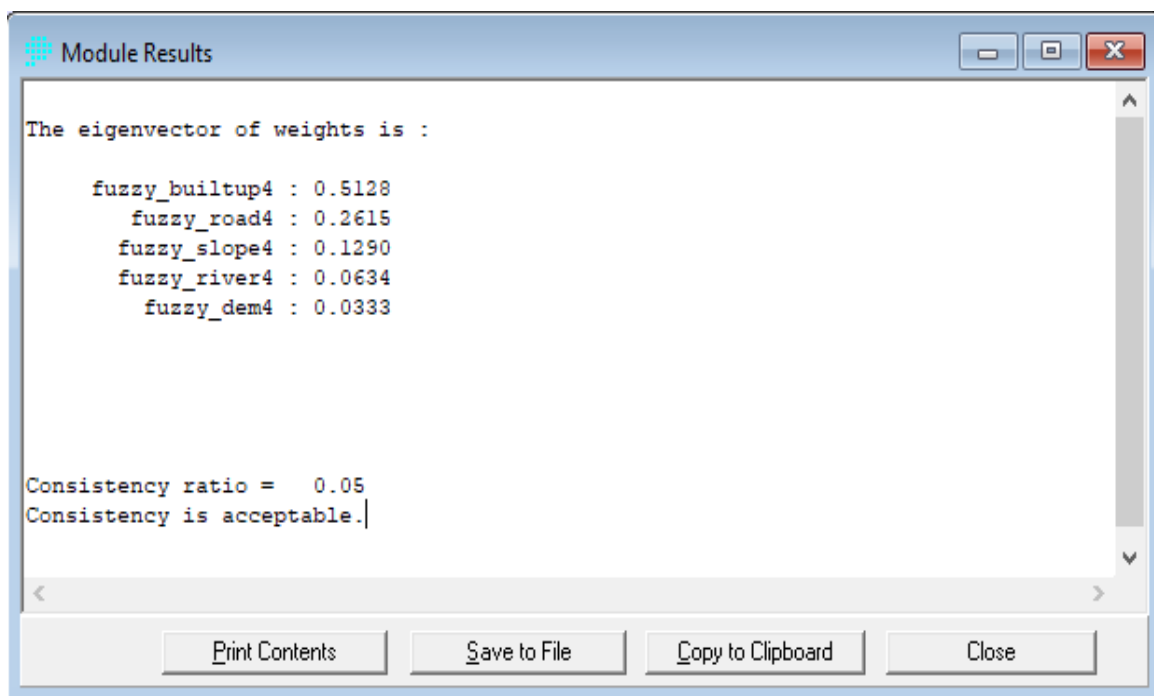
Pairwise Comparison 9 Point Continuous Rating Scale

1/9	1/7	1/5	1/3	1	3	5	7	9
extremely	very strongly	strongly	moderately	equally	moderately	strongly	very strongly	extremely
Less Important					More Important			

Pairwise comparison file to be saved : ...

	fuzzy_builtup4	fuzzy_road4	fuzzy_slope4	fuzzy_river4	fuzzy_dem4
fuzzy_builtup4	1				
fuzzy_road4	1/3	1			
fuzzy_slope4	1/5	1/3	1		
fuzzy_river4	1/7	1/5	1/3	1	
fuzzy_dem4	1/9	1/7	1/5	1/3	1

Compare the relative importance of fuzzy_dem4 to fuzzy_river4



Appendix-F: model validation statistics simulated and actual 2020.

Module Results

Cross-tabulation of tmp166 (columns) against 2020_new_new (rows)

	0	1	2	3	4	5	Total
0	232718	0	0	0	0	0	232718
1	0	57465	460	253	99	547	58824
2	0	174	10075	1370	39	2	11660
3	0	2157	2974	73949	3630	144	82854
4	0	10101	1778	39835	140390	1464	193568
5	0	7	293	77	10	377	764
Total	232718	69904	15580	115484	144168	2534	580388

Chi Square = 1634829.25000
df = 25
P-Level = 0.0000
Cramer's V = 0.7506

Proportional Crosstabulation

	0	1	2	3	4	5	Total
0	0.4010	0.0000	0.0000	0.0000	0.0000	0.0000	0.4010
1	0.0000	0.0990	0.0008	0.0004	0.0002	0.0009	0.1014
2	0.0000	0.0003	0.0174	0.0024	0.0001	0.0000	0.0201
3	0.0000	0.0037	0.0051	0.1274	0.0063	0.0002	0.1428
4	0.0000	0.0174	0.0031	0.0686	0.2419	0.0025	0.3335
5	0.0000	0.0000	0.0005	0.0001	0.0000	0.0006	0.0013
Total	0.4010	0.1204	0.0268	0.1990	0.2484	0.0044	1.0000

Overall Kappa = 0.8424

Validate: [tmp166] V.S. [2020_new_new] with no stratification

View as Bar | View as Text

Multiples of Base Resolution (MBR): 1 x 1 Information of Quantity

Information of Location	No[n]	Medium[m]	Perfect[p]
Perfect[P(x)]	0.5988	0.9149	1.0000
PerfectStratum[K(x)]	0.5988	0.9149	1.0000
MediumGrid[M(x)]	0.5563	0.8873	0.8542
MediumStratum[H(x)]	0.1667	0.2848	0.3031
No[N(x)]	0.1667	0.2848	0.3031

AgreeGridcell = 0.6025 DisagreeQuantity = 0.0851 Kstandard = 0.8424
AgreeStrata = 0.0000 DisagreeStrata = 0.0000 Kno = 0.8648
AgreeQuantity = 0.1181 DisagreeGridcell = 0.0276 Klocation = 0.9562
AgreeChance = 0.1667 KlocationStrata = 0.9562

MBR: 1 x 1

Save as ... Print... Close << Less